5 - Data Project – Team Winrate - Descriptive Classification&Clustering - Summer 2019

June 1, 2020

[1]:
```
import numpy as np
import pandas as pd
pd.options.display.max_columns=100
from sklearn.model_selection import train_test_split, cross_val_score,␣
 ↪cross_validate
import sklearn.metrics
from sklearn.preprocessing import StandardScaler as SSc
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans as KM, AgglomerativeClustering as AgC,␣
 ↪SpectralClustering as SpC, DBSCAN as DBS
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import scipy.cluster.hierarchy as shc
import graphviz as gviz
%matplotlib inline


#set width of window to preference
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:90% !important; }</style>"))
```

```
<IPython.core.display.HTML object>
```

[2]:
```
#year = "2019"                                                    #choose year␣
 ↪to get data from
#split = "summer"                                                  #choose split␣
 ↪to get data from(spring, summer, worlds)
#infile = r"C:\Users\Triplea657\000 MSCS-335 2020\Datasets\League_"#path
#inf = "-Wrangled.csv"                                             #file to read
#filein = infile+year+"\\"+year+'-'+split+'-'+inf
#data = pd.read_csv(filein,low_memory=False)
#data.head(10)

#changed for submission version
```

```python
data = pd.read_csv("Datasets/League_2019/2019-summer-Wrangled.csv", index_col=0,␣
 ↪low_memory=False)
data.head()
```

[2]:

```
   league_CBLoL  league_LCK  league_LCS  league_LEC  league_LMS  gamelength  \
0           0.0         0.0         1.0         0.0         0.0   35.500000
1           0.0         0.0         1.0         0.0         0.0   35.500000
2           0.0         0.0         1.0         0.0         0.0   29.700000
3           0.0         0.0         1.0         0.0         0.0   29.700000
4           0.0         0.0         1.0         0.0         0.0   31.983333

   result     k     d     a   fb       kpm      okpm      ckpm   fd  \
0     1.0  21.0  14.0  52.0  0.0  0.591549  0.394366  0.985915  0.0
1     0.0  14.0  21.0  32.0  1.0  0.394366  0.591549  0.985915  1.0
2     1.0  11.0   4.0  25.0  1.0  0.370370  0.134680  0.505051  1.0
3     0.0   4.0  11.0  10.0  0.0  0.134680  0.370370  0.505051  0.0
4     1.0  12.0   3.0  26.0  1.0  0.375195  0.093799  0.468994  0.0

      fdtime  teamdragkills  oppdragkills  elementals  oppelementals  \
0  12.556633            2.0           2.0         2.0            2.0
1  12.556633            2.0           2.0         2.0            2.0
2  12.306967            2.0           1.0         2.0            1.0
3  12.306967            1.0           2.0         1.0            2.0
4  10.158933            3.0           1.0         3.0            1.0

   firedrakes  waterdrakes  earthdrakes  airdrakes  elders  oppelders  herald  \
0         2.0          0.0          0.0        0.0     0.0        0.0     1.0
1         1.0          0.0          0.0        1.0     0.0        0.0     0.0
2         0.0          0.0          1.0        1.0     0.0        0.0     0.0
3         0.0          1.0          0.0        0.0     0.0        0.0     1.0
4         1.0          0.0          0.0        2.0     0.0        0.0     0.0

   heraldtime   ft     fttime  firstmidouter  firsttothreetowers  \
0   13.369417  1.0  15.162683            1.0                 0.0
1   13.369417  0.0  15.162683            0.0                 1.0
2   12.377433  1.0  12.791600            1.0                 1.0
3   12.377433  0.0  12.791600            0.0                 0.0
4   12.242783  0.0  14.386333            1.0                 1.0

   teambaronkills  oppbaronkills  dmgtochamps  dmgtochampsperminute  wards  \
0             1.0            0.0      70545.0           1987.183099  109.0
1             0.0            1.0      71736.0           2020.732394  108.0
2             1.0            0.0      51538.0           1735.286195   96.0
3             0.0            1.0      38185.0           1285.690236   93.0
4             1.0            0.0      49421.0           1545.211047  143.0

        wpm  wardkills      wcpm  totalgold    earnedgpm  goldspent      gspd  \
```

```
0  3.070423       51.0  1.436620    69022.0  1293.464789    65108.0   0.110966
1  3.042254       37.0  1.042254    61541.0  1082.732394    58263.0  -0.110966
2  3.232323       44.0  1.481481    59081.0  1330.861953    50910.0   0.135867
3  3.131313       41.0  1.380471    45794.0   883.488215    44433.0  -0.135867
4  4.471079       44.0  1.375717    61326.0  1262.351225    54340.0   0.158169

   monsterkillsownjungle  monsterkillsenemyjungle       cspm  goldat10  \
0                  151.0                     24.0  31.802817   16118.0
1                  155.0                      4.0  32.985915   15436.0
2                  102.0                     56.0  35.656566   16270.0
3                   82.0                      0.0  33.265993   14985.0
4                  128.0                     18.0  34.299114   16157.0

   oppgoldat10  gdat10  goldat15  oppgoldat15  gdat15   xpat10  oppxpat10  \
0      15436.0   682.0   24287.0      23616.0   671.0  19260.0    18621.0
1      16118.0  -682.0   23616.0      24287.0  -671.0  18621.0    19260.0
2      14985.0  1285.0   27399.0      23026.0  4373.0  19015.0    18226.0
3      16270.0 -1285.0   23026.0      27399.0 -4373.0  18226.0    19015.0
4      14365.0  1792.0   26339.0      22782.0  3557.0  19284.0    18656.0

   xpdat10  csat10  oppcsat10  csdat10  csat15  oppcsat15  csdat15
0    639.0   334.0      316.0     18.0   548.0      535.0     13.0
1   -639.0   316.0      334.0    -18.0   535.0      548.0    -13.0
2    789.0   316.0      335.0    -19.0   509.0      506.0      3.0
3   -789.0   335.0      316.0     19.0   506.0      509.0     -3.0
4    628.0   322.0      305.0     17.0   512.0      470.0     42.0
```

[3]:
```python
var = []
for i in data:
    var.append(i)
print(var)
for i, v in enumerate(var):
    print(i, v)
```

```
['league_CBLoL', 'league_LCK', 'league_LCS', 'league_LEC', 'league_LMS',
'gamelength', 'result', 'k', 'd', 'a', 'fb', 'kpm', 'okpm', 'ckpm', 'fd',
'fdtime', 'teamdragkills', 'oppdragkills', 'elementals', 'oppelementals',
'firedrakes', 'waterdrakes', 'earthdrakes', 'airdrakes', 'elders', 'oppelders',
'herald', 'heraldtime', 'ft', 'fttime', 'firstmidouter', 'firsttothreetowers',
'teambaronkills', 'oppbaronkills', 'dmgtochamps', 'dmgtochampsperminute',
'wards', 'wpm', 'wardkills', 'wcpm', 'totalgold', 'earnedgpm', 'goldspent',
'gspd', 'monsterkillsownjungle', 'monsterkillsenemyjungle', 'cspm', 'goldat10',
'oppgoldat10', 'gdat10', 'goldat15', 'oppgoldat15', 'gdat15', 'xpat10',
'oppxpat10', 'xpdat10', 'csat10', 'oppcsat10', 'csdat10', 'csat15', 'oppcsat15',
'csdat15']
0 league_CBLoL
1 league_LCK
```

2 league_LCS
3 league_LEC
4 league_LMS
5 gamelength
6 result
7 k
8 d
9 a
10 fb
11 kpm
12 okpm
13 ckpm
14 fd
15 fdtime
16 teamdragkills
17 oppdragkills
18 elementals
19 oppelementals
20 firedrakes
21 waterdrakes
22 earthdrakes
23 airdrakes
24 elders
25 oppelders
26 herald
27 heraldtime
28 ft
29 fttime
30 firstmidouter
31 firsttothreetowers
32 teambaronkills
33 oppbaronkills
34 dmgtochamps
35 dmgtochampsperminute
36 wards
37 wpm
38 wardkills
39 wcpm
40 totalgold
41 earnedgpm
42 goldspent
43 gspd
44 monsterkillsownjungle
45 monsterkillsenemyjungle
46 cspm
47 goldat10
48 oppgoldat10
49 gdat10

```
50 goldat15
51 oppgoldat15
52 gdat15
53 xpat10
54 oppxpat10
55 xpdat10
56 csat10
57 oppcsat10
58 csdat10
59 csat15
60 oppcsat15
61 csdat15
```

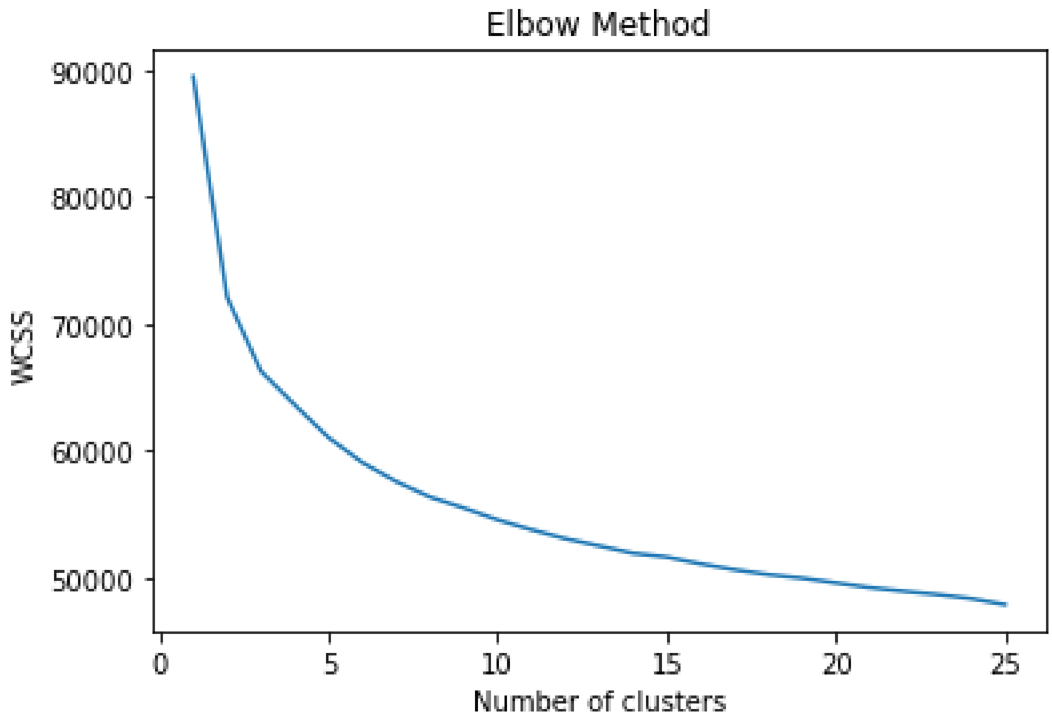
[4]:
```
#transform input data (normalize scaling)
ssc = SSc()
data = pd.DataFrame(ssc.fit_transform(data))
```

[5]:
```
n_samples, n_features = data.shape
print("n_samples  {} \nn_features {}".format(n_samples, n_features))
```

```
n_samples  1444
n_features 62
```

Within cluster sum of squares (WCSS) for determining number of clusters to use (elbow method)

[6]:
```
wcss = []
for i in range(1, 26):
    kmeans = KM(n_clusters=i, init='k-means++', max_iter=300, n_init=10,␣
 ↪random_state=0)
    kmeans.fit(data)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 26), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```

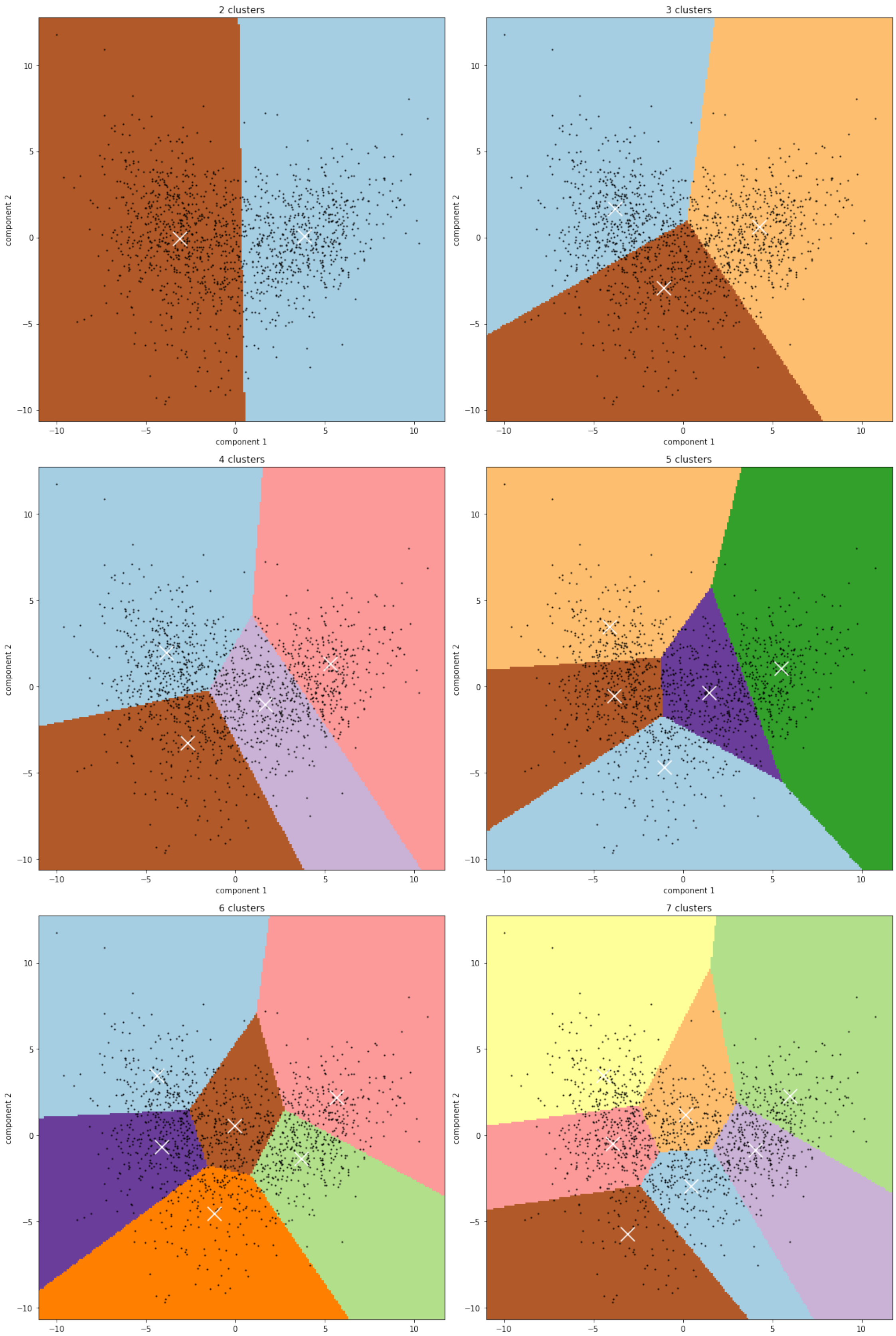



```
[7]: def kmcluster(X, nclusters):
         km = KM(n_clusters=nclusters, random_state=2020).fit(X)
         return km
```

```
[8]: print("\tUsing K-means clustering\n\tThe white Xs are the centroids of each␣
      ↪cluster")

     reduced_data = PCA(n_components=2).fit_transform(data)

     fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6]] = plt.subplots(3,2,figsize=(16,24))
     axes = [ax1,ax2,ax3,ax4,ax5,ax6]
     def addSubplot(subplt_n, reduced_data, n_clstrs):
         meshstep = 0.1
         x_min, x_max = reduced_data[:, 0].min() - 1, reduced_data[:, 0].max() + 1
         y_min, y_max = reduced_data[:, 1].min() - 1, reduced_data[:, 1].max() + 1
         xx, yy = np.meshgrid(np.arange(x_min, x_max, meshstep), np.arange(y_min,␣
      ↪y_max, meshstep))
         kmeans = KM(init='k-means++', n_clusters=n_clstrs, n_init=10)
         kmeans.fit(reduced_data)
         Z = kmeans.predict(np.c_[xx.ravel(), yy.ravel()])
         Z = Z.reshape(xx.shape)

         axes[subplt_n].imshow(Z, interpolation='nearest',
```

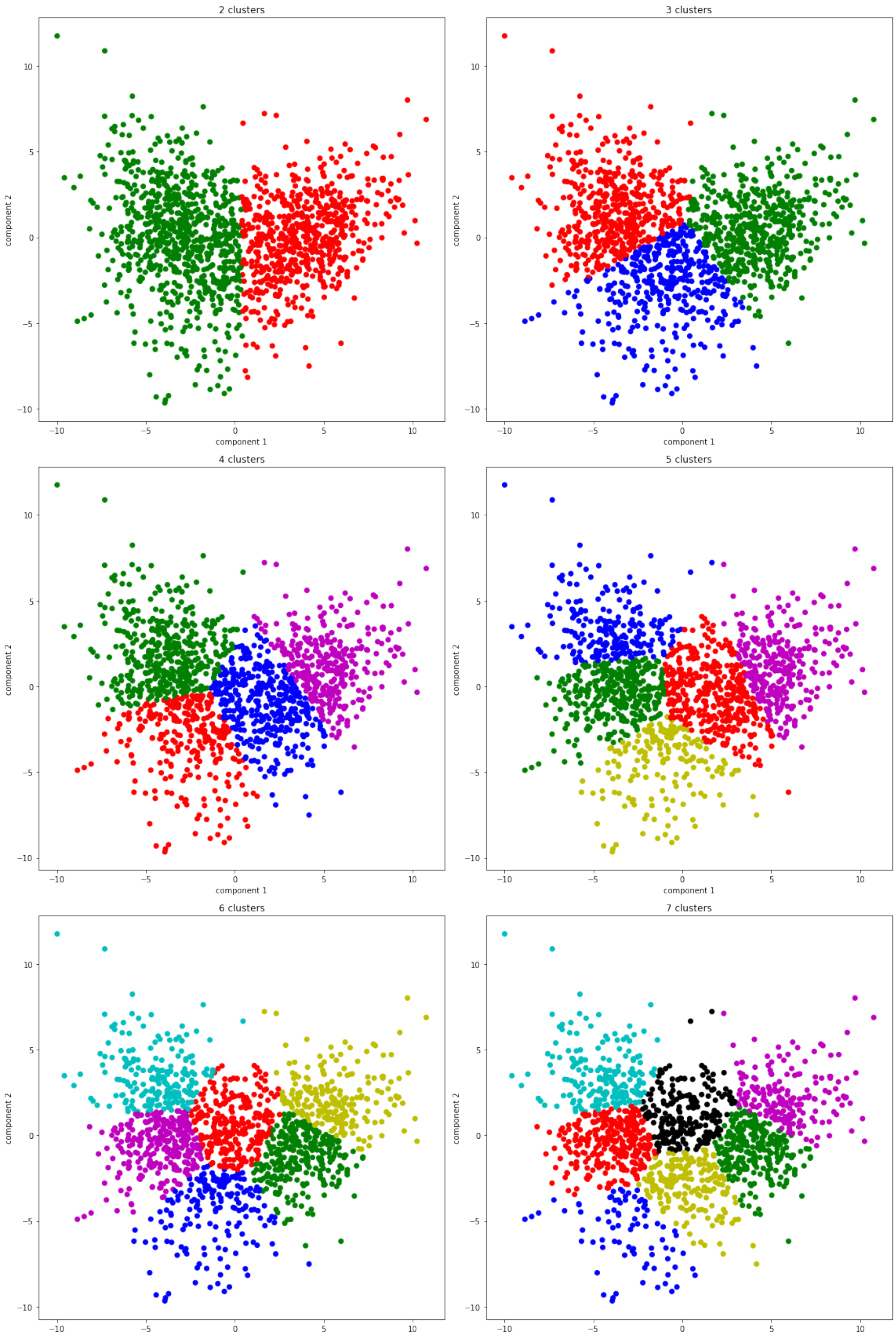
```
                   extent=(xx.min(), xx.max(), yy.min(), yy.max()),
                   cmap=plt.cm.Paired,
                   aspect='auto', origin='lower')
    axes[subplt_n].plot(reduced_data[:,0], reduced_data[:,1], 'k.', markersize=2)
    for cluster in range(0, kmeans.cluster_centers_.shape[0]):
        axes[subplt_n].scatter(kmeans.cluster_centers_[cluster, 0], kmeans.
 ↪cluster_centers_[cluster, 1],
                    marker='x', s=320, linewidths=4,
                    label='Cluster ' + str(cluster),
                    color='w', zorder=4)#, hold=True)
        axes[subplt_n].set_title('{} clusters'.format(n_clstrs))
        axes

for i in range(2,8):
    addSubplot(i-2, reduced_data, i)
for ax in axes:
    ax.set(xlabel='component 1', ylabel='component 2')
plt.tight_layout()
plt.show()
```

```
Using K-means clustering
The white Xs are the centroids of each cluster
```


2 clusters
3 clusters
4 clusters
5 clusters
6 clusters
7 clusters
component 1
component 2

[9]:
```
print("\tAnother graphing method using KMeans clustering\n")
plt.clf()
reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6]] = plt.subplots(3,2,figsize=(16,24))
axes = [ax1,ax2,ax3,ax4,ax5,ax6]

def addSubPlot(subplt_n, reduced_data, n_clustrs):
    axes[subplt_n].set_title('{} clusters'.format(n_clustrs))

    km = KM(n_clusters=n_clustrs, init='k-means++', max_iter=300, n_init=10,␣
 ↪random_state=0)
    km.fit(reduced_data)
    color_no = np.array(km.labels_)
    colors_dict =␣
 ↪['r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','c
    colors = []
    for i in color_no:
        colors.append(colors_dict[i])
    axes[subplt_n].scatter(reduced_data.iloc[:,0], reduced_data.iloc[:,1],␣
 ↪color=colors)
for i in range(2,8):
    addSubPlot(i-2, reduced_data, i)
for ax in axes:
    ax.set(xlabel='component 1', ylabel='component 2')
plt.tight_layout()
plt.show()
```

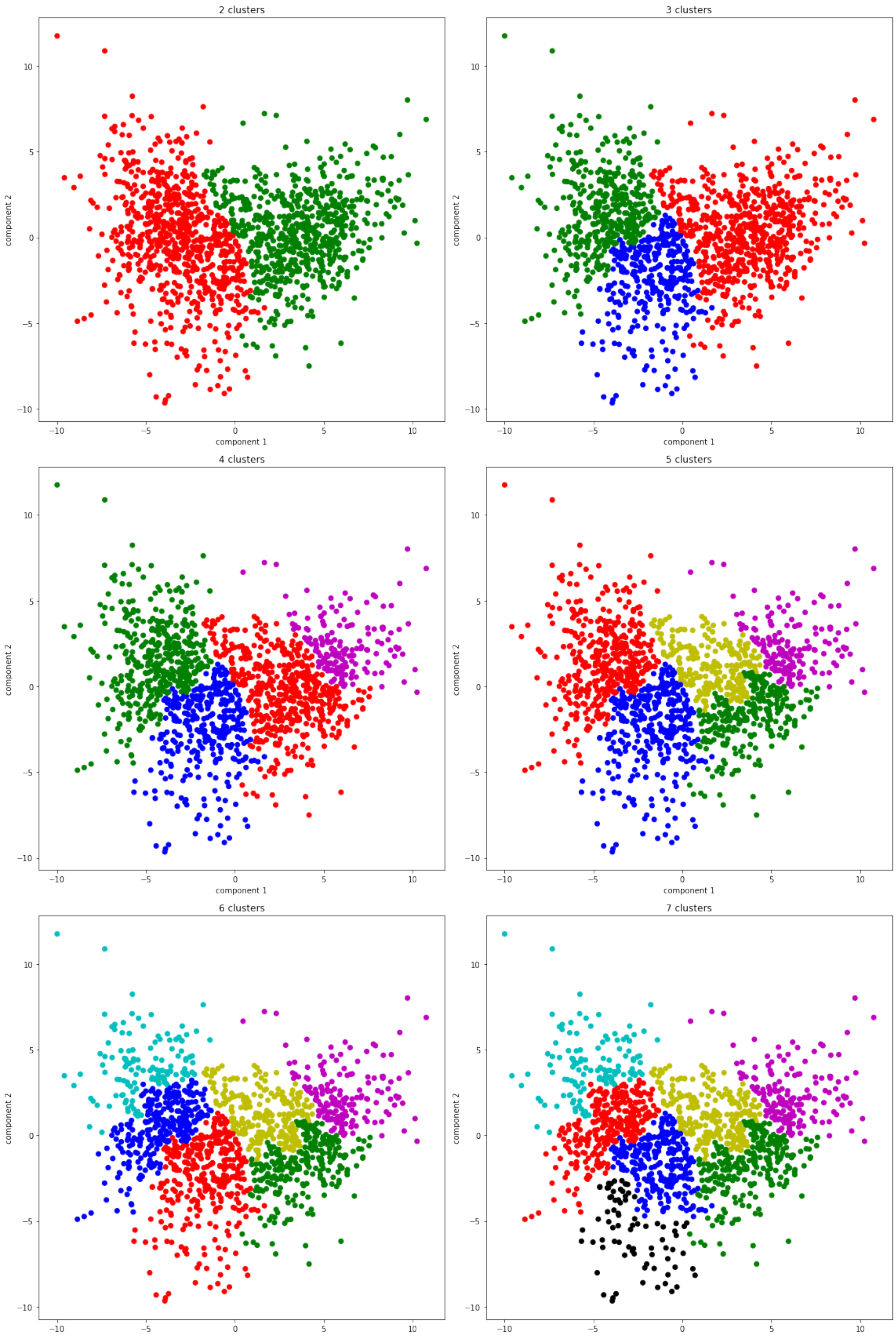
```
        Another graphing method using KMeans clustering

<Figure size 432x288 with 0 Axes>
```


2 clusters
3 clusters
4 clusters
5 clusters
6 clusters
7 clusters
component 1
component 2

[10]:

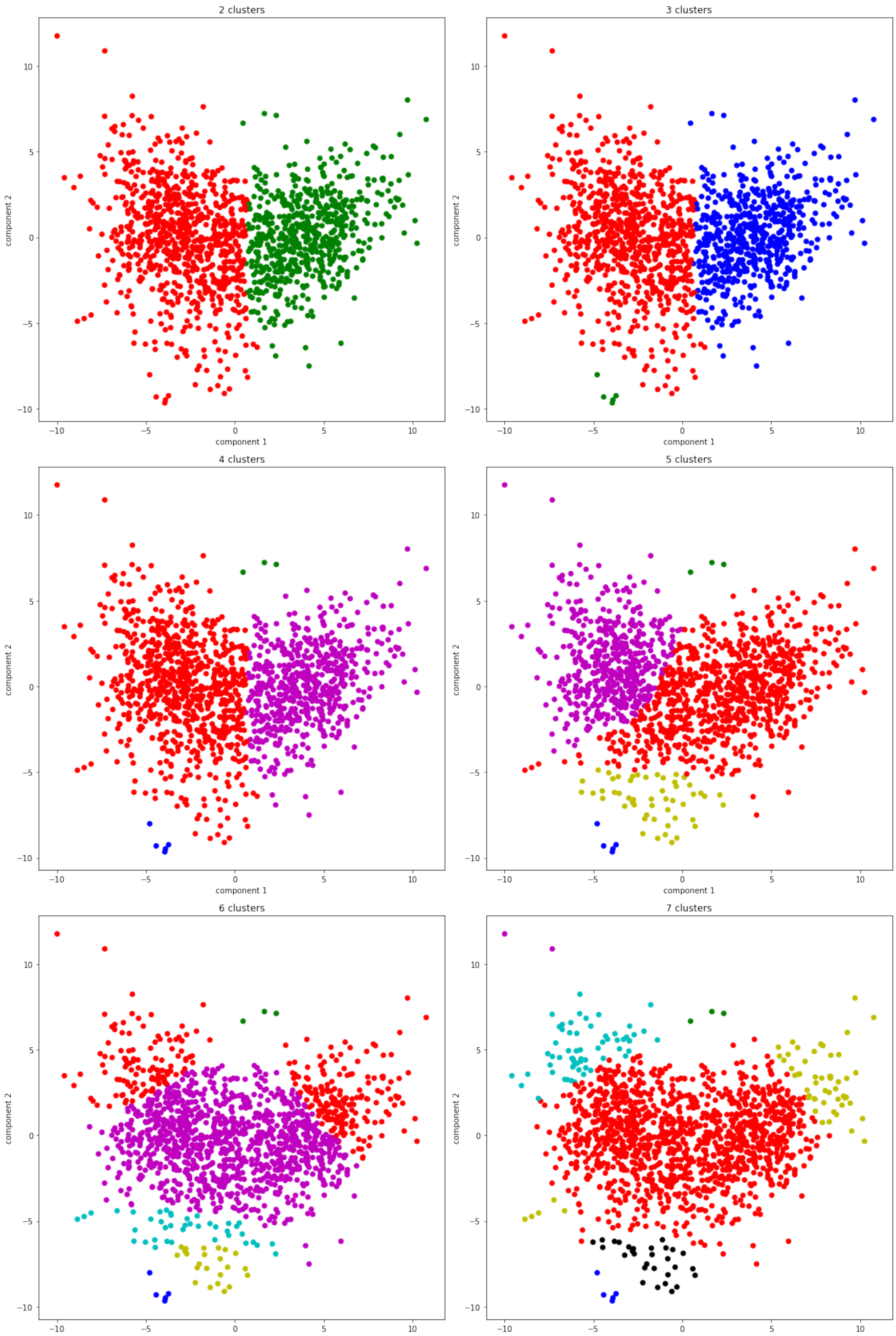
```
print("\tUsing Agglomerative clustering\n")
plt.clf()
reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6]] = plt.subplots(3,2,figsize=(16,24))
axes = [ax1,ax2,ax3,ax4,ax5,ax6]

def addSubPlot(subplt_n, reduced_data, n_clstrs):
    axes[subplt_n].set_title('{} clusters'.format(str(n_clstrs)))

    agc = AgC(n_clusters=n_clstrs)
    agc.fit(reduced_data)

    color_no = np.array(agc.labels_)
    colors_dict = ['r','g','b','m','y','c','k']
    colors = []
    for i in color_no:
        colors.append(colors_dict[i])
    axes[subplt_n].scatter(reduced_data.iloc[:,0], reduced_data.iloc[:,1],␣
 ↪color=colors)
for i in range(2,8):
    addSubPlot(i-2, reduced_data, i)
for ax in axes:
    ax.set(xlabel='component 1', ylabel='component 2')
plt.tight_layout()
plt.show()
```

```
        Using Agglomerative clustering


<Figure size 432x288 with 0 Axes>
```


2 clusters
3 clusters
4 clusters
5 clusters
6 clusters
7 clusters
component 1
component 2

[11]:
```python
print("\tUsing Spectral clustering\n")
plt.clf()
reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6]] = plt.subplots(3,2,figsize=(16,24))
axes = [ax1,ax2,ax3,ax4,ax5,ax6]

def addSubPlot(subplt_n, reduced_data, n_clstrs):
    axes[subplt_n].set_title('{} clusters'.format(str(n_clstrs)))

    spc = SpC(n_clusters=n_clstrs)
    spc.fit(reduced_data)

    color_no = np.array(spc.labels_)
    colors_dict = ['r','g','b','m','y','c','k']
    colors = []
    for i in color_no:
        colors.append(colors_dict[i])
    axes[subplt_n].scatter(reduced_data.iloc[:,0], reduced_data.iloc[:,1],␣
 ↪color=colors)
for i in range(2,8):
    addSubPlot(i-2, reduced_data, i)
for ax in axes:
    ax.set(xlabel='component 1', ylabel='component 2')
plt.tight_layout()
plt.show()
```

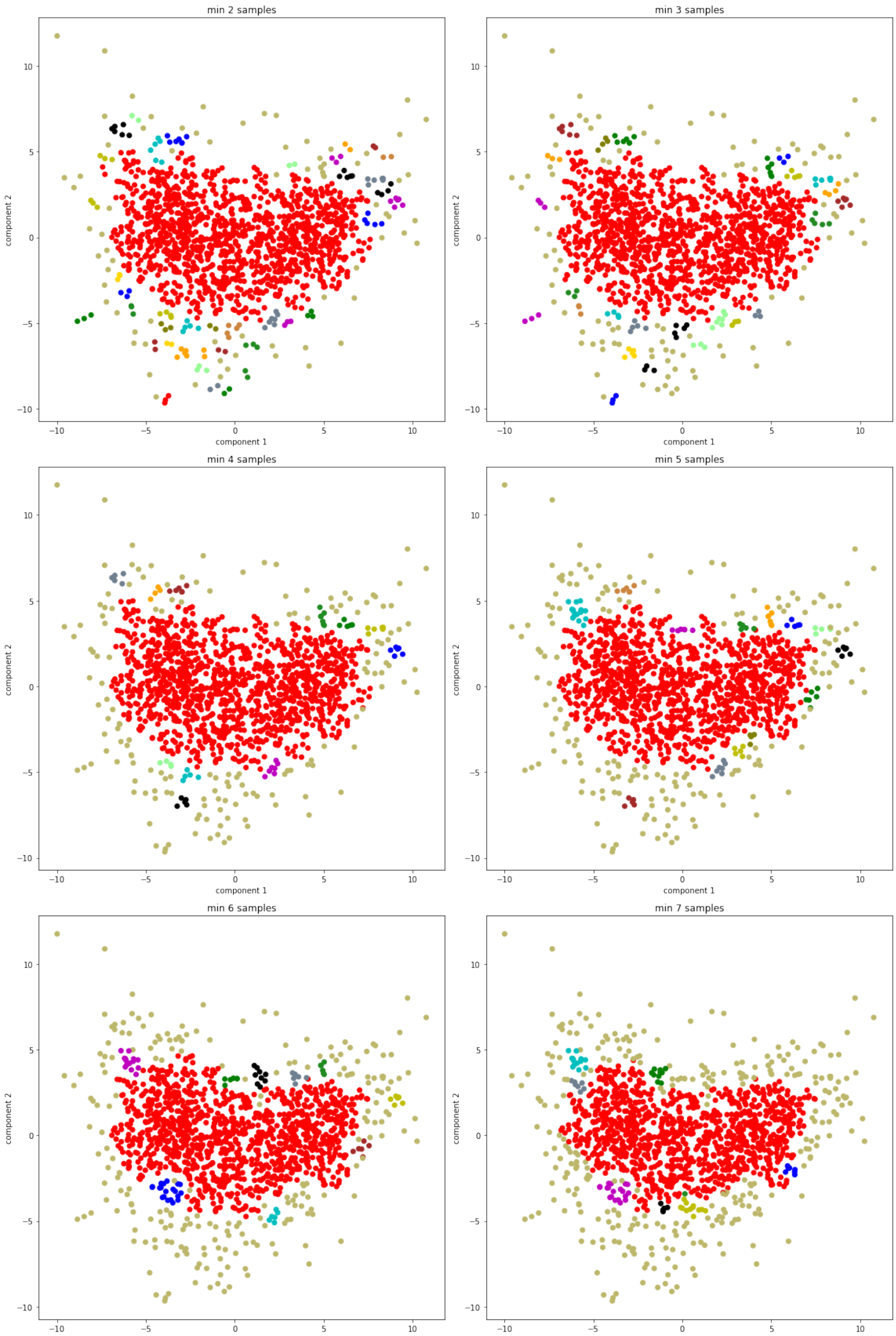
```
        Using Spectral clustering

<Figure size 432x288 with 0 Axes>
```


2 clusters
3 clusters
4 clusters
5 clusters
6 clusters
7 clusters
component 1
component 2

[12]:

```
print("\tUsing DBSCAN clustering\n")
plt.clf()
reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6]] = plt.subplots(3,2,figsize=(16,24))
axes = [ax1,ax2,ax3,ax4,ax5,ax6]

def addSubPlot(subplt_n, reduced_data, min_smpls):
    axes[subplt_n].set_title('min {} samples'.format(str(min_smpls)))

    dbs = DBS(min_samples=min_smpls)
    dbs.fit(reduced_data)
    color_no = np.array(dbs.labels_)
    colors_dict =␣
 ↪['r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','c
    colors = []
    for i in color_no:
        colors.append(colors_dict[i])
    axes[subplt_n].scatter(reduced_data.iloc[:,0], reduced_data.iloc[:,1],␣
 ↪color=colors)
for i in range(2,8):
    addSubPlot(i-2, reduced_data, i)
for ax in axes:
    ax.set(xlabel='component 1', ylabel='component 2')
plt.tight_layout()
plt.show()
```

```
        Using DBSCAN clustering

<Figure size 432x288 with 0 Axes>
```

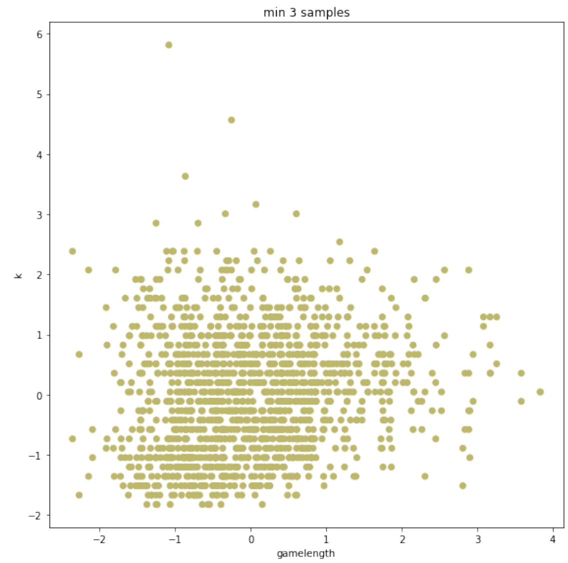


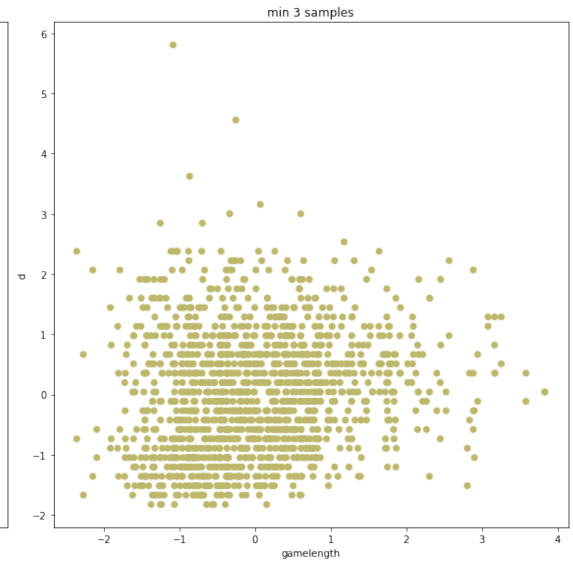
min 2 samples
min 3 samples
min 4 samples
min 5 samples
min 6 samples
min 7 samples
component 1
component 2

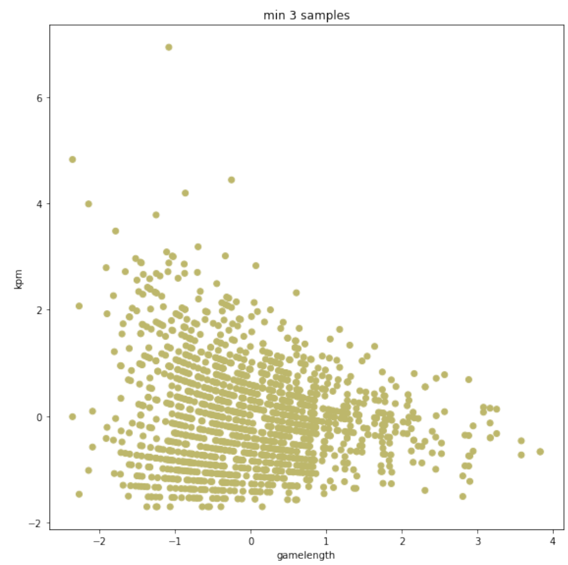
[23]:

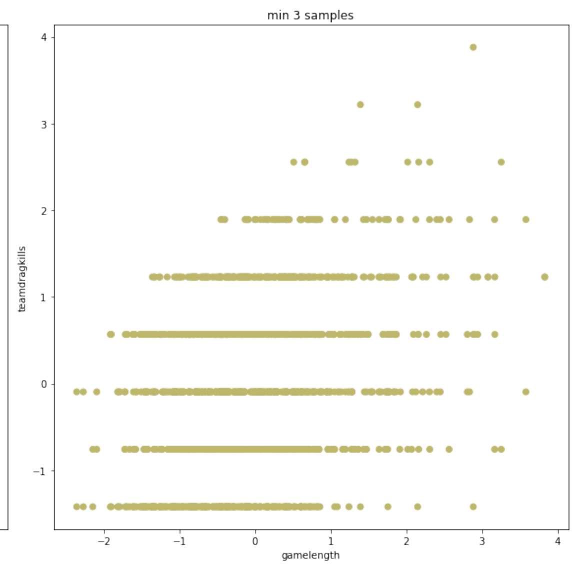
```
print("\tUsing DBSCAN clustering on the data\n")
plt.clf()
interesting_variables = [7,8,11,16,34,37]
#reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6]] = plt.subplots(3,2,figsize=(16,24))
axes = [ax1,ax2,ax3,ax4,ax5,ax6]

dbs = DBS(eps =1.5, min_samples=3)
dbs.fit(data)
color_no = np.array(dbs.labels_)
colors_dict =␣
 ↪['r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','c
          ␣
 ↪'r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','ol
          ␣
 ↪'r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','ol
colors = []
for i in color_no:
    colors.append(colors_dict[i])

def addSubPlot(subplt_n, reduced_data, min_smpls):
    axes[subplt_n].set_title('min {} samples'.format(3))

    axes[subplt_n].scatter(data.iloc[:,5], data.iloc[:
 ↪,interesting_variables[subplt_n]], color=colors)

for i in range(2,8):
    addSubPlot(i-2, reduced_data, i)
idx = 0
for ax in axes:
    ax.set(xlabel=var[5], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()
```

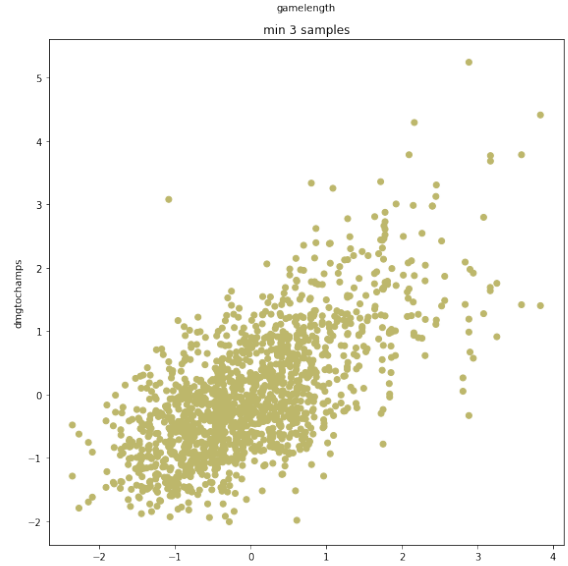
```
	Using DBSCAN clustering on the data

<Figure size 432x288 with 0 Axes>
```

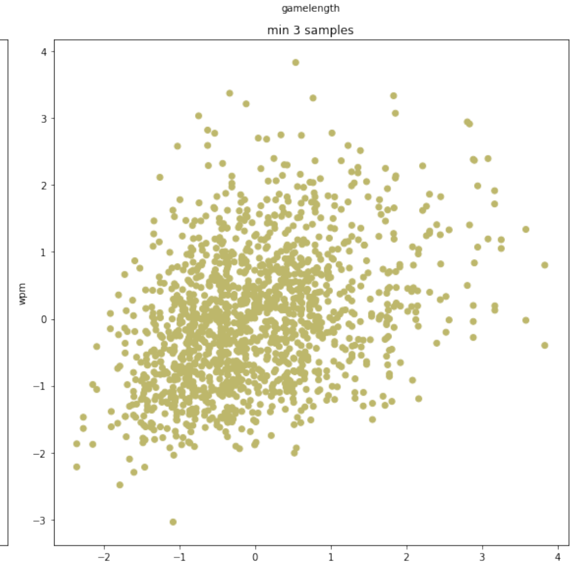

min 3 samples
k
gamelength


min 3 samples
d
gamelength


min 3 samples
kpm
gamelength


min 3 samples
teamdragkills
gamelength

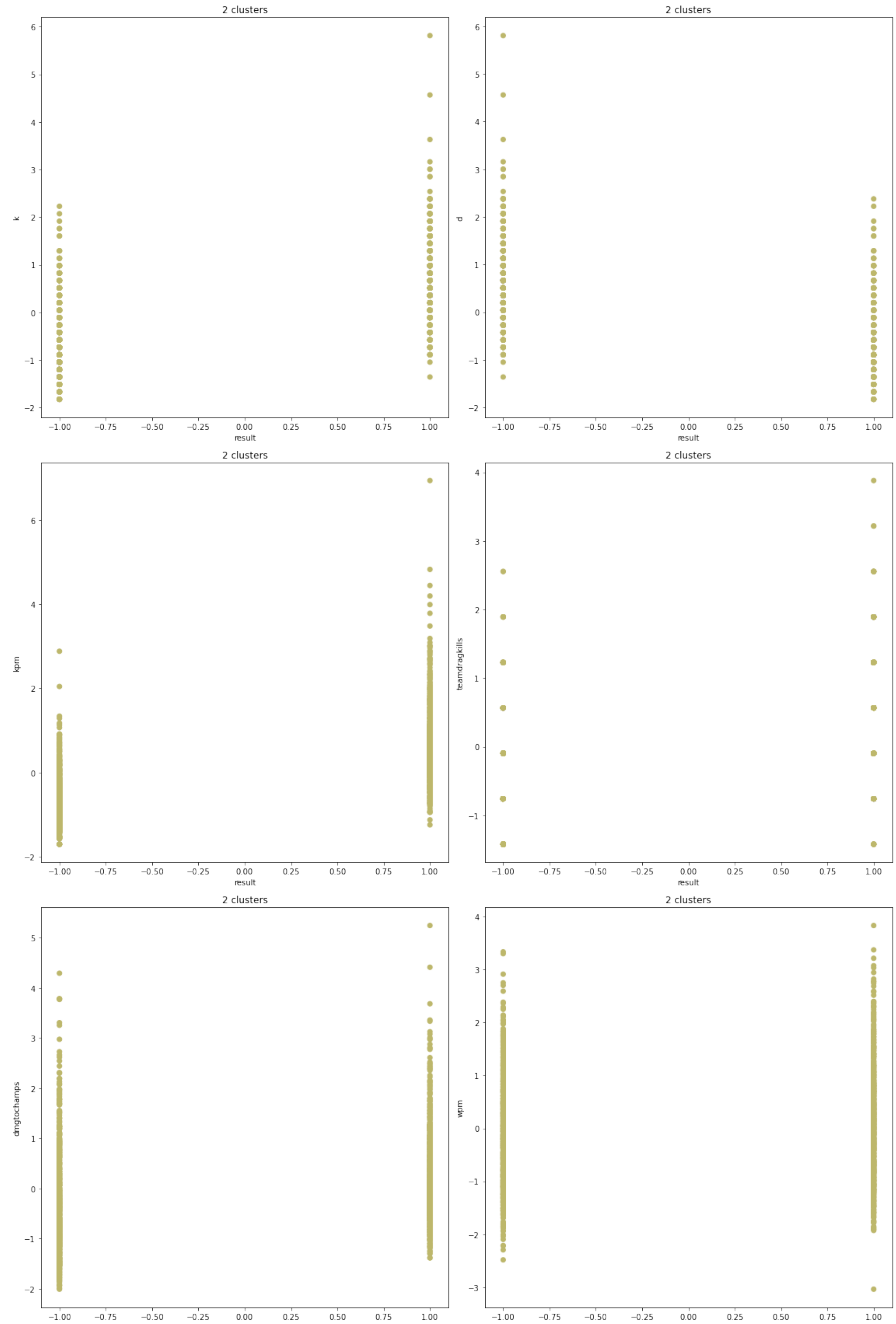

min 3 samples
dmgtochamps
gamelength


min 3 samples
wpm
gamelength

[21]:

```
print("\tUsing DBSCAN clustering\n")
plt.clf()
interesting_variables = [7,8,11,16,34,37]
#reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6]] = plt.subplots(3,2,figsize=(16,24))
axes = [ax1,ax2,ax3,ax4,ax5,ax6]

dbs = DBS(min_samples=3)
dbs.fit(data)
color_no = np.array(dbs.labels_)
colors_dict =␣
↪['r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','c
                ␣
↪'r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','ol
                ␣
↪'r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','ol
colors = []
for i in color_no:
    colors.append(colors_dict[i])

def addSubPlot(subplt_n, reduced_data, n_clstrs):
    axes[subplt_n].set_title('{} clusters'.format(str(2)))
    axes[subplt_n].scatter(data.iloc[:,6], data.iloc[:
↪,interesting_variables[subplt_n]], color=colors)

for i in range(2,8):
    addSubPlot(i-2, reduced_data, i)
idx = 0
for ax in axes:
    ax.set(xlabel=var[6], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()
```

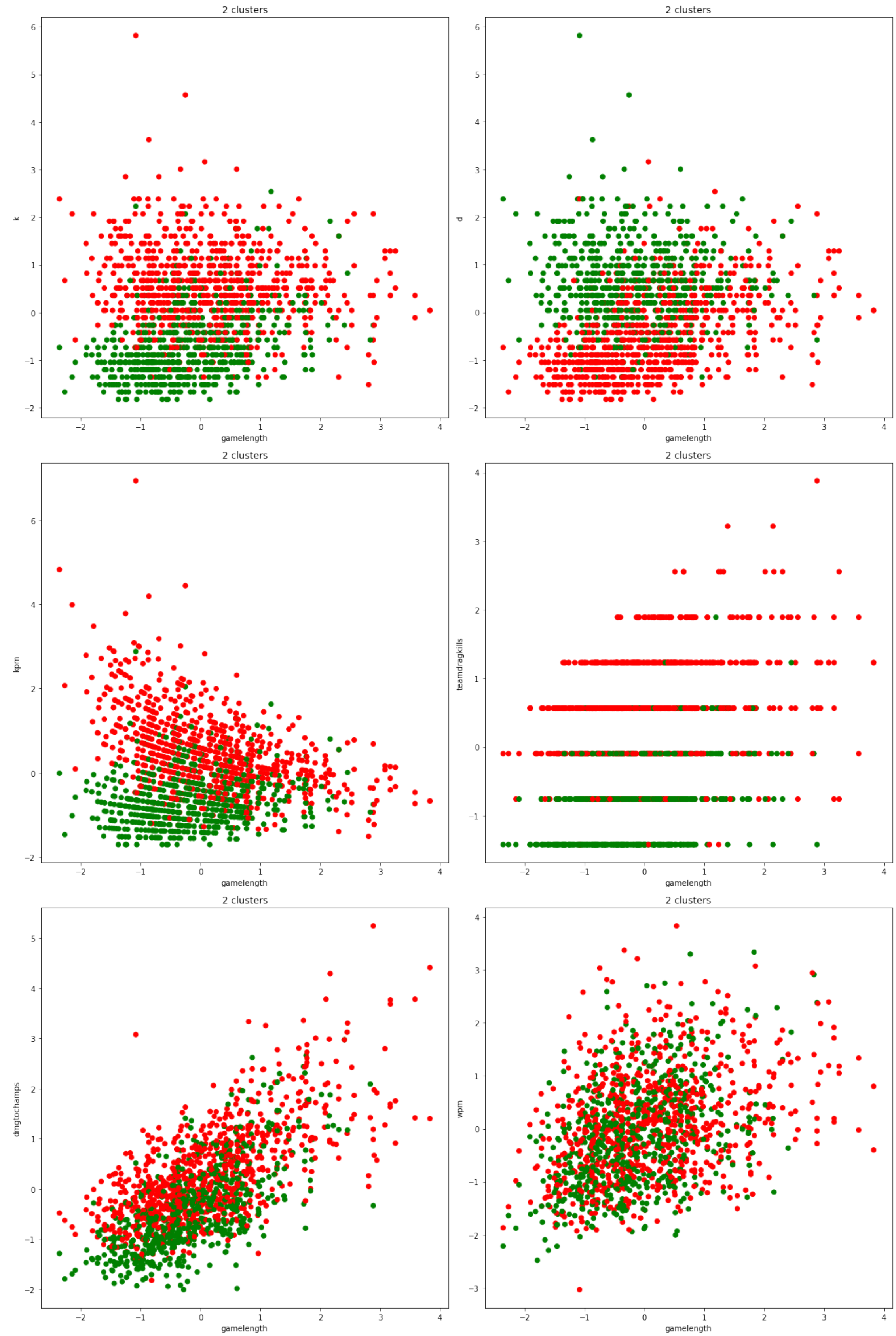
```
        Using DBSCAN clustering


<Figure size 432x288 with 0 Axes>
```


2 clusters
k
result
2 clusters
d
result
2 clusters
kpm
result
2 clusters
teamdragkills
result
2 clusters
dmgtochamps
result
2 clusters
wpm
result

I've tried playing with the variables a fair bit but I can't seem to get DBSCAN to make multiple clusters

[14]:
```
print("\tUsing KMeans clustering on the data\n")
plt.clf()
interesting_variables = [7,8,11,16,34,37]
#reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6]] = plt.subplots(3,2,figsize=(16,24))
axes = [ax1,ax2,ax3,ax4,ax5,ax6]

dbs = KM(init='k-means++', n_clusters=2, n_init=10)
dbs.fit(data)

color_no = np.array(dbs.labels_)
colors_dict =␣
 ↪['r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','c
                ␣
 ↪'r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','ol
                ␣
 ↪'r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','ol
colors = []
for i in color_no:
    colors.append(colors_dict[i])

def addSubPlot(subplt_n, reduced_data, n_clstrs):
    axes[subplt_n].set_title('{} clusters'.format(str(2)))

    axes[subplt_n].scatter(data.iloc[:,5], data.iloc[:
 ↪,interesting_variables[subplt_n]], color=colors)
for i in range(2,8):
    addSubPlot(i-2, reduced_data, i)
idx = 0
for ax in axes:
    ax.set(xlabel=var[5], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()
```

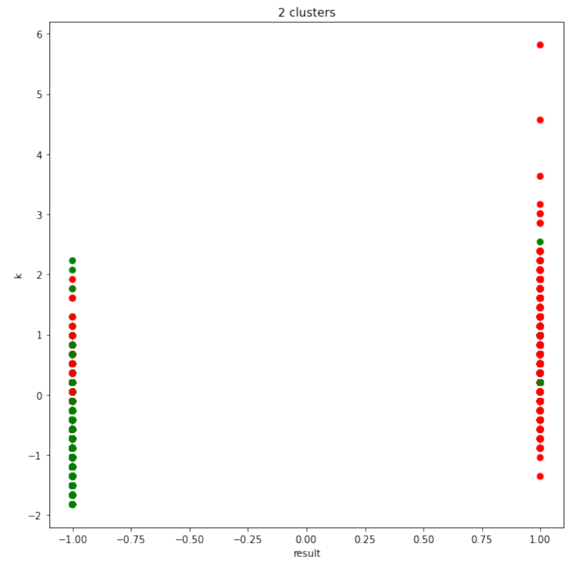
```
        Using KMeans clustering on the data


<Figure size 432x288 with 0 Axes>
```

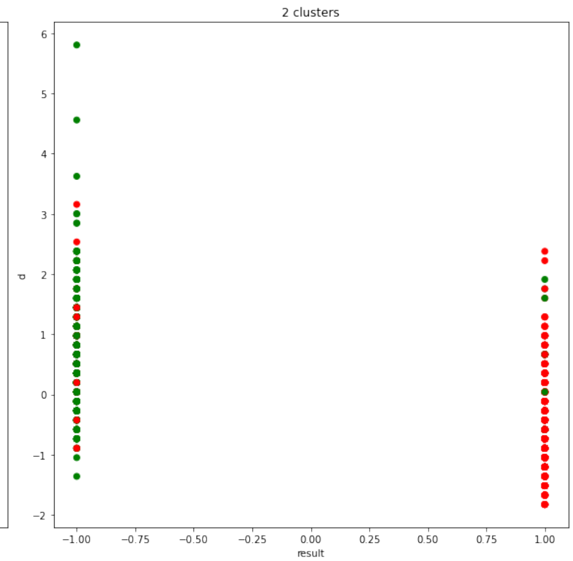

2 clusters
k
gamelength
2 clusters
d
gamelength
2 clusters
kpm
gamelength
2 clusters
teamdragkills
gamelength
2 clusters
dmgtochamps
gamelength
2 clusters
wpm
gamelength

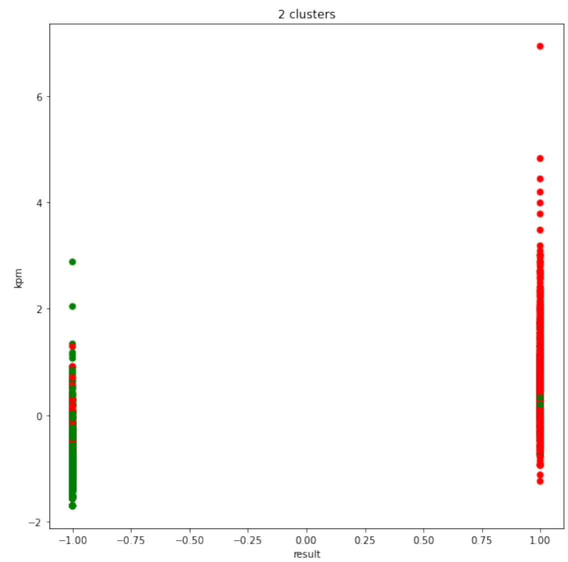
[15]:

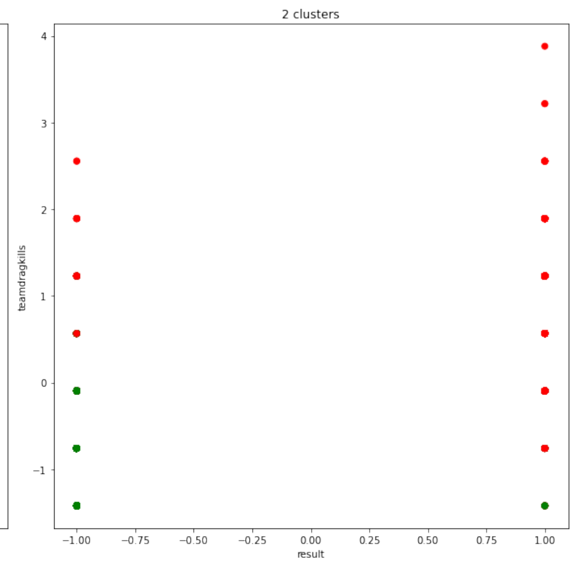
```
print("\tUsing KMeans clustering\n")
plt.clf()
interesting_variables = [7,8,11,16,34,37]
#reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6]] = plt.subplots(3,2,figsize=(16,24))
axes = [ax1,ax2,ax3,ax4,ax5,ax6]

dbs = KM(init='k-means++', n_clusters=2, n_init=10)
dbs.fit(data)
color_no = np.array(dbs.labels_)
colors_dict =␣
 ↪['r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','c
            ␣
 ↪'r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','ol
            ␣
 ↪'r','g','b','m','y','c','k','slategrey','forestgreen','brown','orange','palegreen','peru','ol
colors = []
for i in color_no:
    colors.append(colors_dict[i])

def addSubPlot(subplt_n, reduced_data, n_clstrs):
    axes[subplt_n].set_title('{} clusters'.format(str(2)))
    axes[subplt_n].scatter(data.iloc[:,6], data.iloc[:
 ↪,interesting_variables[subplt_n]], color=colors)

for i in range(2,8):
    addSubPlot(i-2, reduced_data, i)
idx = 0
for ax in axes:
    ax.set(xlabel=var[6], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()
```

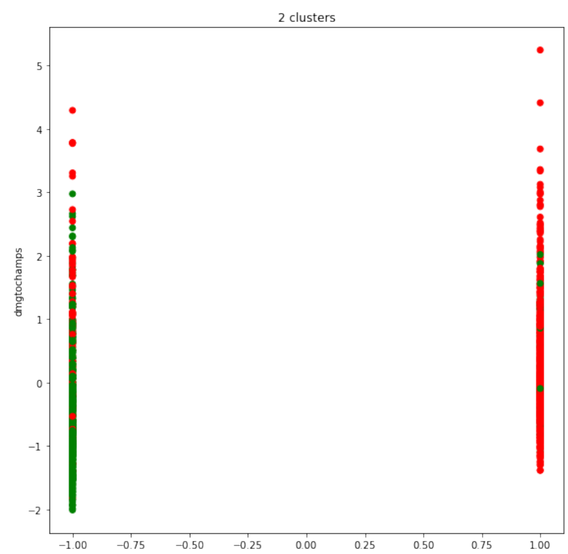
```
	Using KMeans clustering


<Figure size 432x288 with 0 Axes>
```

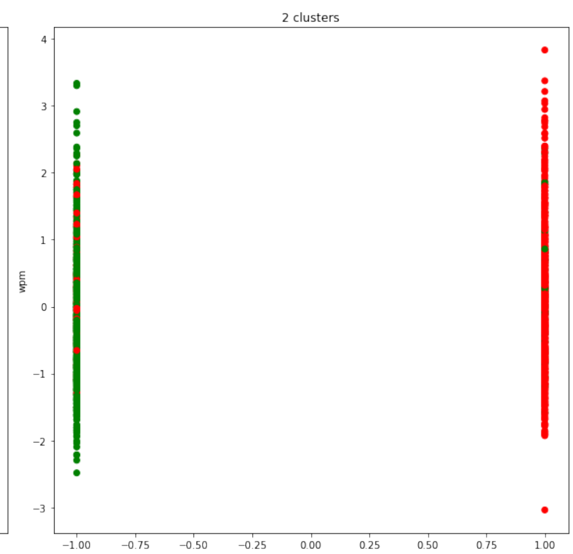

2 clusters
k
result


2 clusters
d
result


2 clusters
kpm
result


2 clusters
teamdragkills
result


2 clusters
dmgtochamps
result


2 clusters
wpm
result

It seems like KMeans at 2 clusters is identifying a pattern based on how well a team is doing in the game, though it's not definitive which could be due to the variability due to the games being played by humans.