SURUTHI S

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In [2]:

```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

In [3]:

```
customer_data = pd.read_csv('Mall_Customers.csv')
customer_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 [4]:

```
customer_data.shape
```

Out[4]:

```
(200, 5)
```

In [5]:

```
customer_data.columns
```

Out[5]:

```
Index(['CustomerID', 'Genre', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

In [6]:

```
customer_data.dtypes
```

Out[6]:

```
CustomerID                 int64
Genre                     object
Age                        int64
Annual Income (k$)         int64
Spending Score (1-100)     int64
dtype: object
```

In [7]:

```
customer_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   CustomerID              200 non-null    int64 
 1   Genre                   200 non-null    object
 2   Age                     200 non-null    int64 
 3   Annual Income (k$)      200 non-null    int64 
 4   Spending Score (1-100)  200 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

In [8]:
```
customer_data.value_counts()
```

Out[8]:
```
CustomerID  Genre   Age  Annual Income (k$)  Spending Score (1-100)
1           Male    19   15                  39                        1
138         Male    32   73                  73                        1
128         Male    40   71                  95                        1
129         Male    59   71                  11                        1
130         Male    38   71                  75                        1
                                                                      ..
70          Female  32   48                  47                        1
71          Male    70   49                  55                        1
72          Female  47   49                  42                        1
73          Female  60   50                  49                        1
200         Male    30   137                 83                        1
Length: 200, dtype: int64
```

Step2 [Label encode gender]

In [9]:
```
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
customer_data['Genre'] = label_encoder.fit_transform(customer_data['Genre'])
customer_data.head()
```

Out[9]:

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

Step3 [Check for variance]

In [10]:
```
customer_data.describe()
```

Out[10]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000	200.000000
mean	100.500000	0.440000	38.850000	60.560000	50.200000
std	57.879185	0.497633	13.969007	26.264721	25.823522
min	1.000000	0.000000	18.000000	15.000000	1.000000
25%	50.750000	0.000000	28.750000	41.500000	34.750000
50%	100.500000	0.000000	36.000000	61.500000	50.000000
75%	150.250000	1.000000	49.000000	78.000000	73.000000
max	200.000000	1.000000	70.000000	137.000000	99.000000

In [11]:
```
customer_data.var()
```

Out[11]:
```
CustomerID                3350.000000
Genre                        0.247638
Age                        195.133166
Annual Income (k$)         689.835578
Spending Score (1-100)     666.854271
dtype: float64
```

In [12]:
```
1 customer_data.corr()
```

Out[12]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
CustomerID	1.000000	0.057400	-0.026763	0.977548	0.013835
Genre	0.057400	1.000000	0.060867	0.056410	-0.058109
Age	-0.026763	0.060867	1.000000	-0.012398	-0.327227
Annual Income (k$)	0.977548	0.056410	-0.012398	1.000000	0.009903
Spending Score (1-100)	0.013835	-0.058109	-0.327227	0.009903	1.000000

Step4 [Check skewness]

In [13]:
```
1 customer_data.skew()
```

Out[13]:
```
CustomerID                0.000000
Genre                     0.243578
Age                       0.485569
Annual Income (k$)        0.321843
Spending Score (1-100)   -0.047220
dtype: float64
```

In [14]:
```
1 customer_data.sort_values(by =['Genre','Age','Annual Income (k$)','Spending Scor
```

Out[14]:

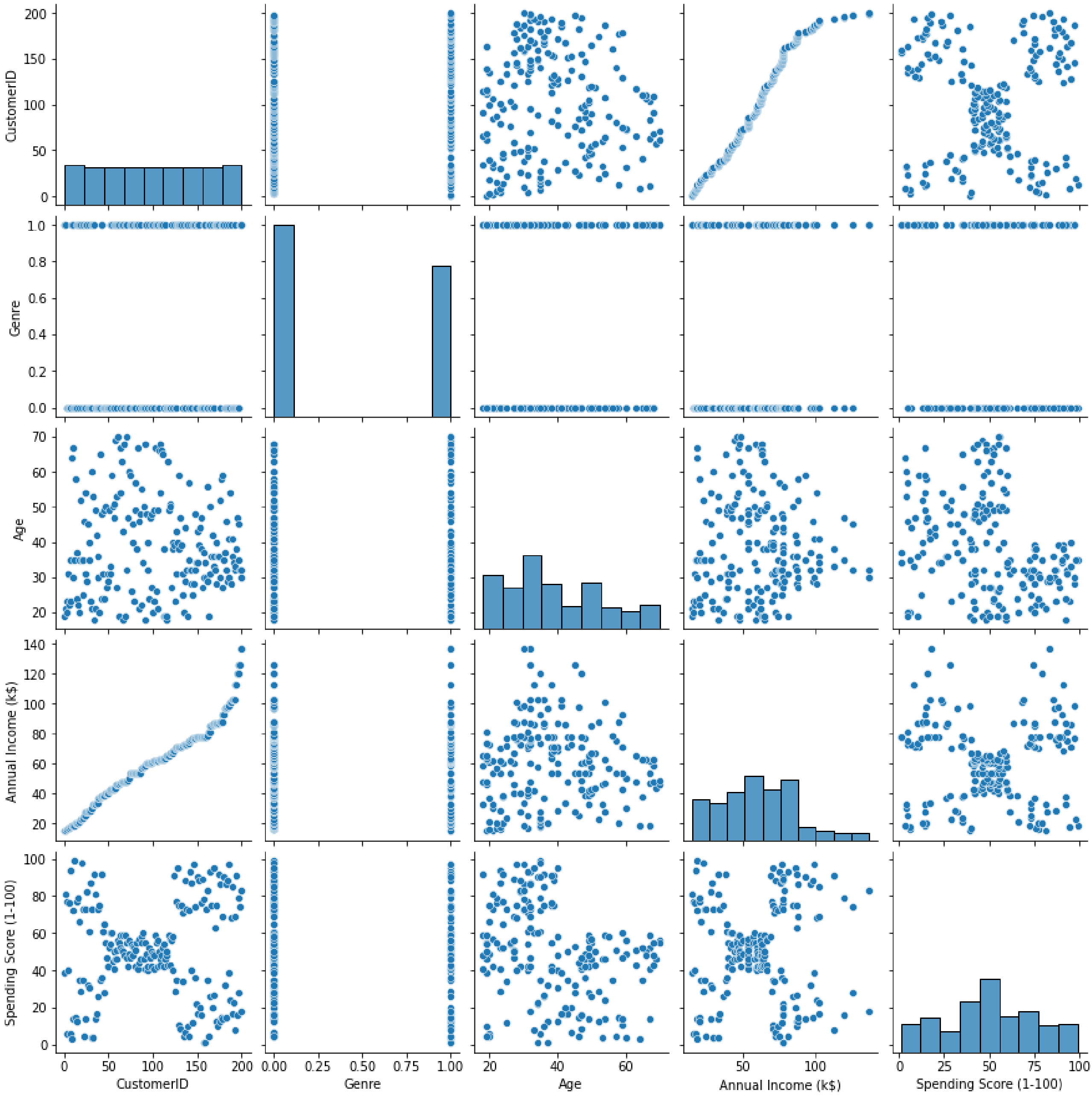
	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
114	115	0	18	65	48
111	112	0	19	63	54
115	116	0	19	65	50
2	3	0	20	16	6
39	40	0	20	37	75
...	...	...	...	...	...
102	103	1	67	62	59
108	109	1	68	63	43
57	58	1	69	44	46
60	61	1	70	46	56
70	71	1	70	49	55

200 rows × 5 columns

Step5 [Pair plot]

In [15]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
sns.pairplot(data=customer_data)
```

Out[15]: <seaborn.axisgrid.PairGrid at 0x7f172d04f130>



Step6 [Build KMeans]

In [16]:
```python
from sklearn.cluster import KMeans
```

In [17]:
```python
customer_data.drop(['CustomerID'],axis=1, inplace=True)
```

In [18]:
```python
KM = KMeans(n_clusters=5)
KM.fit(customer_data)
```

Out[18]: KMeans(n_clusters=5)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [19]:
```
KM.labels_
```

Out[19]:
```
array([3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4,
       3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 1,
       3, 4, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 0, 2, 1, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
       0, 2], dtype=int32)
```

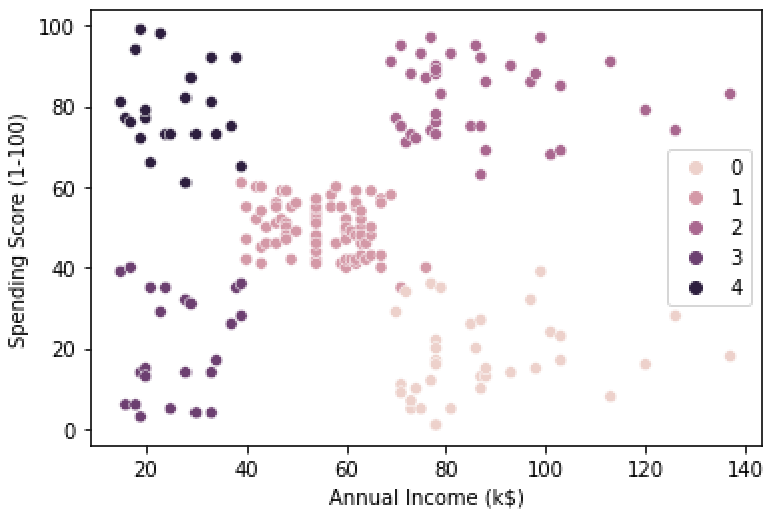
In [20]:
```
print(KM.cluster_centers_)
```

```
[[ 0.52777778 40.66666667 87.75       17.58333333]
 [ 0.4125     42.9375     55.0875     49.7125    ]
 [ 0.46153846 32.69230769 86.53846154 82.12820513]
 [ 0.39130435 45.2173913  26.30434783 20.91304348]
 [ 0.40909091 25.27272727 25.72727273 79.36363636]]
```

Step7 [Scatter Plot]

In [21]:
```
sns.scatterplot(customer_data['Annual Income (k$)'], customer_data['Spending Sco
```

Out[21]:
```
<AxesSubplot:xlabel='Annual Income (k$)', ylabel='Spending Score (1-100)'>
```



Step8 [Cluster Analysis]

In [22]:
```
kmeans2 = KMeans(n_clusters = 5, init='k-means++')
kmeans2.fit(customer_data)
pred = kmeans2.predict(customer_data)
```

In [23]:
```
frame = pd.DataFrame(customer_data)
frame['cluster'] = pred
```

In [24]:
```
frame.cluster.value_counts()
```

Out[24]:
```
1    79
3    39
2    37
0    23
4    22
Name: cluster, dtype: int64
```

In [25]:
```
frame
```

Out[25]:

	Genre	Age	Annual Income (k$)	Spending Score (1-100)	cluster
0	1	19	15	39	0
1	1	21	15	81	4
2	0	20	16	6	0
3	0	23	16	77	4
4	0	31	17	40	0
...	...	...	...	...	...
195	0	35	120	79	3
196	0	45	126	28	2
197	1	32	126	74	3
198	1	32	137	18	2
199	1	30	137	83	3

200 rows × 5 columns

In [26]:
```
C0 = customer_data[customer_data['cluster'] == 0]
C1 = customer_data[customer_data['cluster'] == 1]
C2 = customer_data[customer_data['cluster'] == 2]
C3 = customer_data[customer_data['cluster'] == 3]
C4 = customer_data[customer_data['cluster'] == 4]
```

In [27]:
```
import statistics as ss
print('Average Age : ',C0['Age'].mean())
print('Average Annual Income : ',C0['Annual Income (k$)'].mean())
print('Deviation of the mean for annual Income : ',ss.stdev(C0['Annual Income (k
print('No. of Customers ie shape :' ,C0.shape)
print('From those Customers We have',C0.Genre.value_counts()[1],'males and',C0.G
```

```
Average Age :  45.21739130434783
Average Annual Income :  26.304347826086957
Deviation of the mean for annual Income :  7.893811054517766
No. of Customers ie shape : (23, 5)
From those Customers We have 9 males and 14 females
```

In [28]:
```
print('Average Age : ',C1['Age'].mean())
print('Average Annual Income : ',C1['Annual Income (k$)'].mean())
print('Deviation of the mean for annual Income : ',ss.stdev(C1['Annual Income (k
print('No. of Customers ie shape :' ,C1.shape)
print('From those Customers We have',C1.Genre.value_counts()[1],'males and',C1.G
```

```
Average Age :  43.12658227848101
Average Annual Income :  54.822784810126585
Deviation of the mean for annual Income :  8.576592314850398
No. of Customers ie shape : (79, 5)
From those Customers We have 33 males and 46 females
```

In [29]:

```python
print('Average Age : ',C2['Age'].mean())
print('Average Annual Income : ',C2['Annual Income (k$)'].mean())
print('Deviation of the mean for annual Income : ',ss.stdev(C2['Annual Income (k
print('No. of Customers ie shape :' ,C2.shape)
print('From those Customers We have',C2.Genre.value_counts()[1],'males and',C2.G
```

```
Average Age :  40.32432432432432
Average Annual Income :  87.43243243243244
Deviation of the mean for annual Income :  16.2729163891359
No. of Customers ie shape : (37, 5)
From those Customers We have 19 males and 18 females
```

In [30]:

```python
print('Average Age : ',C3['Age'].mean())
print('Average Annual Income : ',C3['Annual Income (k$)'].mean())
print('Deviation of the mean for annual Income : ',ss.stdev(C3['Annual Income (k
print('No. of Customers ie shape :' ,C3.shape)
print('From those Customers We have',C3.Genre.value_counts()[1],'males and',C3.G
```

```
Average Age :  32.69230769230769
Average Annual Income :  86.53846153846153
Deviation of the mean for annual Income :  16.312484972924967
No. of Customers ie shape : (39, 5)
From those Customers We have 18 males and 21 females
```

In [31]:

```python
print('Average Age : ',C4['Age'].mean())
print('Average Annual Income : ',C4['Annual Income (k$)'].mean())
print('Deviation of the mean for annual Income : ',ss.stdev(C4['Annual Income (k
print('No. of Customers ie shape :' ,C4.shape)
print('From those Customers We have',C4.Genre.value_counts()[1],'males and',C4.G
```

```
Average Age :  25.272727272727273
Average Annual Income :  25.727272727272727
Deviation of the mean for annual Income :  7.566730552584204
No. of Customers ie shape : (22, 5)
From those Customers We have 9 males and 13 females
```

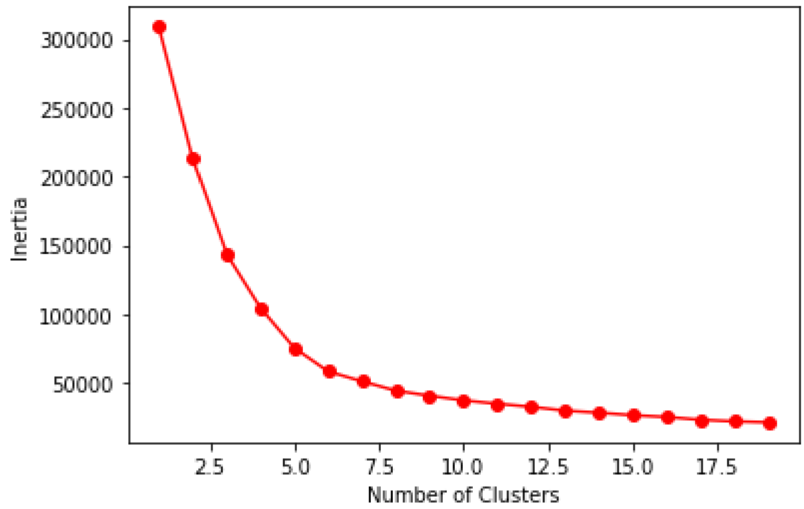
Step9 [Find the best number of clusters]

In [32]:

```python
SSE = []
for clust in range(1,20):
  KM = KMeans(n_clusters= clust, init='k-means++')
  KM = KM.fit(customer_data)
  SSE.append(KM.inertia_)
```

In [33]:
```python
plt.plot(np.arange(1,20), SSE,'ro-')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
```

Out[33]: Text(0, 0.5, 'Inertia')



Step10 [Reduce Dimensions using PCA]

In [34]:
```python
from sklearn.decomposition import PCA
```

In [35]:
```python
pca = PCA(n_components=2)
_PCA = pca.fit_transform(customer_data)
PCA_Components = pd.DataFrame(_PCA)
```

In [36]:
```python
PCA_Components
```

Out[36]:

	0	1
0	-31.534390	-33.349296
1	1.470393	-56.847684
2	-57.281081	-13.768454
3	-1.498970	-53.517338
4	-31.869456	-30.739696
...	...	...
195	58.010363	31.673893
196	19.158738	66.666049
197	58.097007	39.003394
198	20.086571	79.606665
199	71.977659	42.628194

200 rows × 2 columns

In [37]:
```
KM1 = KMeans(n_clusters=5)
KM1.fit(PCA_Components)
KM1.cluster_centers_
```

Out[37]:
```
array([[-44.30512124, -10.54356817],
       [-10.68652483,  42.20770277],
       [ 41.54479999,   2.33729767],
       [ -4.3966484 ,  -3.14441008],
       [  5.57443644, -46.63058222]])
```

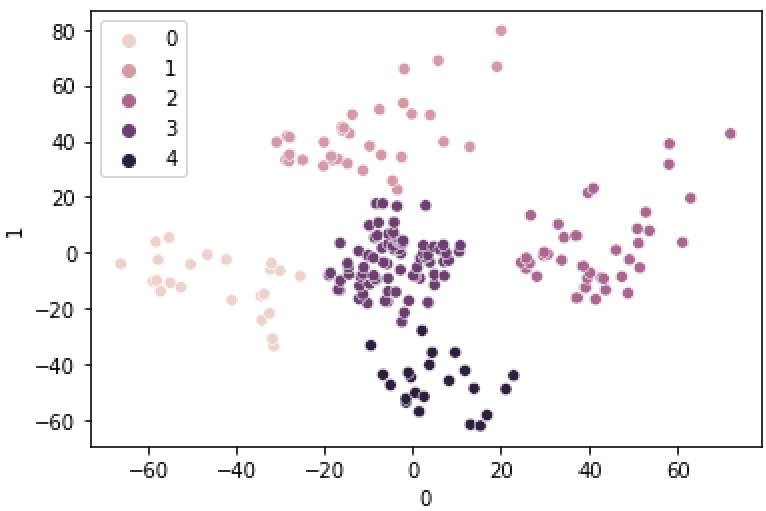
In [38]:
```
KM1.labels_
```

Out[38]:
```
array([0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4,
       0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 3,
       0, 4, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 2, 3, 2, 3, 2, 1, 2, 1, 2,
       3, 2, 1, 2, 1, 2, 1, 2, 1, 2, 3, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
       1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
       1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
       1, 2], dtype=int32)
```

Step11 [Scatter plot]

In [39]:
```
sns.scatterplot(PCA_Components[0], PCA_Components[1], hue=KM1.labels_)
```

Out[39]: <AxesSubplot:xlabel='0', ylabel='1'>



Step12 [MeanShift clustering]

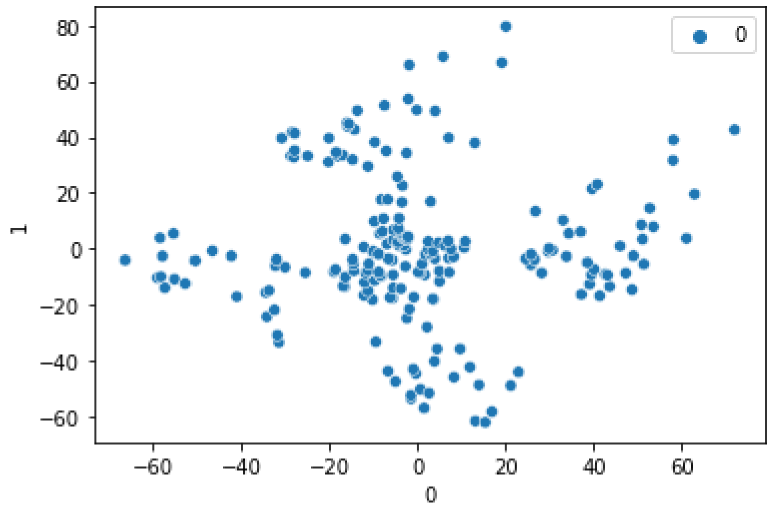
In [40]:
```
from sklearn.cluster import MeanShift, AgglomerativeClustering
```

In [41]:
```
MS = MeanShift(bandwidth = 50)
MS.fit(PCA_Components)
MS.cluster_centers_
```

Out[41]:
```
array([[ 0.3942943 , -4.10083949]])
```

```
In [42]: sns.scatterplot(PCA_Components[0], PCA_Components[1], hue=MS.labels_)
```

Out[42]: <AxesSubplot:xlabel='0', ylabel='1'>



Step13 [Predict hierarchical clusters using AgglomerativeClustering]

```
In [43]: AC = AgglomerativeClustering(n_clusters = 5, linkage='ward',compute_full_tree=Tr
         AC.fit(customer_data)
```

Out[43]: AgglomerativeClustering(compute_full_tree=True, n_clusters=5)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [44]: AC.labels_
```

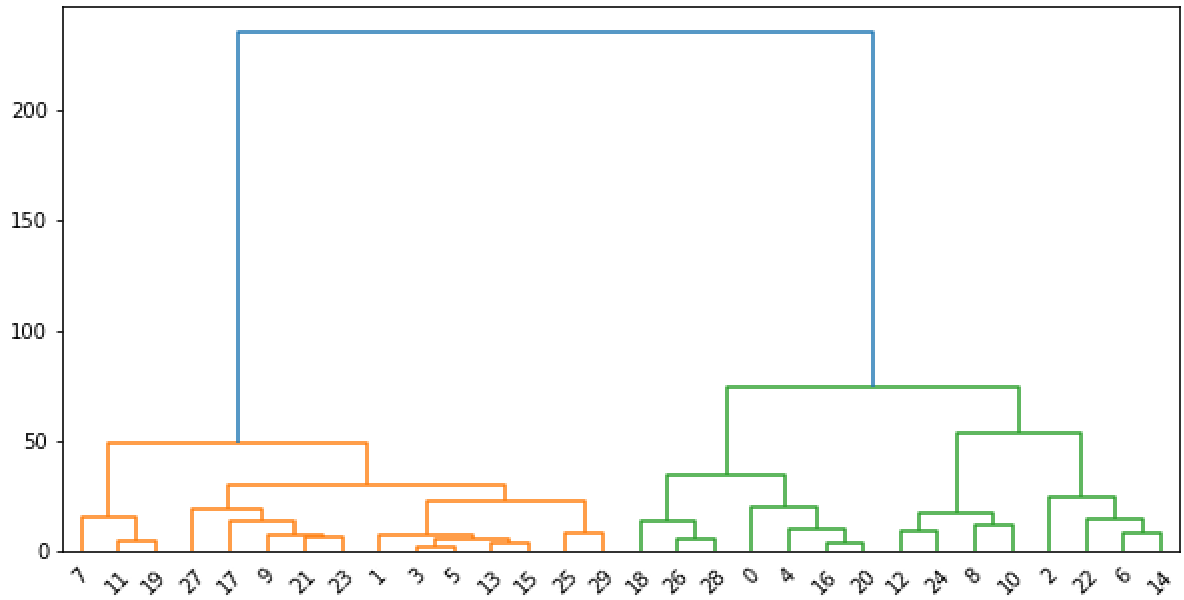
```
Out[44]: array([4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
       4, 3, 4, 3, 4, 0, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 0,
       4, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 2, 1, 2, 1, 2, 1, 2,
       0, 2, 1, 2, 1, 2, 1, 2, 1, 2, 0, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
       1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
       1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
       1, 2])
```

```
In [45]: customer_data['Cluster'] = AC.labels_
```

```
In [46]: import scipy.cluster.hierarchy as sch
```

```
In [47]: from scipy.cluster import hierarchy
```

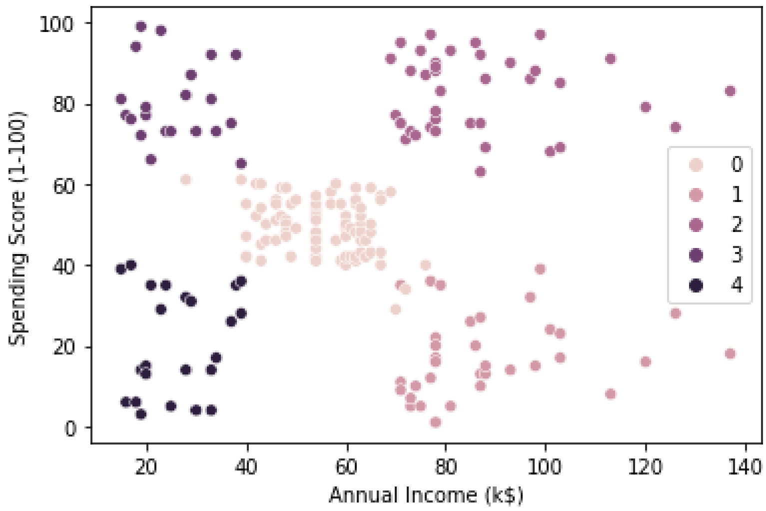
In [48]:
```
Z = hierarchy.linkage(customer_data[:30], 'ward')
plt.figure(figsize=(10,5))
dn = hierarchy.dendrogram(Z)
```



Step14 [Visualize scatter plot with hue as agglomerativeclustering labels_]

In [49]:
```
sns.scatterplot(customer_data['Annual Income (k$)'], customer_data['Spending Sco
```

Out[49]: <AxesSubplot:xlabel='Annual Income (k$)', ylabel='Spending Score (1-100)'>



In [49]:
```

```