### K mediod Clustering when K=4

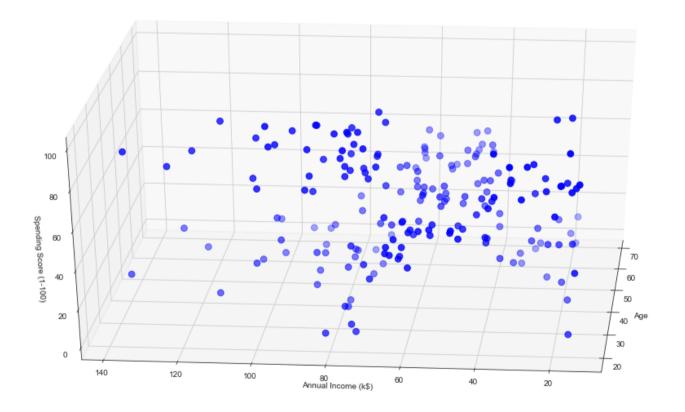
```
In [1]:
            import pandas as pd
          2 import numpy as np
          3 import random
          4 import matplotlib.pyplot as plt
          5 import seaborn as sns
          6 from mpl toolkits.mplot3d import Axes3D
          7 from math import*
            from scipy.spatial.distance import pdist,squareform
         10
         11
In [2]:
            def manhattan distance(person1, person2):
                distance = 0
          2
          3
                distance += abs(person1 - person2)
                return distance
In [3]:
            Assigned cluster = pd.DataFrame(np.zeros((196, 1), dtype=int))
          2
          1 dataset = pd.read csv('Mall Customers.csv')#-----reading dataset
In [4]:
          2 customer = dataset.to numpy()
```

### calculating Disimilarity MAtrix below

```
1 squareform(pdist(customer[:,2:], metric='euclidean'))#-----calculating dissimilarity matrix
In [5]:
Out[5]: array([[ 0. , 42.04759208, 33.03028913, ..., 117.1110584 ,
               124.47489707, 130.15759678],
                                     , 75.01333215, ..., 111.7631424 ,
              [ 42.04759208, 0.
               137.74614332, 122.34786471],
              [ 33.03028913, 75.01333215, 0. , ..., 129.87686476,
               122.18428704, 143.77065069],
              . . . ,
              [117.1110584, 111.7631424, 129.87686476, ..., 0.
                57.07013229, 14.35270009],
              [124.47489707, 137.74614332, 122.18428704, ..., 57.07013229,
                     , 65.03076195],
                 0.
              [130.15759678, 122.34786471, 143.77065069, ..., 14.35270009,
                65.03076195, 0. ]])
In [ ]:
In [6]:
                     -----NUMBER OF CLUSTERS
```

#### Plotting graph before clustering

```
In [7]: 1
2     sns.set_style("white")
3     fig = plt.figure(figsize=(20,10))
4     ax = fig.add_subplot(111, projection='3d')
5     ax.scatter(dataset.Age, dataset["Annual Income (k$)"], dataset["Spending Score (1-100)"], c='blue', s=60)
6     ax.view_init(30, 185)
7     plt.xlabel("Age")
8     plt.ylabel("Annual Income (k$)")
9     ax.set_zlabel('Spending Score (1-100)')
10     plt.show()
```



```
In [12]:
             print(mediod[2, 2])
          2 print(customer.shape)
          3 print(customer_new.shape)
          4 distance_age = 0
          5 distance income = 0
           6 distance score = 0
          7 total_distance_cost = np.zeros((len(customer_new),k))
           8 print(total distance cost.shape)
             print(customer new.shape)
         10 print(dataset 1.shape)
         11 non mediod = 0
          12
         50
         (200, 5)
         (196, 5)
         (196, 4)
         (196, 5)
         (196, 5)
```

Calculating distance between mediod and points and assigning clusters to it

```
In [13]:
             #----comparing when value of k=1
            old cost = 0
            total cost cluster = 0
            difference cost=0
            for 1 in range(len(customer new)):
          7
          8
                distance age k1 = []
                distance income k1 = []
          9
                distance score k1 = []
         10
         11
                total distance k1 = []
         12
                q=0
         13
                w=0
         14
                e=0
         15
                total=0
         16
                i=0
         17
         18
                for j in range(len(customer new)):
                    q = manhattan distance(mediod[i,2],customer new[j,2])
         19
         20
                    distance age k1.append(q)
                    w = manhattan distance(mediod[i,3],customer new[j,3])
         21
         22
                    distance income k1.append(w)
                    e = manhattan distance(mediod[i,4],customer new[j,4])
         23
                    distance score k1.append(e)
         24
         25
                    total = q+w+e
                    total distance k1.append(total)
         26
         27
                #----comparing when value of k=2
         28
         29
         30
                distance age k2 = []
                distance income k2 = []
         31
                distance score k2 = []
         32
         33
                total distance k2 = []
         34
                q=0
         35
                w=0
         36
                e=0
         37
                total=0
         38
                i=1
         39
                for j in range(len(customer new)):
                    q = manhattan_distance(mediod[i,2],customer_new[j,2])
         40
                    distance_age_k2.append(q)
         41
```

```
42
           w = manhattan_distance(mediod[i,3],customer_new[j,3])
43
           distance income k2.append(w)
           e = manhattan_distance(mediod[i,4],customer_new[j,4])
44
           distance_score_k2.append(e)
45
           total = q+w+e
46
           total distance k2.append(total)
47
48
       #----comparing when value of k=3
49
50
       distance age k3 = []
       distance income k3 = []
51
       distance score k3 = []
52
53
       total distance k3 = []
54
        q=0
55
        w=0
56
        e=0
57
        total=0
58
        i=2
59
60
       for j in range(len(customer new)):
61
           q = manhattan distance(mediod[i,2],customer new[j,2])
62
63
           distance age k3.append(q)
           w = manhattan distance(mediod[i,3],customer new[j,3])
64
           distance income k3.append(w)
65
           e = manhattan distance(mediod[i,4],customer new[j,4])
66
           distance score k3.append(e)
67
68
           total = q+w+e
69
           total distance k3.append(total)
70
71
       #----comparing when value of k=4
72
73
       distance age k4 = []
       distance income k4 = []
74
75
       distance score k4 = []
       total distance k4 = []
76
77
        q=0
78
        w=0
79
        e=0
80
       total=0
81
        i=3
82
       for j in range(len(customer_new)):
           q = manhattan_distance(mediod[i,2],customer_new[j,2])
83
```

```
84
             distance age k4.append(q)
 85
            w = manhattan_distance(mediod[i,3],customer_new[j,3])
             distance income k4.append(w)
 86
 87
             e = manhattan distance(mediod[i,4],customer new[j,4])
 88
             distance score k4.append(e)
            total = q+w+e
 89
            total distance k4.append(total)
 90
 91
 92
 93
 94
 95
         cost 1 = pd.DataFrame({'Cost 1':total distance k1})
 96
         cost 2 = pd.DataFrame({'Cost 2':total distance k2})
 97
 98
         cost 3 = pd.DataFrame({'Cost 3':total distance k3})
         cost 4 = pd.DataFrame({'Cost 4':total distance k4})
 99
100
101
         dataset 1 = dataset 1.assign(cost 1=cost 1.values,cost 2=cost 2.values,cost 3=cost 3.values,cost 4=cost 4.value
102
103
104
105
         customer new = dataset 1.to numpy()
         #print(customer new[0:10, :])#-----combined dataset which displays cost of all k, the last four colour
106
107
108
109
110
         #***********
111
         #----now we will create 4 clusters as the value of k = 4 on the basis of total distance or cost
112
113
114
115
         cluster 1 = []
         cluster 2 = []
116
         cluster 3 = []
117
         cluster 4 = []
118
119
         q=0
120
         w=0
121
         e=0
122
         r=0
123
         i=0
124
         for i in range(len(customer new)):
125
```

```
126
127
             if(customer new[i][5] <= customer new[i][6] and customer new[i][5] <= customer new[i][7] and customer new[i</pre>
                 #print("five")
128
                 q = customer new[i]
129
130
                 cluster 1.append(q)
                 dataset 1.iloc[i, dataset 1.columns.get loc('Assigned cluster')] = "Cluster 1"
131
132
133
134
             if(customer new[i][6] <= customer new[i][5] and customer new[i][6] <= customer new[i][7] and customer new[i</pre>
                 #print("six")
135
136
                 w = customer new[i]
137
                 cluster 2.append(w)
                 dataset 1.iloc[i, dataset 1.columns.get loc('Assigned cluster')] = "Cluster 2"
138
139
             if(customer new[i][7] <= customer new[i][6] and customer new[i][7] <= customer new[i][5] and customer new[i</pre>
140
141
                # print("seven")
142
                 e = customer new[i]
                 cluster 3.append(e)
143
                 dataset 1.iloc[i, dataset 1.columns.get loc('Assigned cluster')] = "Cluster 3"
144
145
             if(customer new[i][8] <= customer new[i][6] and customer new[i][8] <= customer new[i][7] and customer new[i</pre>
146
147
                # print("eight")
148
                 r = customer new[i]
                 cluster 4.append(r)
149
150
                 dataset 1.iloc[i, dataset 1.columns.get loc('Assigned cluster')] = "Cluster 4"
151
152
         print("lenth is", + len(cluster 4))
153
154
         if(len(cluster 4) == 0):
             cluster 4 = cluster 4 old
155
         if(len(cluster 3) == 0):
156
157
             cluster 3 = cluster 3 old
         if(len(cluster 2) == 0):
158
             cluster 2 = cluster 2 old
159
160
         if(len(cluster 1) == 0):
161
             cluster 1 = cluster 2 old
         total cost cluster = 0
162
         cluster_1 = np.asarray(cluster_1)
163
164
         cluster 2 = np.asarray(cluster 2)
165
         cluster 3 = np.asarray(cluster 3)
166
         cluster 4 = np.asarray(cluster 4)
         sum cluster 1 = cluster 1[:,5].sum(axis=0)#-----adding all the particalura coloumn which is cost of partical
167
```

```
168
         sum cluster 2 = cluster 2[:,6].sum(axis=0)
169
         sum cluster 3 = cluster 3[:,7].sum(axis=0)#-----adding all the minimum cost of particular clusters
         sum cluster 4 = cluster 4[:,8].sum(axis=0)
170
         total cost cluster = sum cluster 1 + sum cluster 2 + sum cluster 3 +sum cluster 4
171
172
         print(total cost cluster, l+1)
173
         #print(mediod)
174
175
         difference cost= total cost cluster - old cost
         if (difference cost<=0):#-----bad cost</pre>
176
177
             non mediod = customer new[np.random.choice(customer new.shape[0], 1, replace=False), :]#------for cluste
178
             non mediod = np.delete(non mediod, np.s [4:9], axis=1)
179
             mediod[3]= non mediod
             old cost = total cost cluster
180
             #print("difference is", + difference cost)
181
182
         cluster 4 old = cluster 4
         old cost = total cost cluster
183
184
185
         difference cost= total cost cluster - old cost
         if (difference cost<=0):#-----bad cost</pre>
186
187
             non mediod = customer new[np.random.choice(customer new.shape[0], 1, replace=False), :]#------for cluster
             non mediod = np.delete(non mediod, np.s [4:9], axis=1)
188
189
             mediod[2]= non mediod
             old cost = total cost cluster
190
             #print("difference is", + difference cost)
191
192
         cluster 3 old = cluster 3
         old cost = total cost cluster
193
194
195
         if (difference cost<=0):#-----bad cost</pre>
196
197
             non mediod = customer new[np.random.choice(customer new.shape[0], 1, replace=False), :]#------for cluste
198
             non mediod = np.delete(non mediod, np.s [4:9], axis=1)
199
             mediod[1]= non mediod
             old cost = total cost cluster
200
             #print("difference is", + difference cost)
201
202
         cluster 2 old = cluster 2
         old cost = total cost cluster
203
204
         if (difference cost<=0):#-----bad cost</pre>
205
             non mediod = customer new[np.random.choice(customer new.shape[0], 1, replace=False), :]#------for cluste
206
207
             non mediod = np.delete(non mediod, np.s [4:9], axis=1)
             mediod[0]= non mediod
208
209
             old cost = total cost cluster
```

```
#print("difference is", + difference_cost)
210
211
         cluster_1_old = cluster_1
212
         old_cost = total_cost_cluster
213
lenth is 41
7988 1
lenth is 79
13166 2
lenth is 53
13366 3
lenth is 83
13374 4
lenth is 60
12880 5
lenth is 66
14507 6
lenth is 50
14139 7
lenth is 49
14261 8
lenth is 30
15029 9
lenth is 21
44570 40
```

### New coloumn added below for assigned cluster

In [14]: 1 dataset\_1

Out[14]:

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)	cost_1	cost_2	cost_3	cost_4	Assigned_cluster
0	1	Male	19	15	39	132	70	97	110	Cluster_2
1	2	Male	21	15	81	172	114	137	150	Cluster_2
2	3	Female	20	16	6	97	37	62	75	Cluster_2
3	4	Female	23	16	77	165	111	130	143	Cluster_2
4	5	Female	31	17	40	123	81	84	97	Cluster_2
195	196	Female	35	120	79	107	169	142	129	Cluster_1
196	197	Female	45	126	28	72	134	107	94	Cluster_1
197	198	Male	32	126	74	105	167	140	127	Cluster_1
198	199	Male	32	137	18	60	122	95	82	Cluster_1
199	200	Male	30	137	83	123	185	162	149	Cluster_1

196 rows × 10 columns

# **Calculating silhoutte width for each clusters**

```
In [26]:
              distance_age_k2 = []
           3 distance_income_k2 = []
             distance score k2 = []
           5 total distance k2 = []
           6 distance sil = []
              average sill = []
           8 total=0
              q=0
           9
          10
              w=0
          11
              e=0
          12
              a=0
          13
          14
              total=0
          15
              for i in range(len(cluster 1)):
          16
                  for j in range(len(cluster 1)):#-----calcualting distance
          17
                      q = manhattan distance(cluster 1[i,2],cluster 1[j,2])
          18
                      #distance age k2.append(q)
          19
                      w = manhattan_distance(cluster_1[i,3],cluster_1[j,3])
          20
                      #distance income k2.append(w)
          21
          22
                      e = manhattan distance(cluster 1[i,4],cluster 1[j,4])
          23
                      #distance score.append(e)
                      total = q+w+e
          24
          25
                      distance sil.append(total/3)
          26
                  a sil = sum(distance sil)/len(cluster 1)
          27
                  #print(a sil)
                  distance sil.clear()
          28
          29
          30
                  cluster min=0
          31
          32
          33
                  distance age k2 = []
                  distance income k2 = []
          34
          35
                  distance score k2 = []
                  total distance k2 = []
          36
                  distance sil = []
          37
          38
                  q=0
          39
                  w=0
          40
                  e=0
          41
                  a=0
```

```
42
43
        total=0
       n=0#-----for cluster 1
44
       for j in range(len(mediod)):#-----calcualting nearest cluster
45
46
            q = manhattan distance(mediod[n,2],mediod[j,2])
           #distance age k2.append(q)
47
           w = manhattan distance(mediod[n,3],mediod[j,3])
48
49
           #distance income k2.append(w)
50
           e = manhattan distance(mediod[n,4],mediod[i,4])
           #distance score.append(e)
51
52
           total = q+w+e
53
           distance sil.append(total)
54
       #print(distance sil)
55
       index = [i for i in range(0,4)]
56
       #print(index)
       index=np.asarray(index)
57
       distance sil= np.asarray(distance sil)
58
59
       distance sil.transpose
       #print(distance sil)
60
       distance sil = np.column_stack((index,distance_sil))
61
       #print(distance sil[:,1])
62
       minval = np.min(distance sil[:,1][np.nonzero(distance sil[:,1])])
63
       #print(minval)
64
       for b in range(len(distance sil)):
65
           if (minval == distance sil[b,1]):
66
                cluster min = b
67
68
               #print(cluster min)
69
70
71
72
73
       #----now find the value of b
       if (cluster_min == 0):
74
75
                selected cluster= cluster 1
       if (cluster min == 1):
76
                selected cluster= cluster 2
77
78
       if (cluster min == 2):
                selected_cluster= cluster_3
79
80
       if (cluster min == 3):
81
                selected cluster= cluster 4
       if (cluster_min == 4):
82
                selected_cluster= cluster_5
83
```

```
84
 85
         distance age k2 = []
         distance_b= []
 86
 87
         distance income k2 = []
 88
         distance score k2 = []
         total distance k2 = []
 89
         distance sil = []
 90
 91
         q=0
 92
         w=0
 93
         e=0
 94
         a=0
 95
         s=0
 96
 97
         total=0
 98
         for j in range(len(selected cluster)):#-----calcualting distance
 99
100
101
             q = manhattan distance(cluster 1[i,2],selected cluster[j,2])
102
             #distance age k2.append(q)
103
             w = manhattan_distance(cluster_1[i,3],selected_cluster[j,3])
104
105
             #distance income k2.append(w)
             e = manhattan distance(cluster 1[i,4],selected cluster[j,4])
106
             #distance score.append(e)
107
108
             total = q+w+e
             distance b.append(total)
109
110
        # print(min(distance b))
111
         b = min(distance b)
         maxi = max(b, a sil)
112
         #print("a is", + maxi)
113
114
         d = b - a sil
         sill = ((b - a sil) / maxi)#-----silhoutte widht formulae
115
         print("Silhoutte width for each point in cluster 1", + sill)
116
117
118
         average sill.append(sill)
     s c1 = sum(average sill)/len(average sill)
119
120
     print("Average silhoutee width for cluster 1", + s c1)
121
122
```

Silhoutte width for each point in cluster 1 0.48893105629348516 Silhoutte width for each point in cluster 1 0.5996339510409516 Silhoutte width for each point in cluster 1 0.6308243727598568 Silhoutte width for each point in cluster 1 0.6693975081071856 Silhoutte width for each point in cluster 1 0.6170250896057348 Silhoutte width for each point in cluster 1 0.6731182795698925 Silhoutte width for each point in cluster 1 0.5685483870967742 Silhoutte width for each point in cluster 1 0.5504851822711776 Silhoutte width for each point in cluster 1 0.6062048298959987 Silhoutte width for each point in cluster 1 0.7070707070707071 Silhoutte width for each point in cluster 1 0.6251221896383187 Silhoutte width for each point in cluster 1 0.7289359653346174 Silhoutte width for each point in cluster 1 0.6990876507005539 Silhoutte width for each point in cluster 1 0.7337216248506571 Silhoutte width for each point in cluster 1 0.5916601101494886 Silhoutte width for each point in cluster 1 0.7374770521898768 Silhoutte width for each point in cluster 1 0.6575268817204302 Silhoutte width for each point in cluster 1 0.6851851851852 Silhoutte width for each point in cluster 1 0.720269619643717 Silhoutte width for each point in cluster 1 0.7502986857825568 Silhoutte width for each point in cluster 1 0.7214706902532085 Silhoutte width for each point in cluster 1 0.7089093701996928 Silhoutte width for each point in cluster 1 0.747800586510264 Silhoutte width for each point in cluster 1 0.7643966547192352 Silhoutte width for each point in cluster 1 0.7310577644411103 Silhoutte width for each point in cluster 1 0.7545239968528717 Silhoutte width for each point in cluster 1 0.7237083661159193 Silhoutte width for each point in cluster 1 0.7475678443420378 Silhoutte width for each point in cluster 1 0.7443841158309379 Silhoutte width for each point in cluster 1 0.7557313856766078 Average silhoutee width for cluster 1 0.6770991968983566

```
In [27]:
           1 distance age k2 = []
           2 distance_income_k2 = []
           3 distance_score_k2 = []
             total distance k2 = []
           5 distance sil = []
             average sill = []
              total=0
           8
              q=0
              w=0
          10
              e=0
          11
              a=0
          12
          13
              total=0
          14
              for i in range(len(cluster 2)):
          15
                  for j in range(len(cluster 2)):#-----calcualting distance
          16
                      q = manhattan_distance(cluster_2[i,2],cluster_2[j,2])
          17
                      #distance age k2.append(a)
          18
                      w = manhattan distance(cluster_2[i,3],cluster_2[j,3])
          19
                      #distance income k2.append(w)
          20
                      e = manhattan distance(cluster 2[i,4],cluster 2[j,4])
          21
          22
                      #distance score.append(e)
                      total = q+w+e
          23
                      distance sil.append(total/3)
          24
          25
                  a sil = sum(distance sil)/len(cluster 2)
          26
                  #print(a sil)
          27
                  distance sil.clear()
          28
          29
          30
                  cluster min=0
          31
          32
          33
                  distance age k2 = []
                  distance income k2 = []
          34
          35
                  distance score k2 = []
                  total distance k2 = []
          36
                  distance sil = []
          37
          38
                  q=0
          39
                  w=0
          40
                  e=0
          41
                  a=0
```

```
42
43
        total=0
       n=1#-----for cluster 2
44
       for j in range(len(mediod)):#-----calcualting nearest cluster
45
46
            q = manhattan distance(mediod[n,2],mediod[j,2])
           #distance age k2.append(q)
47
           w = manhattan distance(mediod[n,3],mediod[j,3])
48
49
           #distance income k2.append(w)
50
           e = manhattan distance(mediod[n,4],mediod[i,4])
           #distance score.append(e)
51
52
           total = q+w+e
53
           distance sil.append(total)
54
       #print(distance sil)
55
       index = [i for i in range(0,4)]
56
       #print(index)
       index=np.asarray(index)
57
       distance sil= np.asarray(distance sil)
58
59
       distance sil.transpose
       #print(distance sil)
60
       distance sil = np.column_stack((index,distance_sil))
61
       #print(distance sil[:,1])
62
       minval = np.min(distance sil[:,1][np.nonzero(distance sil[:,1])])
63
       #print(minval)
64
       for b in range(len(distance sil)):
65
           if (minval == distance sil[b,1]):
66
                cluster min = b
67
68
               #print(cluster min)
69
70
71
72
73
       #----now find the value of b
       if (cluster_min == 0):
74
75
                selected cluster= cluster 1
       if (cluster min == 1):
76
77
                selected cluster= cluster 2
78
       if (cluster min == 2):
                selected_cluster= cluster_3
79
80
       if (cluster min == 3):
81
                selected cluster= cluster 4
       if (cluster_min == 4):
82
                selected_cluster= cluster_5
83
```

```
84
 85
         distance age k2 = []
         distance_b= []
 86
 87
         distance income k2 = []
 88
         distance score k2 = []
         total distance k2 = []
 89
         distance sil = []
 90
 91
         q=0
 92
         w=0
 93
         e=0
 94
         a=0
 95
         s=0
 96
 97
         total=0
 98
         for j in range(len(selected cluster)):#-----calcualting distance
 99
100
101
             q = manhattan distance(cluster 2[i,2],selected cluster[j,2])
102
             #distance age k2.append(q)
103
             w = manhattan_distance(cluster_2[i,3],selected_cluster[j,3])
104
105
             #distance income k2.append(w)
             e = manhattan distance(cluster 2[i,4],selected cluster[j,4])
106
             #distance score.append(e)
107
108
             total = q+w+e
             distance b.append(total)
109
110
        # print(min(distance b))
         b = min(distance b)
111
         maxi = max(b, a sil)
112
         #print("a is", + maxi)
113
         d = b - a sil
114
         sill = ((b - a sil) / maxi)#-----silhoutte widht formulae
115
         print("Silhoutte width for each point in cluster 2", + sill)
116
117
         average sill.append(sill)
118
     s c2 = sum(average sill)/len(average sill)
119
120
     print("Average silhoutee width for cluster 1", + s c2)
121
```

Silhoutte width for each point in cluster 2 0.7154667837284167

Silhoutte width for each point in cluster 2 0.6806546975268585 Silhoutte width for each point in cluster 2 0.5570423743352204 Silhoutte width for each point in cluster 2 0.6713208152784463 Silhoutte width for each point in cluster 2 0.7021908003840447 Silhoutte width for each point in cluster 2 0.6816710100292189 Silhoutte width for each point in cluster 2 0.6340604668962877 Silhoutte width for each point in cluster 2 0.6354793198188163 Silhoutte width for each point in cluster 2 0.5421354764638348 Silhoutte width for each point in cluster 2 0.6746268656716418 Silhoutte width for each point in cluster 2 0.5625049356392638 Silhoutte width for each point in cluster 2 0.5895114590979531 Silhoutte width for each point in cluster 2 0.5617448471926084 Silhoutte width for each point in cluster 2 0.6631753513136075 Silhoutte width for each point in cluster 2 0.6682740145426712 Silhoutte width for each point in cluster 2 0.6722127069570182 Silhoutte width for each point in cluster 2 0.6903445734291507 Silhoutte width for each point in cluster 2 0.714680565426834 Silhoutte width for each point in cluster 2 0.667762880512691 Silhoutte width for each point in cluster 2 0.5710732054015636 Silhoutte width for each point in cluster 2 0.6808116281338408 Silhoutte width for each point in cluster 2 0.6846126510305615 Silhoutte width for each point in cluster 2 0.5294117647058824 Silhoutte width for each point in cluster 2 0.651842826682912 Silhoutte width for each point in cluster 2 0.5539947322212468 Silhoutte width for each point in cluster 2 0.6140724946695094 Silhoutte width for each point in cluster 2 0.6381633499170812 Silhoutte width for each point in cluster 2 0.6905269570514774 Silhoutte width for each point in cluster 2 0.6543811554472535 Silhoutte width for each point in cluster 2 0.5909667349526875 Silhoutte width for each point in cluster 2 0.44928419128845554 Silhoutte width for each point in cluster 2 0.669983416252073 Silhoutte width for each point in cluster 2 0.4650153487879751 Silhoutte width for each point in cluster 2 0.5744007236544549 Silhoutte width for each point in cluster 2 0.5212824765063571 Silhoutte width for each point in cluster 2 0.6169154228855723 Silhoutte width for each point in cluster 2 0.5558872305140964 Silhoutte width for each point in cluster 2 0.5924038344861061 Silhoutte width for each point in cluster 2 0.6170235777633571 Silhoutte width for each point in cluster 2 0.5963659961064246 Silhoutte width for each point in cluster 2 0.5685572139303484 Silhoutte width for each point in cluster 2 0.49366802351876976 Silhoutte width for each point in cluster 2 0.5442524221000262

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Silhoutte width for each point in cluster 2 0.5865268253327955 Silhoutte width for each point in cluster 2 0.5814262023217248 Silhoutte width for each point in cluster 2 0.590049751243781 Silhoutte width for each point in cluster 2 0.5804726368159203 Silhoutte width for each point in cluster 2 0.5743504698728579 Silhoutte width for each point in cluster 2 0.5937418172296413 Silhoutte width for each point in cluster 2 0.574212271973466 Silhoutte width for each point in cluster 2 0.531370923161968 Silhoutte width for each point in cluster 2 0.5526652452025587 Silhoutte width for each point in cluster 2 0.4835820895522388 Silhoutte width for each point in cluster 2 0.5793373557743201 Silhoutte width for each point in cluster 2 0.3547079417726185 Silhoutte width for each point in cluster 2 0.42603648424543944 Silhoutte width for each point in cluster 2 0.4104477611940298 Silhoutte width for each point in cluster 2 0.48428312980551824 Silhoutte width for each point in cluster 2 0.3670110983543819 Silhoutte width for each point in cluster 2 0.2799464217374663 Silhoutte width for each point in cluster 2 0.5571200600769736 Silhoutte width for each point in cluster 2 0.40398009950248764 Silhoutte width for each point in cluster 2 0.38773872572620754 Silhoutte width for each point in cluster 2 0.37744610281923735 Silhoutte width for each point in cluster 2 0.08054963278843849 Silhoutte width for each point in cluster 2 0.007462686567164134 Silhoutte width for each point in cluster 2 0.1630735212824765 Average silhoutee width for cluster 1 0.551302933979199

```
In [28]:
           1 distance age k2 = []
           2 distance_income_k2 = []
           3 distance_score_k2 = []
              total distance k2 = []
           5 distance sil = []
             average sill = []
              total=0
           8
              q=0
              w=0
          10
              e=0
          11
              a=0
          12
          13
              total=0
          14
          15
              for i in range(len(cluster 3)):
                  for j in range(len(cluster 3)):#-----calcualting distance
          16
                      q = manhattan_distance(cluster_3[i,2],cluster_3[j,2])
          17
                      #distance age k2.append(a)
          18
                      w = manhattan_distance(cluster_3[i,3],cluster_3[j,3])
          19
          20
                      #distance income k2.append(w)
                      e = manhattan distance(cluster 3[i,4],cluster 3[j,4])
          21
          22
                      #distance score.append(e)
          23
                      total = q+w+e
                      distance sil.append(total/3)
          24
          25
                  a sil = sum(distance sil)/len(cluster 3)
          26
                  #print(a_sil)
          27
                  distance sil.clear()
          28
          29
          30
                  cluster_min=0
          31
          32
                  distance_age_k2 = []
          33
                  distance_income_k2 = []
                  distance score k2 = []
          34
          35
                  total distance k2 = []
                  distance sil = []
          36
          37
                  q=0
          38
                  w=0
          39
                  e=0
          40
                  a=0
          41
```

```
42
        total=0
        n=2#-----for cluster 2
43
        for j in range(len(mediod)):#-----calcualting nearest cluster
44
            q = manhattan_distance(mediod[n,2],mediod[j,2])
45
           #distance age k2.append(q)
46
           w = manhattan distance(mediod[n,3],mediod[j,3])
47
            #distance income k2.append(w)
48
49
            e = manhattan distance(mediod[n,4],mediod[j,4])
50
            #distance score.append(e)
           total = q+w+e
51
52
            distance sil.append(total)
53
        #print(distance sil)
54
        index = [i for i in range(0,4)]
55
        #print(index)
56
        index=np.asarray(index)
        distance sil= np.asarray(distance sil)
57
58
        distance sil.transpose
59
        #print(distance sil)
        distance sil = np.column stack((index,distance sil))
60
        #print(distance sil[:,1])
61
        minval = np.min(distance_sil[:,1][np.nonzero(distance_sil[:,1])])
62
63
        #print(minval)
        for b in range(len(distance sil)):
64
            if (minval == distance sil[b,1]):
65
                cluster min = b
66
                #print(cluster min)
67
68
69
70
71
72
        #----now find the value of b
        if (cluster min == 0):
73
                selected cluster= cluster 1
74
75
        if (cluster min == 1):
                selected cluster= cluster 2
76
        if (cluster min == 2):
77
78
                selected cluster= cluster 3
        if (cluster_min == 3):
79
80
                selected cluster= cluster 4
81
        if (cluster min == 4):
                selected_cluster= cluster_5
82
83
```

```
84
         distance_age_k2 = []
 85
         distance b= []
         distance_income_k2 = []
 86
 87
         distance score k2 = []
 88
         total distance k2 = []
         distance sil = []
 89
 90
         q=0
 91
         w=0
 92
         e=0
 93
         a=0
 94
         s=0
 95
         total=0
 96
 97
 98
         for j in range(len(selected cluster)):#-----calcualting distance
 99
100
101
             q = manhattan distance(cluster 3[i,2],selected cluster[j,2])
             #distance age k2.append(q)
102
103
             w = manhattan distance(cluster_3[i,3],selected_cluster[j,3])
104
             #distance income k2.append(w)
             e = manhattan distance(cluster 3[i,4],selected cluster[j,4])
105
             #distance score.append(e)
106
107
             total = q+w+e
108
             distance b.append(total)
        # print(min(distance b))
109
110
         b = min(distance b)
111
         maxi = max(b, a sil)
         #print("a is", + maxi)
112
         d = b - a sil
113
114
         sill = ((b - a sil) / maxi)#-----silhoutte widht formulae
115
         print("Silhoutte width for each point in cluster 3", + sill)
116
117
         average sill.append(sill)
     s c3 = sum(average sill)/len(average sill)
118
     print("Average silhoutee width for cluster 1", + s c3)
119
120
121
122
```

Silhoutte width for each point in cluster 3 0.7216296296297 Silhoutte width for each point in cluster 3 0.6790990990990993 Silhoutte width for each point in cluster 3 0.7112820512820514 Silhoutte width for each point in cluster 3 0.700624999999998 Silhoutte width for each point in cluster 3 0.7 Silhoutte width for each point in cluster 3 0.6585416666666666 Silhoutte width for each point in cluster 3 0.726938775510204 Silhoutte width for each point in cluster 3 0.5637681159420288 Silhoutte width for each point in cluster 3 0.6827083333333334 Silhoutte width for each point in cluster 3 0.6306666666666667 Silhoutte width for each point in cluster 3 0.3079166666666667 Silhoutte width for each point in cluster 3 0.66213333333333334 Silhoutte width for each point in cluster 3 0.6315942028985507 Silhoutte width for each point in cluster 3 0.43958333333333333 Silhoutte width for each point in cluster 3 0.6683950617283949 Silhoutte width for each point in cluster 3 0.530999999999998 Silhoutte width for each point in cluster 3 0.6152688172043013 Silhoutte width for each point in cluster 3 0.5477192982456139 Silhoutte width for each point in cluster 3 0.5687719298245614 Silhoutte width for each point in cluster 3 0.6358024691358026 Silhoutte width for each point in cluster 3 0.255416666666664 Silhoutte width for each point in cluster 3 0.42070175438596497 Silhoutte width for each point in cluster 3 0.38410256410256405 Silhoutte width for each point in cluster 3 0.6935135135135135 Silhoutte width for each point in cluster 3 0.52208333333333333 Silhoutte width for each point in cluster 3 -0.07216494845360835 Silhoutte width for each point in cluster 3 0.32488888888888 Silhoutte width for each point in cluster 3 0.22428571428571434 Silhoutte width for each point in cluster 3 0.483111111111111116 Silhoutte width for each point in cluster 3 0.22615384615384612 Silhoutte width for each point in cluster 3 0.132666666666668 Silhoutte width for each point in cluster 3 0.4149999999999987 Silhoutte width for each point in cluster 3 0.35333333333333333 Silhoutte width for each point in cluster 3 0.34611111111111111111 Silhoutte width for each point in cluster 3 0.64933333333333333 Silhoutte width for each point in cluster 3 -0.3686109440769693 Silhoutte width for each point in cluster 3 0.5114814814814815 Silhoutte width for each point in cluster 3 0.432424242424227 Silhoutte width for each point in cluster 3 0.5976923076923076 Silhoutte width for each point in cluster 3 0.13266666666666663 Silhoutte width for each point in cluster 3 0.4428571428571429 Silhoutte width for each point in cluster 3 0.5647222222222222

```
In [29]:
           1 distance age k2 = []
           2 distance_income_k2 = []
           3 distance_score_k2 = []
             total distance k2 = []
           5 distance sil = []
             average sill = []
           7 total=0
           8
              q=0
              w=0
          10
              e=0
          11
              a=0
          12
          13
              total=0
          14
          15
              for i in range(len(cluster 4)):
                  for j in range(len(cluster 4)):#-----calcualting distance
          16
                      q = manhattan_distance(cluster_4[i,2],cluster_4[j,2])
          17
                      #distance age k2.append(a)
          18
                      w = manhattan distance(cluster_4[i,3],cluster_4[j,3])
          19
                      #distance income k2.append(w)
          20
                      e = manhattan distance(cluster 4[i,4],cluster 4[j,4])
          21
          22
                      #distance score.append(e)
                      total = q+w+e
          23
                      distance sil.append(total/3)
          24
          25
                  a sil = sum(distance sil)/len(cluster 4)
          26
                  #print(a sil)
          27
                  distance sil.clear()
          28
          29
          30
          31
          32
          33
                  cluster_min=0
          34
          35
                  distance age k2 = []
          36
                  distance income k2 = []
                  distance_score_k2 = []
          37
          38
                  total_distance_k2 = []
          39
                  distance sil = []
          40
                  q=0
          41
                  w=0
```

```
42
        e=0
43
        a=0
44
45
        total=0
46
        n=3#-----for cluster 4
        for j in range(len(mediod)):#-----calcualting nearest cluster
47
            q = manhattan distance(mediod[n,2],mediod[j,2])
48
49
            #distance age k2.append(q)
50
           w = manhattan distance(mediod[n,3],mediod[j,3])
            #distance income k2.append(w)
51
            e = manhattan distance(mediod[n,4],mediod[j,4])
52
           #distance_score.append(e)
53
54
           total = q+w+e
55
            distance sil.append(total)
56
        #print(distance sil)
        index = [i for i in range(0,4)]
57
58
        #print(index)
59
        index=np.asarray(index)
        distance sil= np.asarray(distance sil)
60
        distance sil.transpose
61
        #print(distance sil)
62
63
        distance sil = np.column stack((index,distance sil))
        #print(distance sil[:,1])
64
        minval = np.min(distance_sil[:,1][np.nonzero(distance_sil[:,1])])
65
        #print(minval)
66
        for b in range(len(distance sil)):
67
68
           if (minval == distance sil[b,1]):
                cluster min = b
69
                #print(cluster min)
70
71
72
73
74
75
        #----now find the value of b
        if (cluster min == 0):
76
                selected cluster= cluster 1
77
78
        if (cluster min == 1):
                selected_cluster= cluster_2
79
80
        if (cluster_min == 2):
81
                selected cluster= cluster 3
        if (cluster_min == 3):
82
                selected_cluster= cluster_4
83
```

```
84
         if (cluster min == 4):
 85
                 selected_cluster= cluster_5
 86
 87
         distance_age_k2 = []
 88
         distance b= []
         distance income k2 = []
 89
 90
         distance score k2 = []
 91
         total distance k2 = []
 92
         distance sil = []
 93
         q=0
 94
         w=0
 95
         e=0
 96
         a=0
 97
         s=0
 98
 99
         total=0
100
         for j in range(len(selected cluster)):#-----calcualting distance
101
102
103
             q = manhattan distance(cluster 4[i,2],selected cluster[j,2])
104
105
             #distance age k2.append(q)
             w = manhattan distance(cluster 4[i,3],selected cluster[j,3])
106
             #distance income k2.append(w)
107
108
             e = manhattan distance(cluster 4[i,4],selected cluster[j,4])
             #distance score.append(e)
109
110
             total = q+w+e
111
             distance b.append(total)
        # print(min(distance b))
112
         b = min(distance b)
113
114
         maxi = max(b, a sil)
115
         #print("a is", + maxi)
         d = b - a sil
116
         sill = ((b - a sil) / maxi)#-----silhoutte widht formulae
117
         print("Silhoutte width for each point in cluster 4", + sill)
118
119
120
         average sill.append(sill)
     s_c4 = sum(average_sill)/len(average_sill)
     print("Average silhoutee width for cluster 1", + s c4)
122
123
```

Silhoutte width for each point in cluster 4 -0.4558772235786535 Silhoutte width for each point in cluster 4 -0.5785411038209186 Silhoutte width for each point in cluster 4 -0.6812423375561913 Silhoutte width for each point in cluster 4 -0.08657465495608561 Silhoutte width for each point in cluster 4 0.5876532887402452 Silhoutte width for each point in cluster 4 0.12019230769230785 Silhoutte width for each point in cluster 4 0.5002003205128204 Silhoutte width for each point in cluster 4 0.18184885290148434 Silhoutte width for each point in cluster 4 0.6134992458521871 Silhoutte width for each point in cluster 4 0.44673382173382176 Silhoutte width for each point in cluster 4 0.5214342948717948 Silhoutte width for each point in cluster 4 0.5409382284382283 Silhoutte width for each point in cluster 4 0.5182291666666667 Silhoutte width for each point in cluster 4 0.14878542510121456 Silhoutte width for each point in cluster 4 0.4649725274725275 Silhoutte width for each point in cluster 4 0.5467032967032968 Silhoutte width for each point in cluster 4 0.6204309874522641 Silhoutte width for each point in cluster 4 0.6057692307692306 Silhoutte width for each point in cluster 4 0.5057692307692307 Silhoutte width for each point in cluster 4 0.5405518394648829 Silhoutte width for each point in cluster 4 0.4984526967285587 Silhoutte width for each point in cluster 4 0.5620845204178536 Silhoutte width for each point in cluster 4 0.645586785009862 Silhoutte width for each point in cluster 4 0.25993589743589746 Silhoutte width for each point in cluster 4 0.6392525913802508 Silhoutte width for each point in cluster 4 0.5904403567447046 Silhoutte width for each point in cluster 4 0.6556931768796175 Silhoutte width for each point in cluster 4 0.26660839160839184 Silhoutte width for each point in cluster 4 0.5796703296703296 Silhoutte width for each point in cluster 4 0.5902496626180836 Silhoutte width for each point in cluster 4 0.6493589743589743 Silhoutte width for each point in cluster 4 0.6088286713286714 Silhoutte width for each point in cluster 4 0.6677761341222881 Silhoutte width for each point in cluster 4 0.597222222222221 Silhoutte width for each point in cluster 4 0.6254807692307692 Silhoutte width for each point in cluster 4 0.5843531468531469 Silhoutte width for each point in cluster 4 0.6377060439560438 Silhoutte width for each point in cluster 4 0.6283577533577533 Silhoutte width for each point in cluster 4 0.6567796610169492 Silhoutte width for each point in cluster 4 0.5958073458073458 Silhoutte width for each point in cluster 4 0.3552166224580018

```
Silhoutte width for each point in cluster 4 0.6483707264957265 Silhoutte width for each point in cluster 4 0.6044429708222812 Silhoutte width for each point in cluster 4 0.6756844850065189 Silhoutte width for each point in cluster 4 0.5447191697191698 Silhoutte width for each point in cluster 4 0.6309731934731935 Silhoutte width for each point in cluster 4 0.6187232905982907 Silhoutte width for each point in cluster 4 0.6763822115384615 Silhoutte width for each point in cluster 4 0.5754807692307693 Silhoutte width for each point in cluster 4 0.5209276018099546 Silhoutte width for each point in cluster 4 0.6532838506522719 Silhoutte width for each point in cluster 4 0.6814204314204315 Average silhoutee width for cluster 1 0.46897590767698333
```

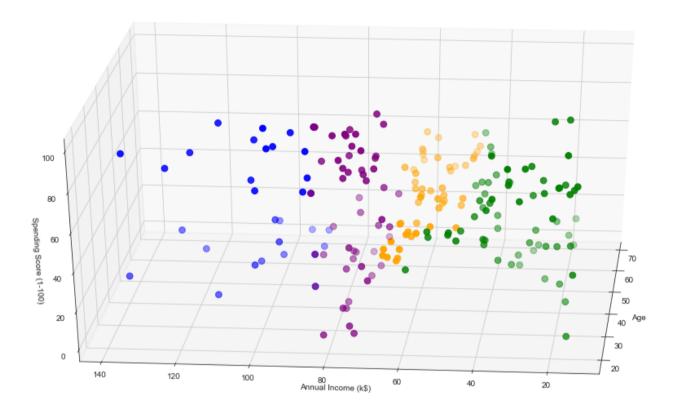
### Average silhoutte width of dataset

```
In [33]: 1 Average_dataset = (s_c1+s_c2+s_c3+s_c4)/4
2 print("Average silhoutte width of dataset", + Average_dataset)

Average silhoutte width of dataset 0.5325300537791802
In []: 1
```

### Plotting assigned clusters below

```
In [31]:
           2 cluster 1 = np.asarray(cluster 1)
           3 cluster 2 = np.asarray(cluster 2)
            cluster 3 = np.asarray(cluster 3)
           5 cluster 4 = np.asarray(cluster 4)
            sns.set style("white")
           7 fig = plt.figure(figsize=(20,10))
           8 ax = fig.add subplot(111, projection='3d')
           9 clusterX1 = cluster 1[:,2].tolist()
          10 clusterY1 = cluster 1[:,3].tolist()
          11 clusterZ1 = cluster 1[:,4].tolist()
          12 clusterX2 = cluster 2[:,2].tolist()
          13 clusterY2 = cluster 2[:,3].tolist()
          14 clusterZ2 = cluster 2[:,4].tolist()
          15 | clusterX3 = cluster 3[:,2].tolist()
          16 | clusterY3 = cluster 3[:,3].tolist()
          17 | clusterZ3 = cluster 3[:,4].tolist()
          18 clusterX4 = cluster 4[:,2].tolist()
          19 clusterY4 = cluster 4[:,3].tolist()
          20 clusterZ4 = cluster 4[:,4].tolist()
          21 ax.scatter(clusterX1, clusterY1, clusterZ1, c='blue', s=60)
          22 ax.scatter(clusterX2, clusterY2, clusterZ2, c='green', s=60)
          23 ax.scatter(clusterX3, clusterY3, clusterZ3, c='orange', s=60)
          24 ax.scatter(clusterX4, clusterY4, clusterZ4, c='purple', s=60)
          25 ax.view init(30, 185)
          26 plt.xlabel("Age")
          27 plt.vlabel("Annual Income (k$)")
          28 ax.set zlabel('Spending Score (1-100)')
             plt.show()
```



## Saving to csv file

```
In [35]: Lakehead Study material\Big data\Assignment 2\K mediod\Work directory\k_is_4\clusters_k.csv', index = None, header=True)
In []: 1
In []: 1
```