

```
In [26]: ## Import Library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="darkgrid")
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler
from yellowbrick.cluster import KElbowVisualizer
from sklearn.metrics import silhouette_samples, silhouette_score
import matplotlib.cm as cm

## Load Data
dataset = pd.read_csv(r"C:\Users\djbro\OneDrive\Desktop\Clustering\Mall_Customers.csv")
dataset.head()
```

```
Out[26]:
```

	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

```
In [27]: dataset.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   Gender                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
```

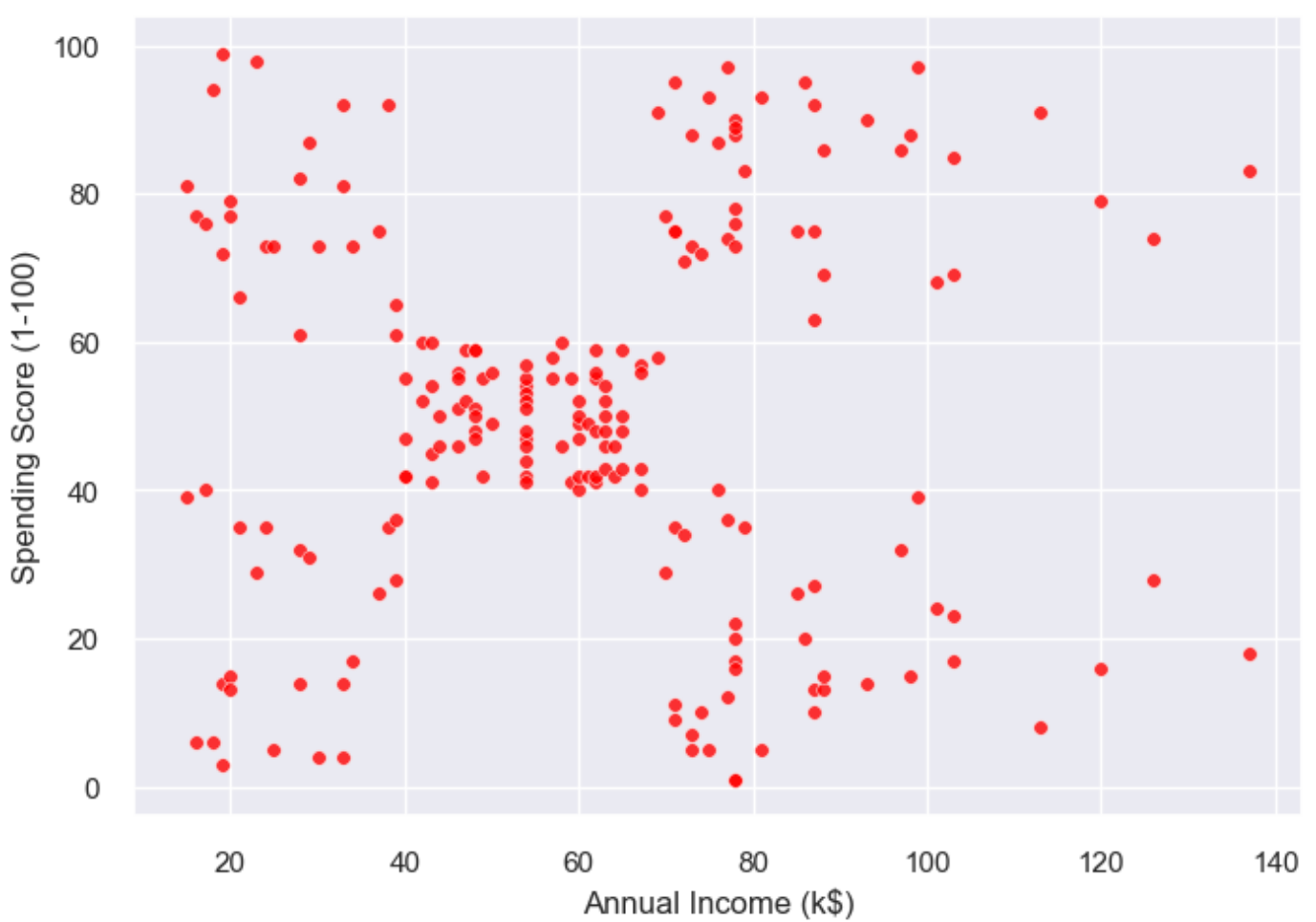
```
In [28]: #We are only performing 2 feature Clustering
data = dataset.drop(["CustomerID", "Gender", "Age"], axis = 1)
data.head()
```

```
Out[28]:
```

	Annual Income (k\$)	Spending Score (1-100)
0	15	39
1	15	81
2	16	6
3	16	77
4	17	40

```
In [29]: #Plot
sns.scatterplot(x="Annual Income (k$)", y="Spending Score (1-100)", data=data, s=30, col

Out[29]: <AxesSubplot:xlabel='Annual Income (k$)', ylabel='Spending Score (1-100)')>
```



```
In [30]: #specify our cluster features
data_x = dataset.iloc[:, 3:5]
data_x.head()

x_array = np.array(data_x)
print(x_array)
```

```
[[ 15  39]
 [ 15  81]
 [ 16   6]
 [ 16  77]
 [ 17  40]
 [ 17  76]
 [ 18   6]
 [ 18  94]
 [ 19   3]
 [ 19  72]
 [ 19  14]
 [ 19  99]
 [ 20  15]
 [ 20  77]
 [ 20  13]
 [ 20  79]
 [ 21  35]
 [ 21  66]
 [ 23  29]
 [ 23  98]
 [ 24  35]
 [ 24  73]
 [ 25   5]
 [ 25  73]
 [ 28  14]
 [ 28  82]
 [ 28  32]]
```

[28 61]
[29 31]
[29 87]
[30 4]
[30 73]
[33 4]
[33 92]
[33 14]
[33 81]
[34 17]
[34 73]
[37 26]
[37 75]
[38 35]
[38 92]
[39 36]
[39 61]
[39 28]
[39 65]
[40 55]
[40 47]
[40 42]
[40 42]
[42 52]
[42 60]
[43 54]
[43 60]
[43 45]
[43 41]
[44 50]
[44 46]
[46 51]
[46 46]
[46 56]
[46 55]
[47 52]
[47 59]
[48 51]
[48 59]
[48 50]
[48 48]
[48 59]
[48 47]
[49 55]
[49 42]
[50 49]
[50 56]
[54 47]
[54 54]
[54 53]
[54 48]
[54 52]
[54 42]
[54 51]
[54 55]
[54 41]
[54 44]
[54 57]
[54 46]
[57 58]
[57 55]
[58 60]
[58 46]
[59 55]
[59 41]
[60 49]

[60 40]
[60 42]
[60 52]
[60 47]
[60 50]
[61 42]
[61 49]
[62 41]
[62 48]
[62 59]
[62 55]
[62 56]
[62 42]
[63 50]
[63 46]
[63 43]
[63 48]
[63 52]
[63 54]
[64 42]
[64 46]
[65 48]
[65 50]
[65 43]
[65 59]
[67 43]
[67 57]
[67 56]
[67 40]
[69 58]
[69 91]
[70 29]
[70 77]
[71 35]
[71 95]
[71 11]
[71 75]
[71 9]
[71 75]
[72 34]
[72 71]
[73 5]
[73 88]
[73 7]
[73 73]
[74 10]
[74 72]
[75 5]
[75 93]
[76 40]
[76 87]
[77 12]
[77 97]
[77 36]
[77 74]
[78 22]
[78 90]
[78 17]
[78 88]
[78 20]
[78 76]
[78 16]
[78 89]
[78 1]
[78 78]
[78 1]

```

[ 78  73]
[ 79  35]
[ 79  83]
[ 81   5]
[ 81  93]
[ 85  26]
[ 85  75]
[ 86  20]
[ 86  95]
[ 87  27]
[ 87  63]
[ 87  13]
[ 87  75]
[ 87  10]
[ 87  92]
[ 88  13]
[ 88  86]
[ 88  15]
[ 88  69]
[ 93  14]
[ 93  90]
[ 97  32]
[ 97  86]
[ 98  15]
[ 98  88]
[ 99  39]
[ 99  97]
[101  24]
[101  68]
[103  17]
[103  85]
[103  23]
[103  69]
[113   8]
[113  91]
[120  16]
[120  79]
[126  28]
[126  74]
[137  18]
[137  83]]

```

```

In [31]: # Scale features
scaler = MinMaxScaler()
x_scaled = scaler.fit_transform(x_array)
x_scaled

```

```

Out[31]: array([[0.          , 0.3877551 ],
 [0.          , 0.81632653],
 [0.00819672, 0.05102041],
 [0.00819672, 0.7755102 ],
 [0.01639344, 0.39795918],
 [0.01639344, 0.76530612],
 [0.02459016, 0.05102041],
 [0.02459016, 0.94897959],
 [0.03278689, 0.02040816],
 [0.03278689, 0.7244898 ],
 [0.03278689, 0.13265306],
 [0.03278689, 1.          ],
 [0.04098361, 0.14285714],
 [0.04098361, 0.7755102 ],
 [0.04098361, 0.12244898],
 [0.04098361, 0.79591837],
 [0.04918033, 0.34693878],
 [0.04918033, 0.66326531],
 [0.06557377, 0.28571429],

```

[0.06557377, 0.98979592],
[0.07377049, 0.34693878],
[0.07377049, 0.73469388],
[0.08196721, 0.04081633],
[0.08196721, 0.73469388],
[0.10655738, 0.13265306],
[0.10655738, 0.82653061],
[0.10655738, 0.31632653],
[0.10655738, 0.6122449],
[0.1147541 , 0.30612245],
[0.1147541 , 0.87755102],
[0.12295082, 0.03061224],
[0.12295082, 0.73469388],
[0.14754098, 0.03061224],
[0.14754098, 0.92857143],
[0.14754098, 0.13265306],
[0.14754098, 0.81632653],
[0.1557377 , 0.16326531],
[0.1557377 , 0.73469388],
[0.18032787, 0.25510204],
[0.18032787, 0.75510204],
[0.18852459, 0.34693878],
[0.18852459, 0.92857143],
[0.19672131, 0.35714286],
[0.19672131, 0.6122449],
[0.19672131, 0.2755102],
[0.19672131, 0.65306122],
[0.20491803, 0.55102041],
[0.20491803, 0.46938776],
[0.20491803, 0.41836735],
[0.20491803, 0.41836735],
[0.22131148, 0.52040816],
[0.22131148, 0.60204082],
[0.2295082 , 0.54081633],
[0.2295082 , 0.60204082],
[0.2295082 , 0.44897959],
[0.2295082 , 0.40816327],
[0.23770492, 0.5],
[0.23770492, 0.45918367],
[0.25409836, 0.51020408],
[0.25409836, 0.45918367],
[0.25409836, 0.56122449],
[0.25409836, 0.55102041],
[0.26229508, 0.52040816],
[0.26229508, 0.59183673],
[0.2704918 , 0.51020408],
[0.2704918 , 0.59183673],
[0.2704918 , 0.5],
[0.2704918 , 0.47959184],
[0.2704918 , 0.59183673],
[0.2704918 , 0.46938776],
[0.27868852, 0.55102041],
[0.27868852, 0.41836735],
[0.28688525, 0.48979592],
[0.28688525, 0.56122449],
[0.31967213, 0.46938776],
[0.31967213, 0.54081633],
[0.31967213, 0.53061224],
[0.31967213, 0.47959184],
[0.31967213, 0.52040816],
[0.31967213, 0.41836735],
[0.31967213, 0.51020408],
[0.31967213, 0.55102041],
[0.31967213, 0.40816327],
[0.31967213, 0.43877551],
[0.31967213, 0.57142857],

[0.31967213, 0.45918367],
[0.3442623 , 0.58163265],
[0.3442623 , 0.55102041],
[0.35245902, 0.60204082],
[0.35245902, 0.45918367],
[0.36065574, 0.55102041],
[0.36065574, 0.40816327],
[0.36885246, 0.48979592],
[0.36885246, 0.39795918],
[0.36885246, 0.41836735],
[0.36885246, 0.52040816],
[0.36885246, 0.46938776],
[0.36885246, 0.5],
[0.37704918, 0.41836735],
[0.37704918, 0.48979592],
[0.3852459 , 0.40816327],
[0.3852459 , 0.47959184],
[0.3852459 , 0.59183673],
[0.3852459 , 0.55102041],
[0.3852459 , 0.56122449],
[0.3852459 , 0.41836735],
[0.39344262, 0.5],
[0.39344262, 0.45918367],
[0.39344262, 0.42857143],
[0.39344262, 0.47959184],
[0.39344262, 0.52040816],
[0.39344262, 0.54081633],
[0.40163934, 0.41836735],
[0.40163934, 0.45918367],
[0.40983607, 0.47959184],
[0.40983607, 0.5],
[0.40983607, 0.42857143],
[0.40983607, 0.59183673],
[0.42622951, 0.42857143],
[0.42622951, 0.57142857],
[0.42622951, 0.56122449],
[0.42622951, 0.39795918],
[0.44262295, 0.58163265],
[0.44262295, 0.91836735],
[0.45081967, 0.28571429],
[0.45081967, 0.7755102],
[0.45901639, 0.34693878],
[0.45901639, 0.95918367],
[0.45901639, 0.10204082],
[0.45901639, 0.75510204],
[0.45901639, 0.08163265],
[0.45901639, 0.75510204],
[0.46721311, 0.33673469],
[0.46721311, 0.71428571],
[0.47540984, 0.04081633],
[0.47540984, 0.8877551],
[0.47540984, 0.06122449],
[0.47540984, 0.73469388],
[0.48360656, 0.09183673],
[0.48360656, 0.7244898],
[0.49180328, 0.04081633],
[0.49180328, 0.93877551],
[0.5 , 0.39795918],
[0.5 , 0.87755102],
[0.50819672, 0.1122449],
[0.50819672, 0.97959184],
[0.50819672, 0.35714286],
[0.50819672, 0.74489796],
[0.51639344, 0.21428571],
[0.51639344, 0.90816327],
[0.51639344, 0.16326531],

```

[0.51639344, 0.8877551 ],
[0.51639344, 0.19387755],
[0.51639344, 0.76530612],
[0.51639344, 0.15306122],
[0.51639344, 0.89795918],
[0.51639344, 0.      ],
[0.51639344, 0.78571429],
[0.51639344, 0.      ],
[0.51639344, 0.73469388],
[0.52459016, 0.34693878],
[0.52459016, 0.83673469],
[0.54098361, 0.04081633],
[0.54098361, 0.93877551],
[0.57377049, 0.25510204],
[0.57377049, 0.75510204],
[0.58196721, 0.19387755],
[0.58196721, 0.95918367],
[0.59016393, 0.26530612],
[0.59016393, 0.63265306],
[0.59016393, 0.12244898],
[0.59016393, 0.75510204],
[0.59016393, 0.09183673],
[0.59016393, 0.92857143],
[0.59836066, 0.12244898],
[0.59836066, 0.86734694],
[0.59836066, 0.14285714],
[0.59836066, 0.69387755],
[0.63934426, 0.13265306],
[0.63934426, 0.90816327],
[0.67213115, 0.31632653],
[0.67213115, 0.86734694],
[0.68032787, 0.14285714],
[0.68032787, 0.8877551 ],
[0.68852459, 0.3877551 ],
[0.68852459, 0.97959184],
[0.70491803, 0.23469388],
[0.70491803, 0.68367347],
[0.72131148, 0.16326531],
[0.72131148, 0.85714286],
[0.72131148, 0.2244898 ],
[0.72131148, 0.69387755],
[0.80327869, 0.07142857],
[0.80327869, 0.91836735],
[0.86065574, 0.15306122],
[0.86065574, 0.79591837],
[0.90983607, 0.2755102 ],
[0.90983607, 0.74489796],
[1.      , 0.17346939],
[1.      , 0.83673469]])

```

```

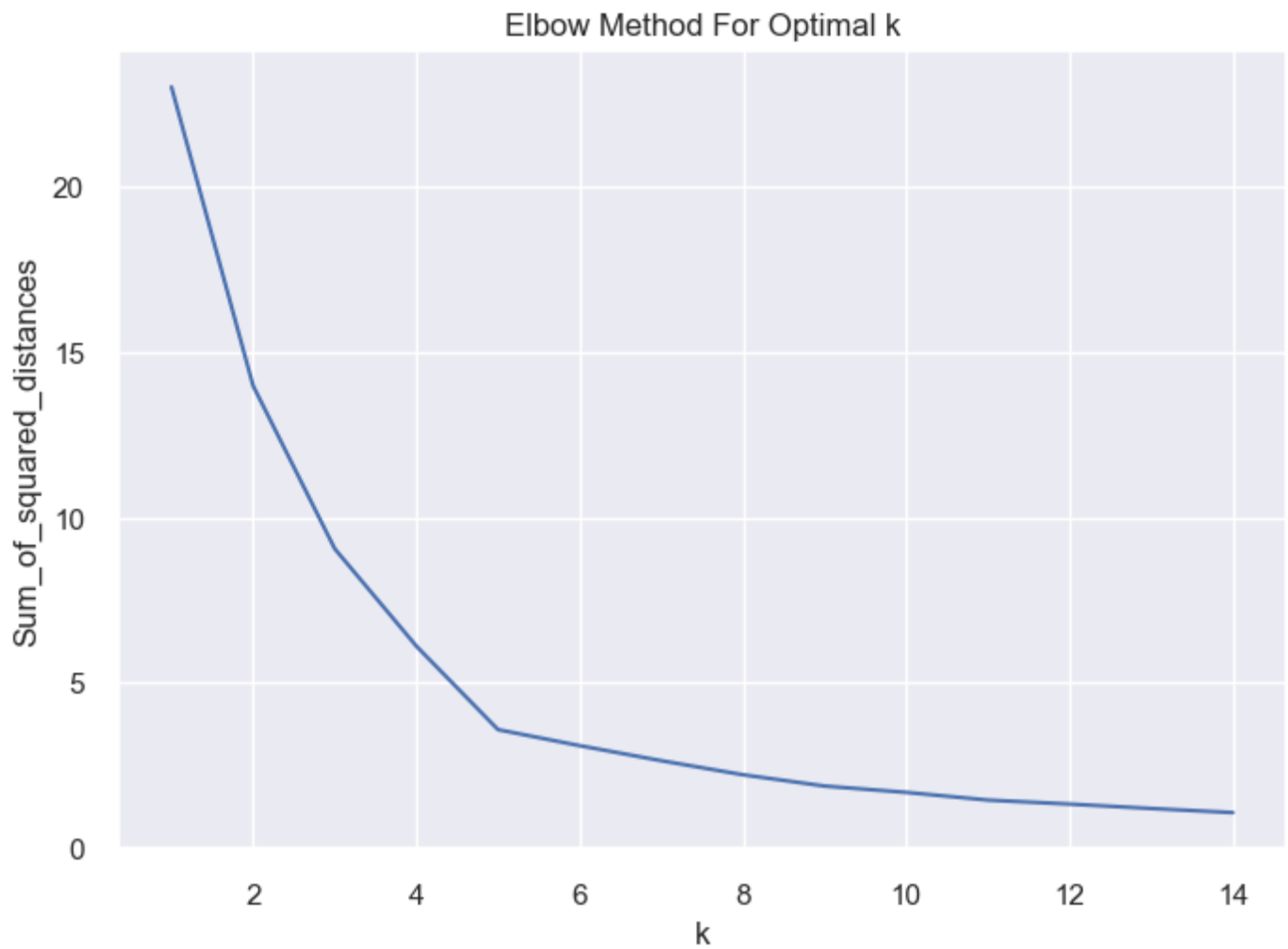
In [32]: #Elbow method to minimize WSS (within-cluster Sum of Square)
Sum_of_squared_distances =[]
K = range(1,15)
for k in K:
    km =KMeans(n_clusters =k)
    km =km.fit(x_scaled)
    Sum_of_squared_distances.append(km.inertia_)
###plotting Elbow
plt.plot(K, Sum_of_squared_distances, 'bx-')
plt.xlabel('k')
plt.ylabel('Sum_of_squared_distances')
plt.title('Elbow Method For Optimal k')
plt.show()

```

C:\Users\djbro\anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:1036: UserWarning:

KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.

```
warnings.warn(
```



```
In [33]: #Now if we observe the point after which there isn't a sudden change in WCSS in K=5.  
#So we will choose K=5 as an appropriate number of clusters.
```

```
In [34]: #Silhouette Coefficient method, the silhouette coefficient of a data  
#measures how well data are assigned to its own cluster and how far they  
#are from other clusters. A silhouette close to 1 means the data points  
#are in an appropriate cluster and a silhouette  
#coefficient close to -1 implies out data is in the wrong cluster.
```

```
In [35]: model = KMeans(random_state=123)  
# Instantiate the KElbowVisualizer with the number of clusters and the metric  
visualizer = KElbowVisualizer(model, k=(2,6), metric='silhouette', timings=False)  
# Fit the data and visualize  
visualizer.fit(x_scaled)  
visualizer.poof()
```

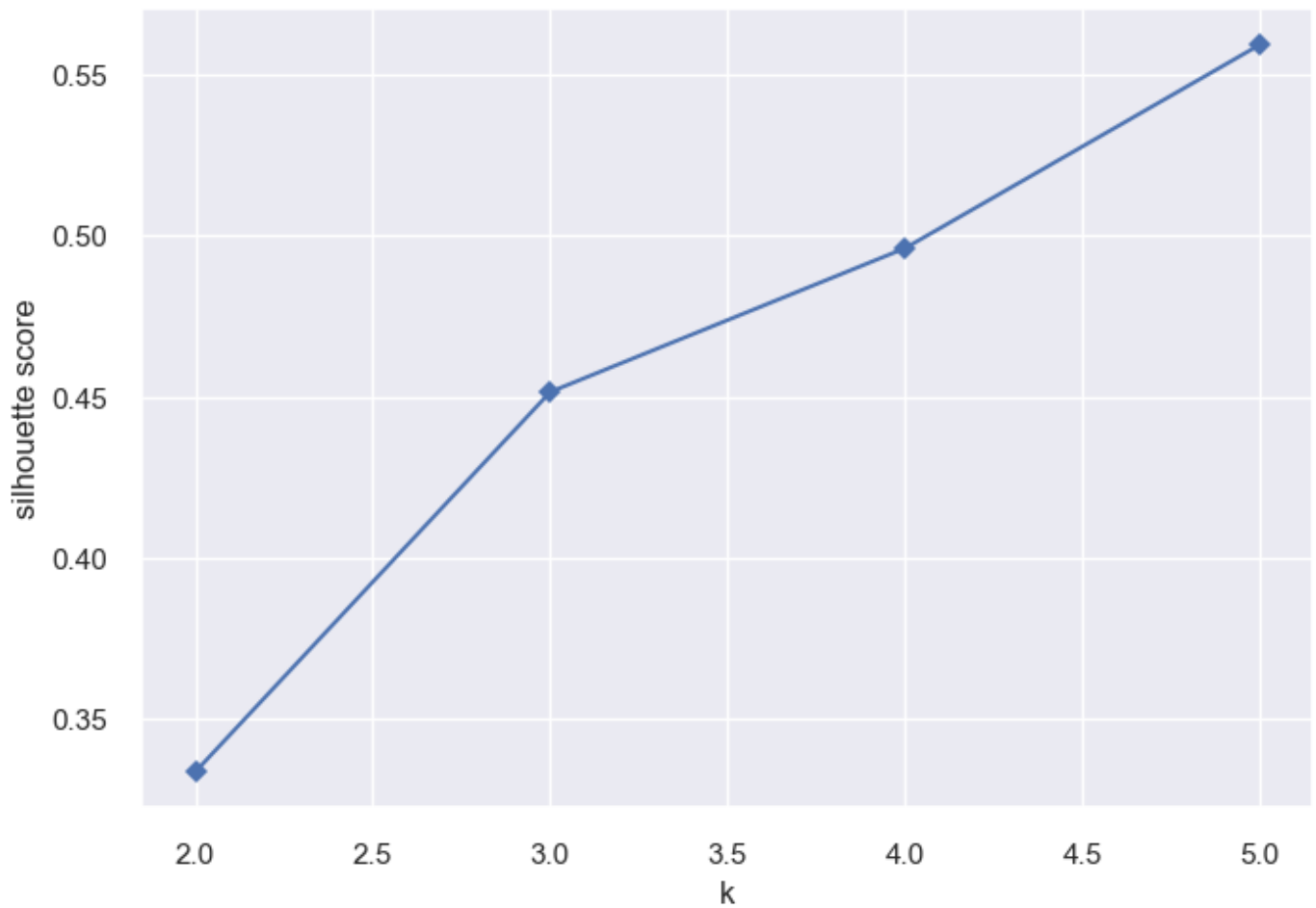
```
C:\Users\djbro\anaconda3\lib\site-packages\yellowbrick\utils\kneed.py:156: YellowbrickWarning: No 'knee' or 'elbow point' detected This could be due to bad clustering, no actual clusters being formed etc.
```

```
warnings.warn(warning_message, YellowbrickWarning)
```

```
C:\Users\djbro\anaconda3\lib\site-packages\yellowbrick\cluster\elbow.py:374: YellowbrickWarning: No 'knee' or 'elbow' point detected, pass `locate_elbow=False` to remove the warning
```

```
warnings.warn(warning_message, YellowbrickWarning)
```

Silhouette Score Elbow for KMeans Clustering



Out[35]: <AxesSubplot:title={'center':'Silhouette Score Elbow for KMeans Clustering'}, xlabel='k', ylabel='silhouette score'>

In [37]: *# Menentukan kluster dari data*
 model.fit(x_scaled)
Menampilkan pusat cluster
 print(model.cluster_centers_)

```
[[0.33029751 0.49508692]
 [0.58638083 0.82783883]
 [0.6         0.16443149]
 [0.09265859 0.20319432]
 [0.08792846 0.79962894]]
```

In [38]: *# Menampilkan hasil kluster*
 print(model.labels_)

```
[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 0 3 4 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 1 2 1 0 1 2 1 2 1 0 1 2 1 2 1 2 1 0 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]
```

In [39]: *# Menambahkan kolom "kluster" dalam data frame dataset*
 dataset["kluster"] = model.labels_
 dataset.head()

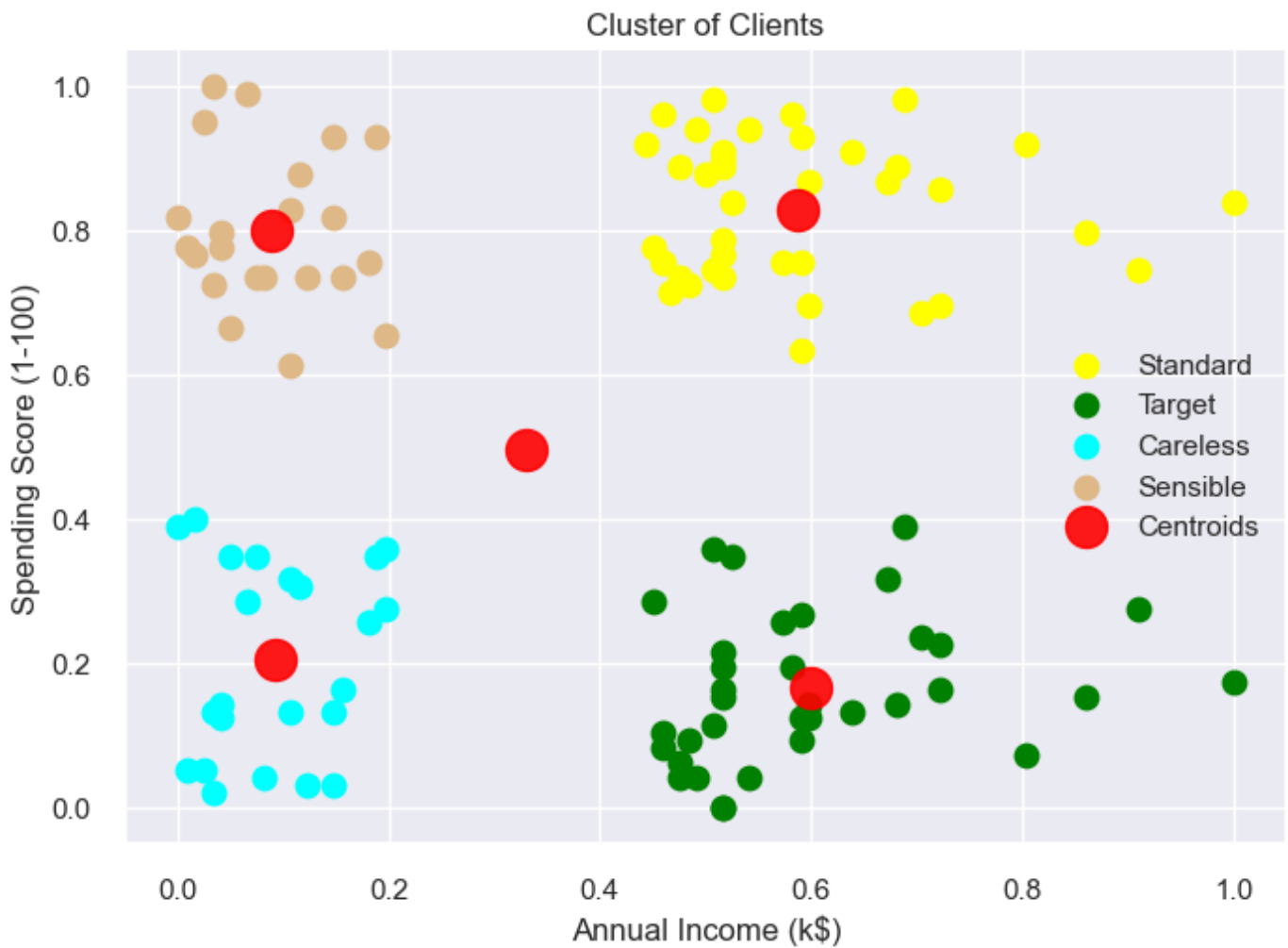
Out[39]:

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)	kluster
0	1	Male	19	15	39	3
1	2	Male	21	15	81	4
2	3	Female	20	16	6	3

3	4	Female	23	16	77	4
4	5	Female	31	17	40	3

```
In [41]: # Memvisualkan hasil kluster
plt.scatter(x_scaled[kmeans.labels_==0,0],x_scaled[kmeans.labels_==0,1],s=80,c='yellow',label='Standard')
plt.scatter(x_scaled[kmeans.labels_==1,0],x_scaled[kmeans.labels_==1,1],s=80,c='green',label='Target')
plt.scatter(x_scaled[kmeans.labels_==2,0],x_scaled[kmeans.labels_==2,1],s=80,c='cyan',label='Careless')
plt.scatter(x_scaled[kmeans.labels_==3,0],x_scaled[kmeans.labels_==3,1],s=80,c='brown',label='Sensible')
plt.scatter(model.cluster_centers_[0,0],model.cluster_centers_[0,1],marker='o',alpha=0.5)
plt.title('Cluster of Clients')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show
```

```
Out[41]: <function matplotlib.pyplot.show(close=None, block=None)>
```



```
In [ ]:
```

```
In [ ]:
```