In [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
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, Sp
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import scipy.cluster.hierarchy as shc
%matplotlib inline


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

In [2]:

```
data = pd.read_csv("Data-Prepped.csv",index_col=0)
data.head()
```

Out[2]:

	Bronze	Silver	Gold	Platinum	Diamond	Master	GrandMaster	LeagueIndex	Age	HoursPerWe
0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	5.0	27.0	1
1	0.0	0.0	0.0	0.0	1.0	0.0	0.0	5.0	23.0	1
2	0.0	0.0	0.0	1.0	0.0	0.0	0.0	4.0	30.0	1
3	0.0	0.0	1.0	0.0	0.0	0.0	0.0	3.0	19.0	2
4	0.0	0.0	1.0	0.0	0.0	0.0	0.0	3.0	32.0	1

In [3]:

```
interesting_vars = ['LeagueIndex','HoursPerWeek','APM','SelectByHotkeys','Un
                    'NumberOfPACs','ActionLatency','TotalMapExplored','
print(interesting_vars)
print(len(interesting_vars))
var = []
for i in data:
    var.append(i)
print(var)

interesting_variables = []
for i, v in enumerate(var):
    print(i, v)
    if(v in interesting_vars):
        interesting_variables.append(i)
print(interesting_variables)
```

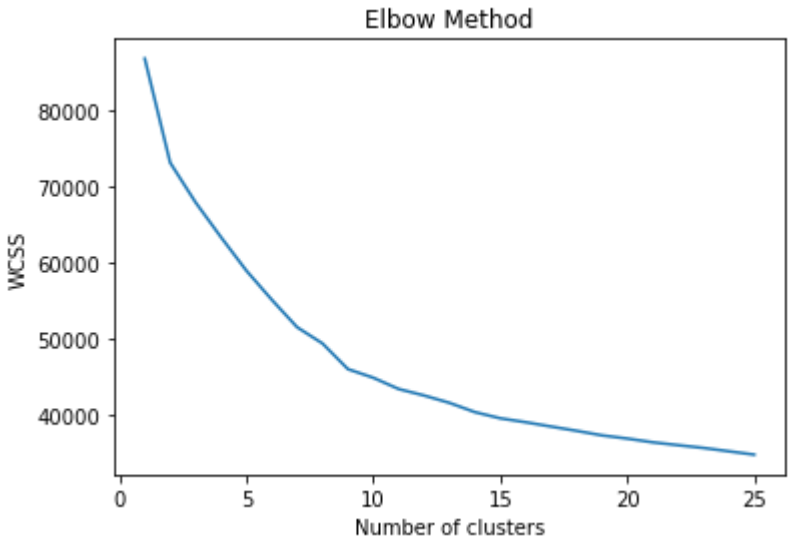
```
['LeagueIndex', 'HoursPerWeek', 'APM', 'SelectByHotkeys', 'UniqueHotkeys', 'Min
imapAttacks', 'NumberOfPACs', 'ActionLatency', 'TotalMapExplored', 'WorkersMad
e', 'ComplexUnitsMade']
11
['Bronze', 'Silver', 'Gold', 'Platinum', 'Diamond', 'Master', 'GrandMaster', 'L
eagueIndex', 'Age', 'HoursPerWeek', 'TotalHours', 'APM', 'SelectByHotkeys', 'As
signToHotkeys', 'UniqueHotkeys', 'MinimapAttacks', 'MinimapRightClicks', 'Numbe
rOfPACs', 'GapBetweenPACs', 'ActionLatency', 'ActionsInPAC', 'TotalMapExplore
d', 'WorkersMade', 'UniqueUnitsMade', 'ComplexUnitsMade', 'ComplexAbilitiesUse
d']
0 Bronze
1 Silver
2 Gold
3 Platinum
4 Diamond
5 Master
6 GrandMaster
7 LeagueIndex
8 Age
9 HoursPerWeek
10 TotalHours
11 APM
12 SelectByHotkeys
13 AssignToHotkeys
14 UniqueHotkeys
15 MinimapAttacks
16 MinimapRightClicks
17 NumberOfPACs
18 GapBetweenPACs
19 ActionLatency
20 ActionsInPAC
21 TotalMapExplored
22 WorkersMade
23 UniqueUnitsMade
24 ComplexUnitsMade
25 ComplexAbilitiesUsed
[7, 9, 11, 12, 14, 15, 17, 19, 21, 22, 24]
```

In [4]:
```
#transform input data (normalize scaling)
ssc = SSc()
data = pd.DataFrame(ssc.fit_transform(data))
n_samples, n_features = data.shape
print("n_samples  {} \nn_features {}".format(n_samples, n_features))
```

```
n_samples  3338
n_features 26
```

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

In [5]:
```
wcss = []
for i in range(1, 26):
    kmeans = KM(n_clusters=i, init='k-means++', max_iter=300, n_init=10, ran
    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()
```

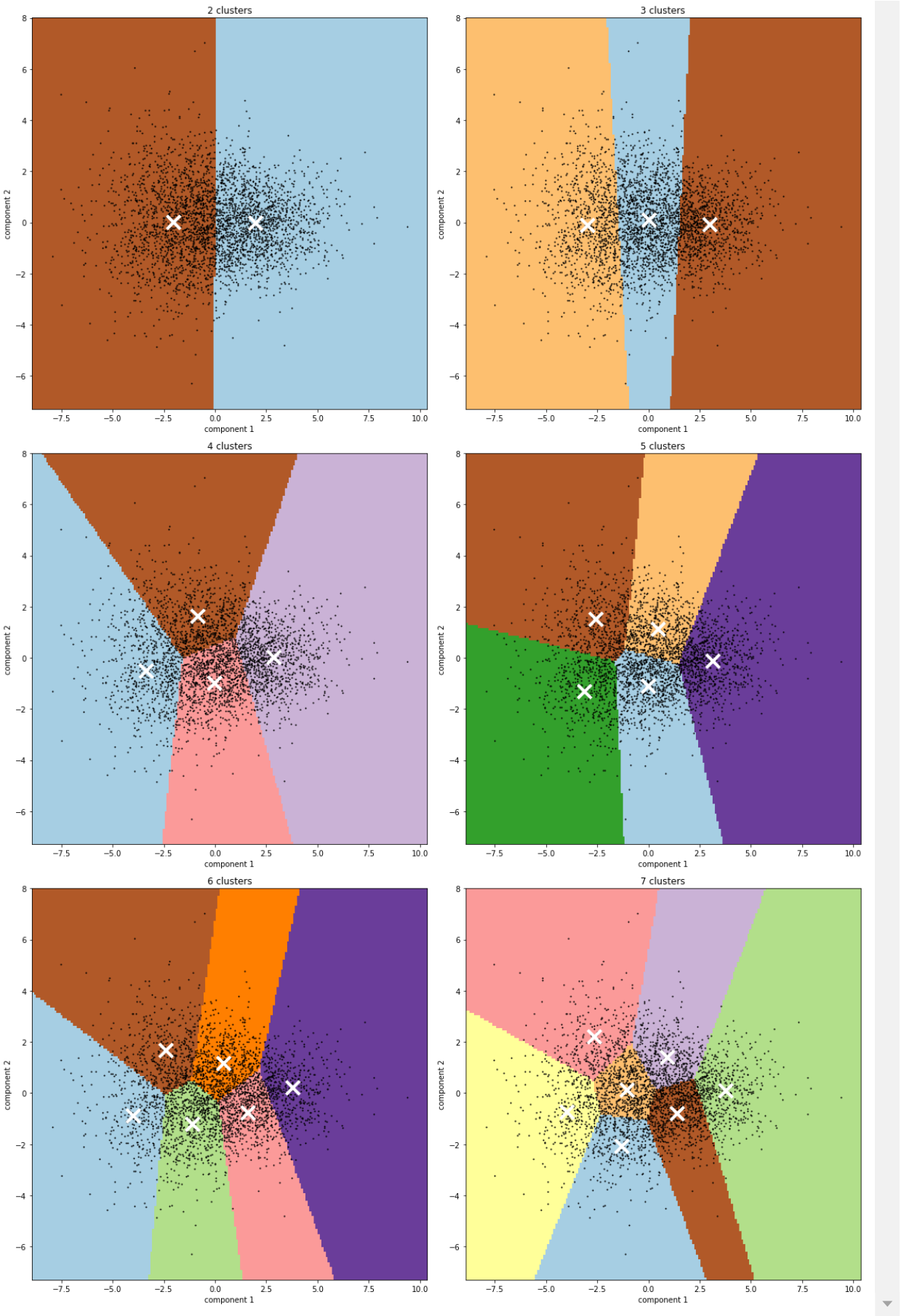


It's pretty smooth throughout, so it will be difficult to find groupings here.

In [6]:

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

print("\tUsing K-means clustering\n\tThe white Xs are the centroids of each

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() +
    y_min, y_max = reduced_data[:, 1].min() - 1, reduced_data[:, 1].max() +
    xx, yy = np.meshgrid(np.arange(x_min, x_max, meshstep), np.arange(y_min,
    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.', markersi
    for cluster in range(0, kmeans.cluster_centers_.shape[0]):
        axes[subplt_n].scatter(kmeans.cluster_centers_[cluster, 0], kmeans.c
                    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
```

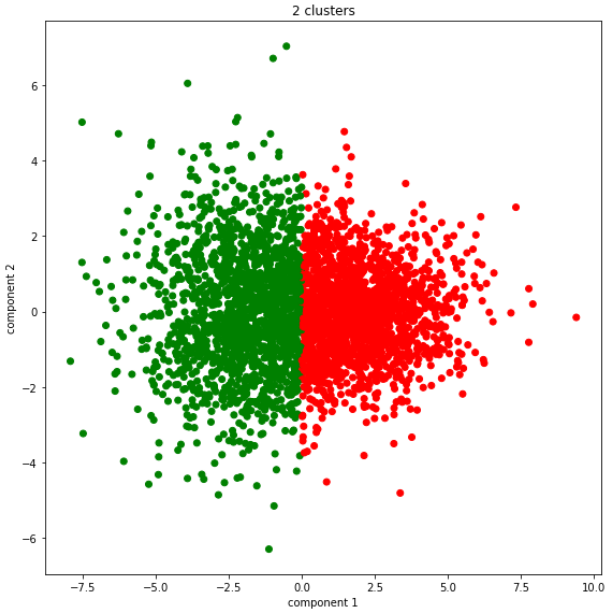


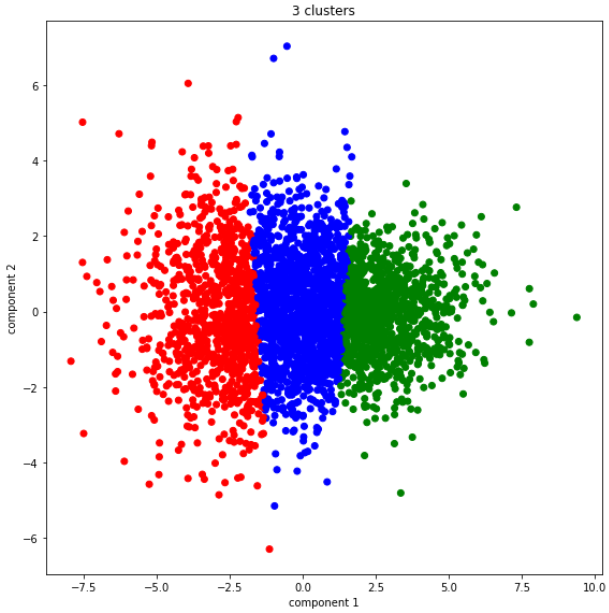
As expected, the data lies in one large cluster so it's hard to find meaningful divisions in the data

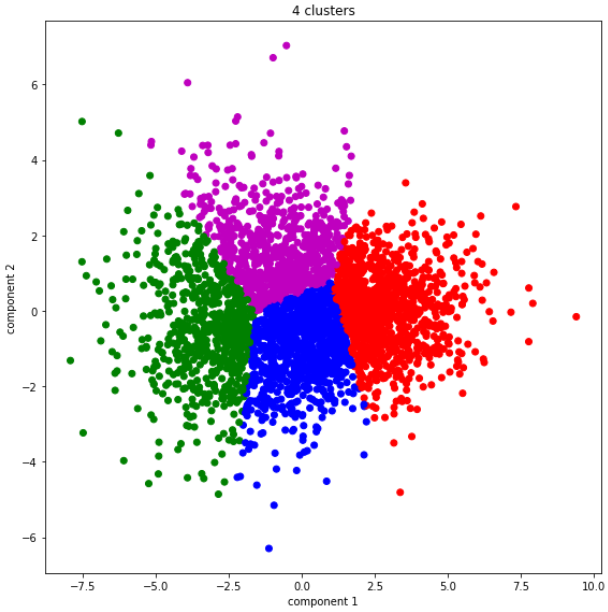
In [7]:

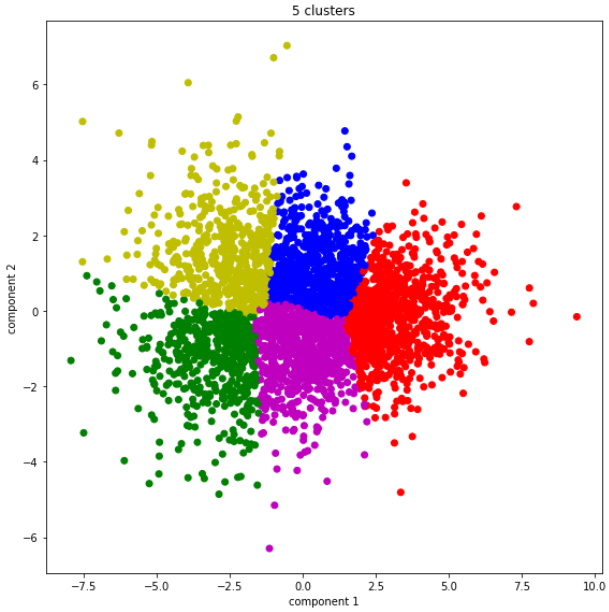
```
print("\tAnother graphing method using KMeans clustering\n")
plt.clf()
reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

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,
    km.fit(reduced_data)
    color_no = np.array(km.labels_)
    colors_dict = ['r','g','b','m','y','c','k','slategrey','forestgreen','br
    colors = []
    for i in color_no:
        colors.append(colors_dict[i])
    axes[subplt_n].scatter(reduced_data.iloc[:,0], reduced_data.iloc[:,1], c
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()
```

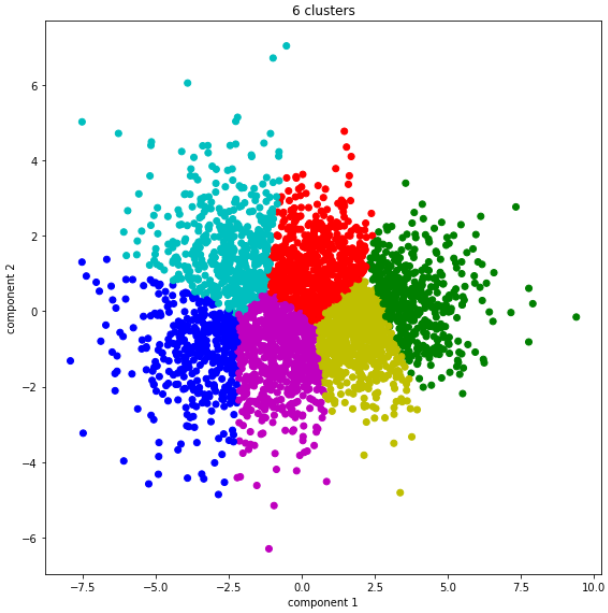
```
    Another graphing method using KMeans clustering

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

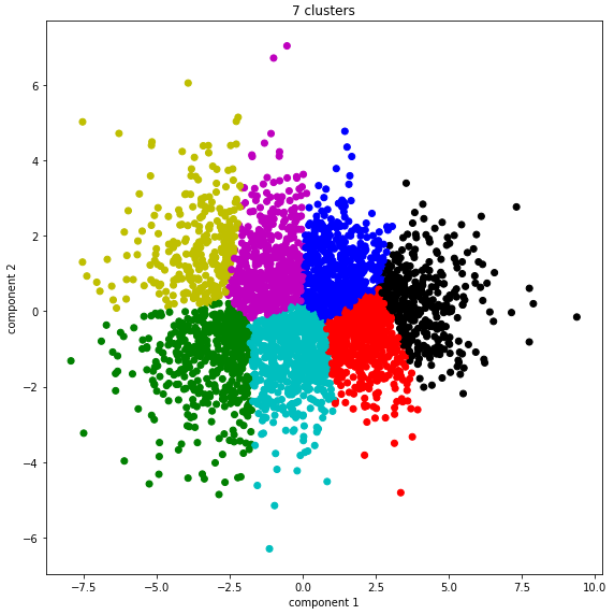

2 clusters
component 2
component 1


3 clusters
component 2
component 1


4 clusters
component 2
component 1


5 clusters
component 2
component 1

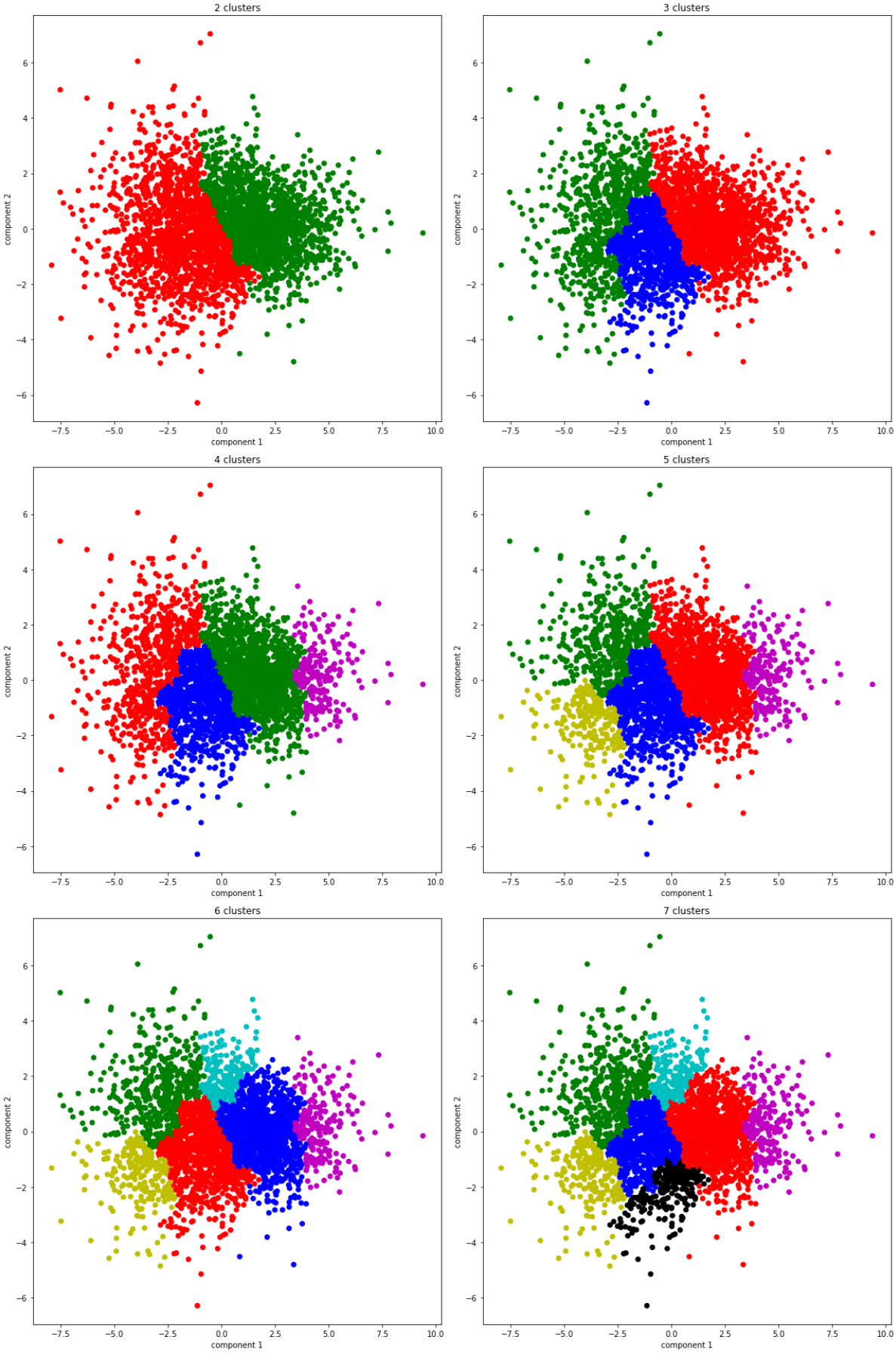

6 clusters
component 2
component 1


7 clusters
component 2
component 1

In [8]:

```
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], c
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()
```

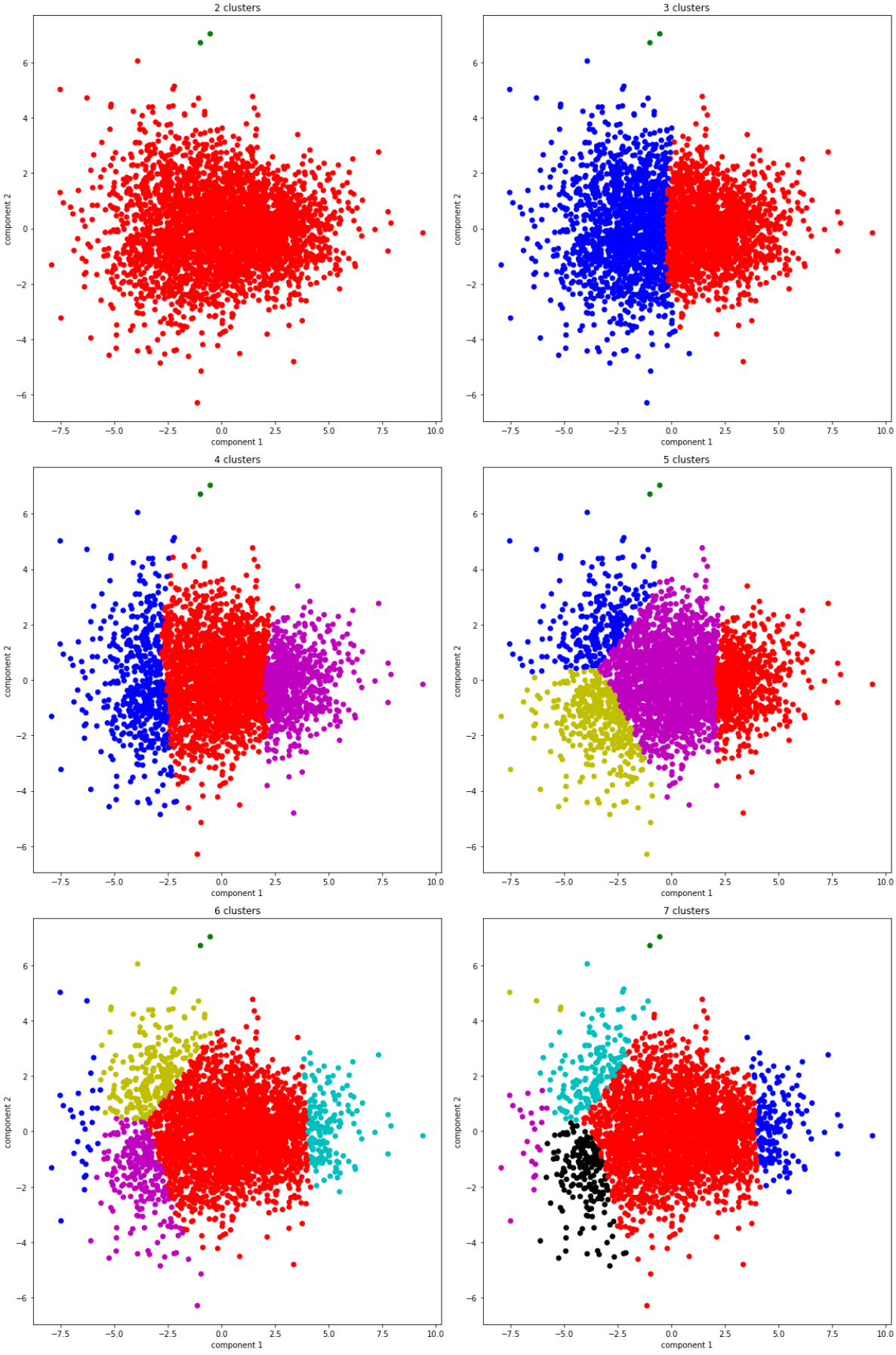
```
        Using Agglomerative clustering

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


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

In [9]:

```
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], c
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()
```

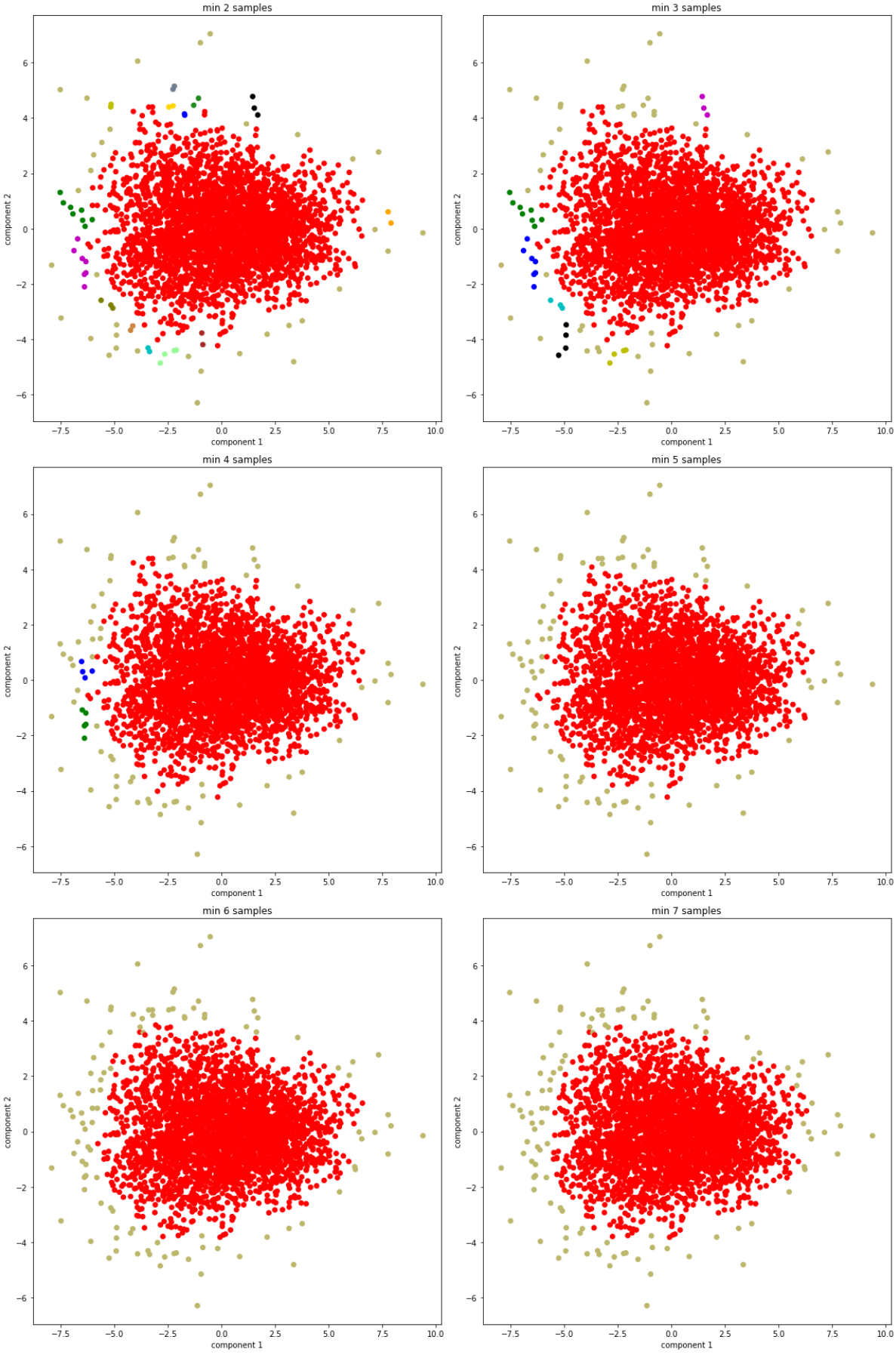
```
        Using Spectral clustering

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


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

In [10]:

```
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','br
    colors = []
    for i in color_no:
        colors.append(colors_dict[i])
    axes[subplt_n].scatter(reduced_data.iloc[:,0], reduced_data.iloc[:,1], c
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()
```

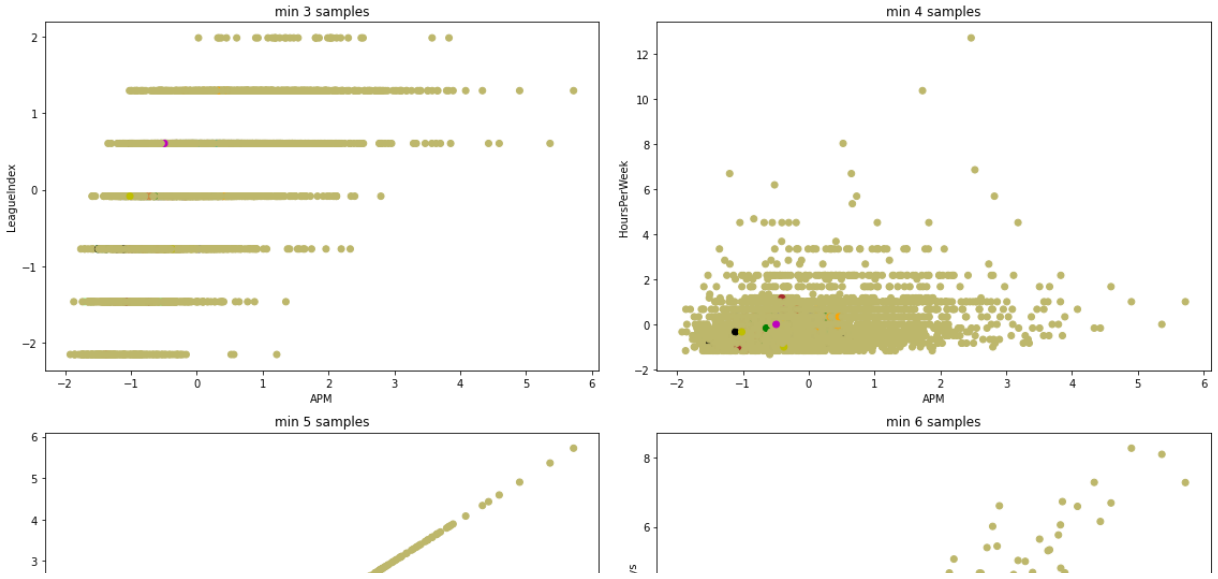
```
        Using DBSCAN clustering

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

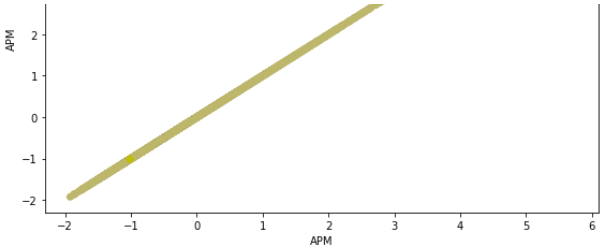

min 2 samples
min 3 samples
min 4 samples
min 5 samples
min 6 samples
min 7 samples
component 1
component 2

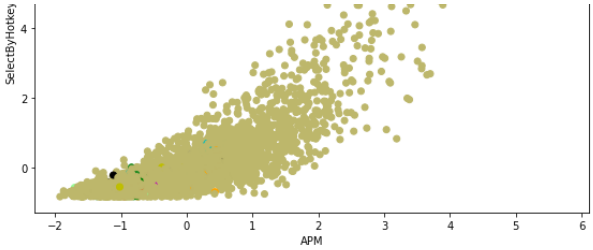
In [18]:

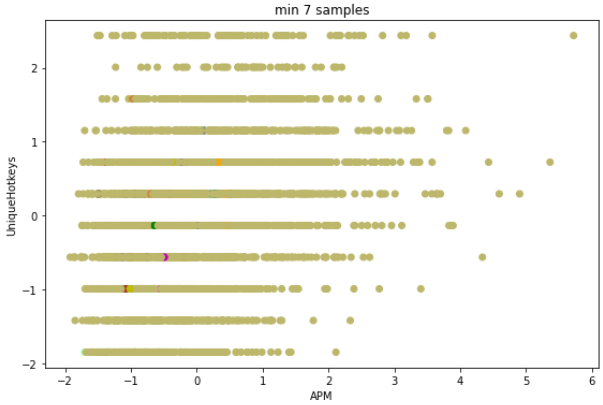
```
print("\tUsing DBSCAN clustering on the data\n")
plt.clf()
#reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

plot_against=11

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6],[ax7,ax8],[ax9,ax10],[ax11,ax12]] = plt.
axes = [ax1,ax2,ax3,ax4,ax5,ax6,ax7,ax8,ax9,ax10,ax11]

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'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
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(min_smpls))

    axes[subplt_n].scatter(data.iloc[:,plot_against], data.iloc[:,interestin

for i in range(1,12):
    addSubPlot(i-1, reduced_data, i+2)
idx = 0
for ax in axes:
    ax.set(xlabel=var[plot_against], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()
```

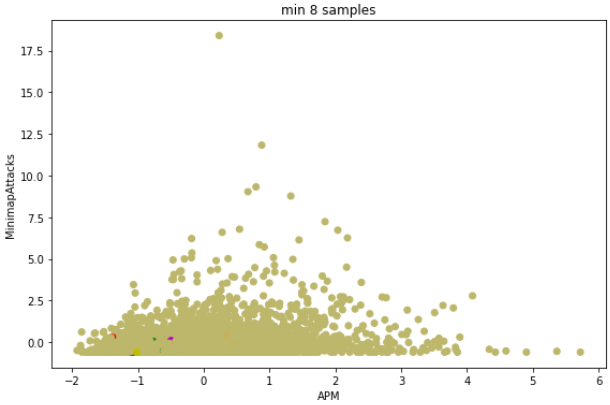
```
    Using DBSCAN clustering on the data

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

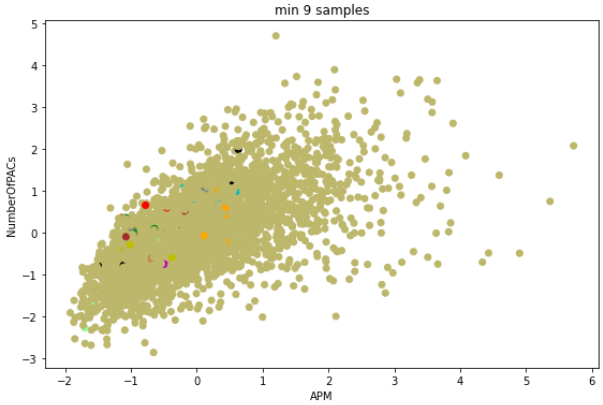


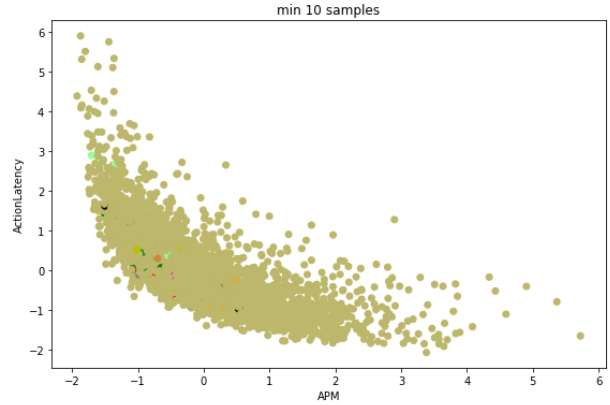

APM
APM

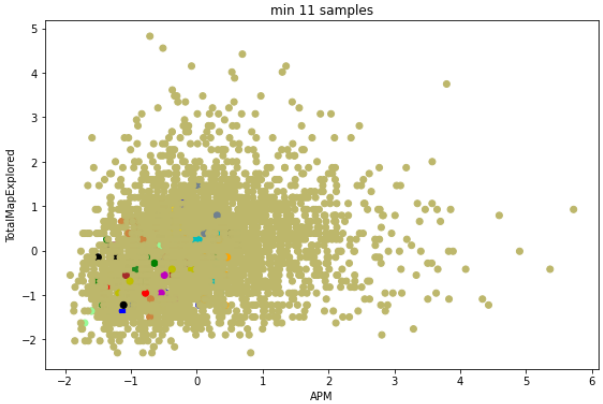

SelectByHotkeys
APM

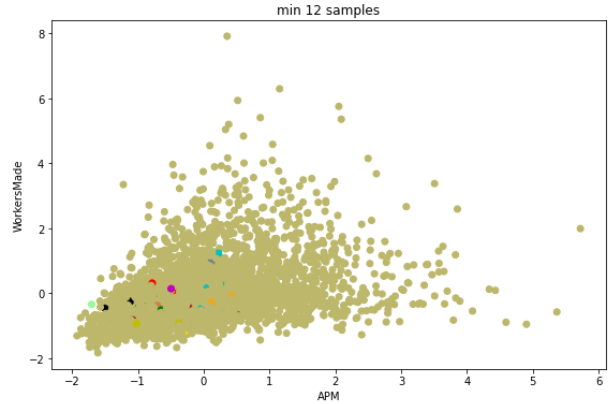

min 7 samples
UniqueHotkeys
APM

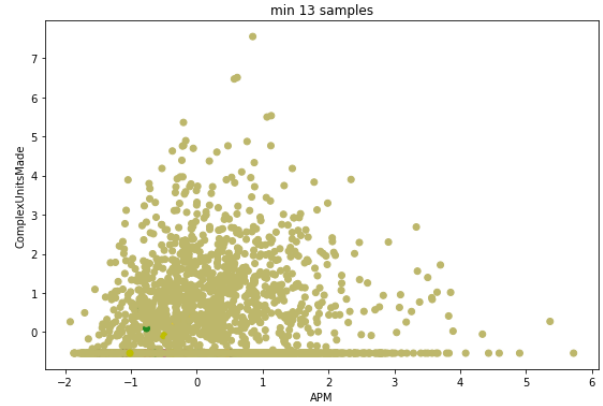

min 8 samples
MinimapAttacks
APM


min 9 samples
NumberOfPACs
APM


min 10 samples
ActionLatency
APM


min 11 samples
TotalMapExplored
APM


min 12 samples
WorkersMade
APM


min 13 samples
ComplexUnitsMade
APM

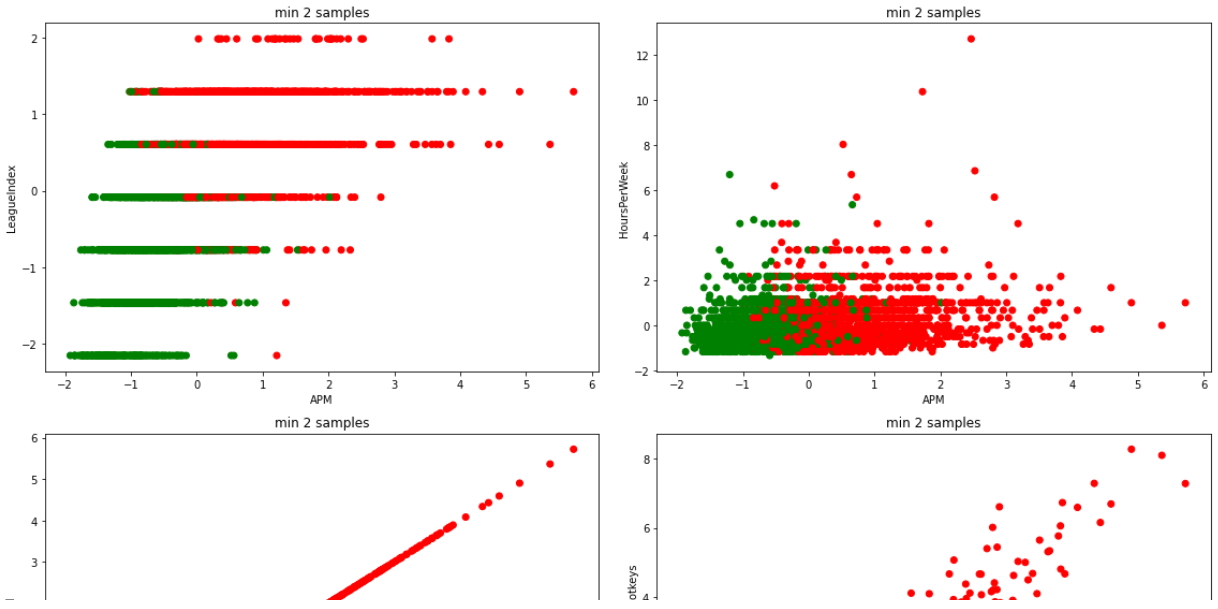
Nothing interesting out of DBSCAN

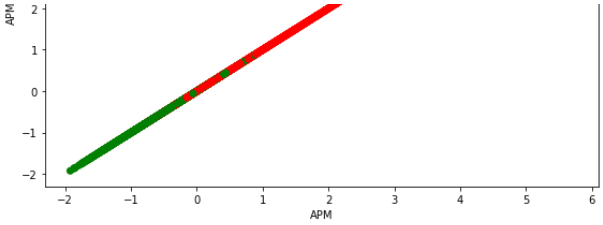
KMeans Clustering

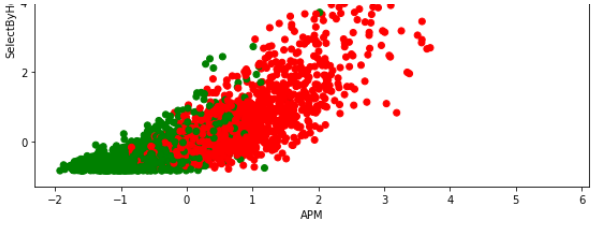
In [19]:

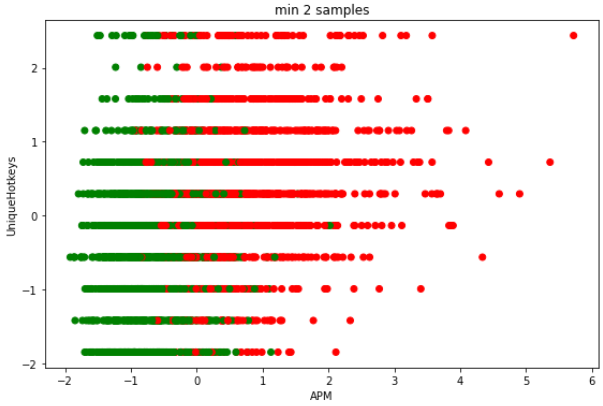
```
print("\tUsing KMeans clustering on the data\n")
plt.clf()
#reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

plot_against=11

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6],[ax7,ax8],[ax9,ax10],[ax11,ax12]] = plt.
axes = [ax1,ax2,ax3,ax4,ax5,ax6,ax7,ax8,ax9,ax10,ax11]

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'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
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(2))

    axes[subplt_n].scatter(data.iloc[:,plot_against], data.iloc[:,interestin

for i in range(1,12):
    addSubPlot(i-1, reduced_data, i+2)
idx = 0
for ax in axes:
    ax.set(xlabel=var[plot_against], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()

```

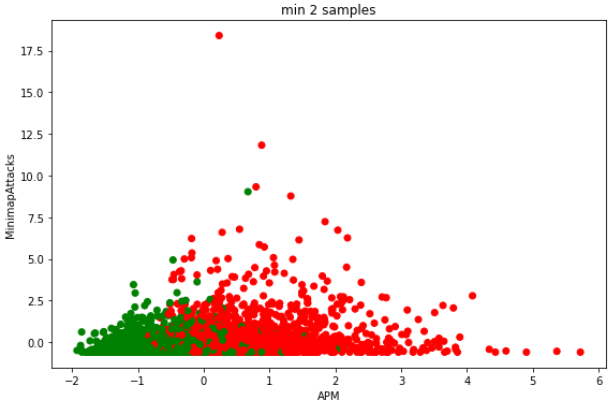
```
        Using KMeans clustering on the data

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

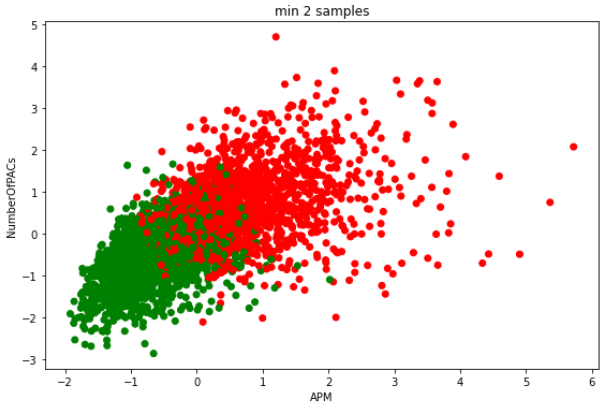


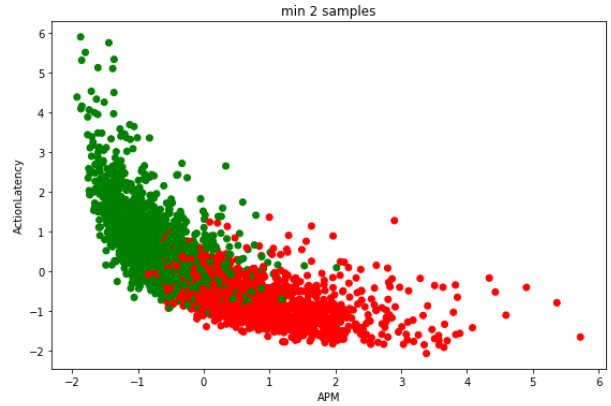

APM
APM

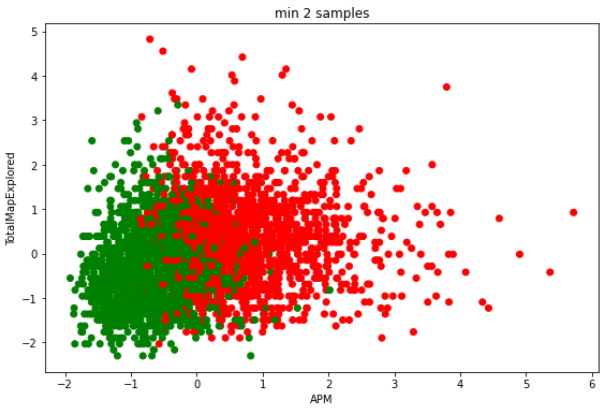

SelectByHi
APM

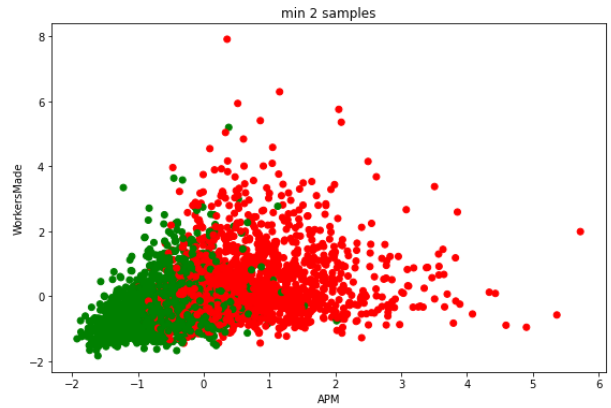

min 2 samples
UniqueHotkeys
APM

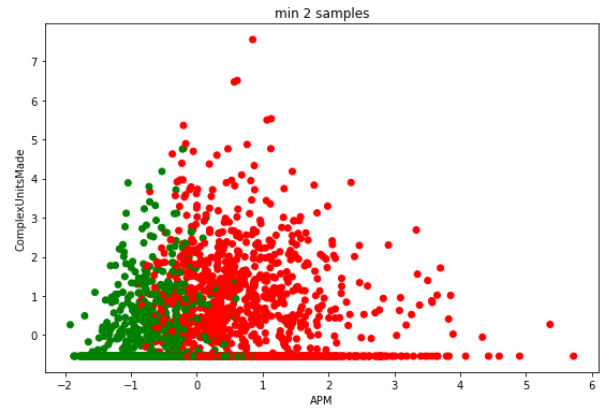

min 2 samples
MinimapAttacks
APM

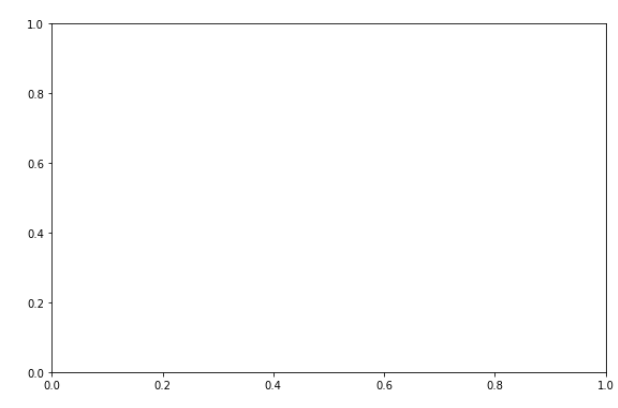

min 2 samples
NumberOfPACs
APM


min 2 samples
ActionLatency
APM


min 2 samples
TotalMapExplored
APM


min 2 samples
WorkersMade
APM


min 2 samples
ComplexUnitsMade
APM

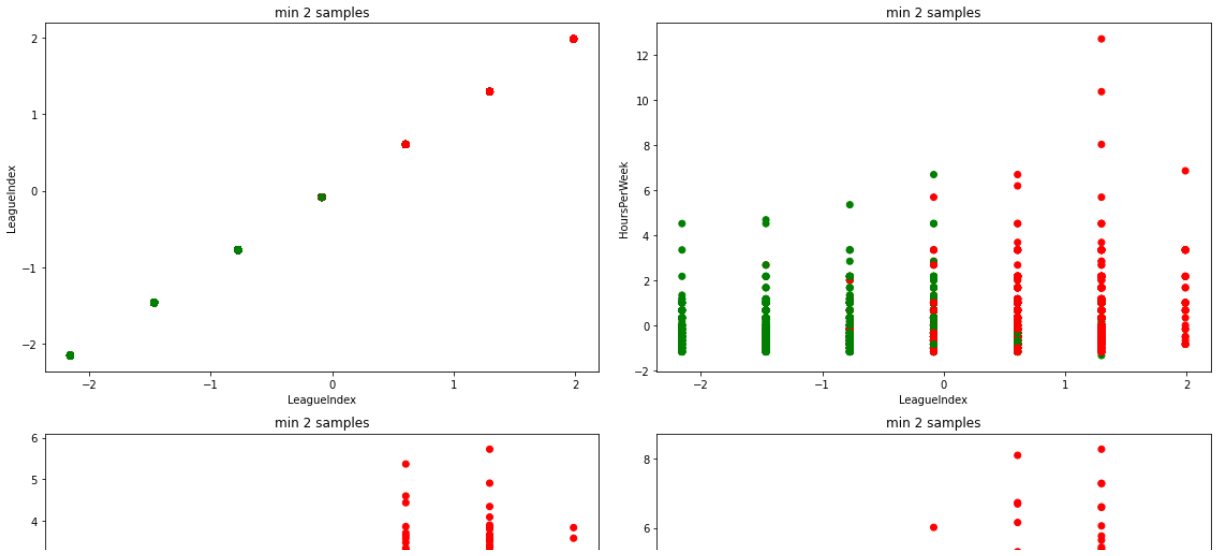


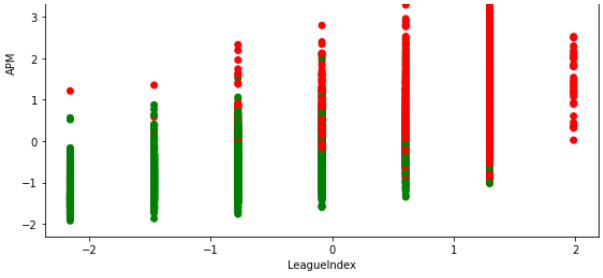
In [22]:

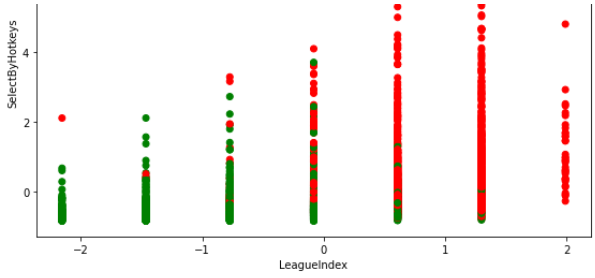
```
print("\tUsing KMeans clustering on the data\n")
plt.clf()
#reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

plot_against=7

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6],[ax7,ax8],[ax9,ax10],[ax11,ax12]] = plt.
axes = [ax1,ax2,ax3,ax4,ax5,ax6,ax7,ax8,ax9,ax10,ax11]

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'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
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(2))

    axes[subplt_n].scatter(data.iloc[:,plot_against], data.iloc[:,interestin

for i in range(1,12):
    addSubPlot(i-1, reduced_data, i+2)
idx = 0
for ax in axes:
    ax.set(xlabel=var[plot_against], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()

```

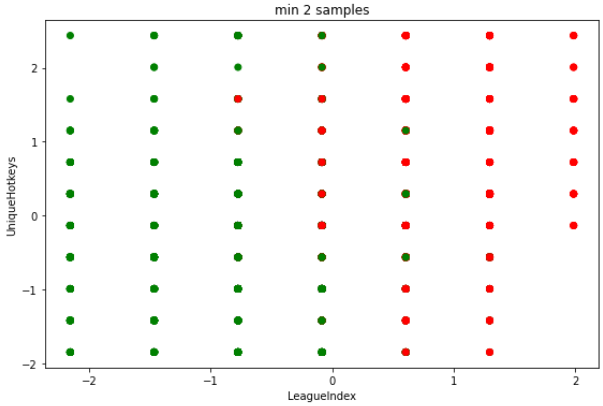
```
	Using KMeans clustering on the data
```

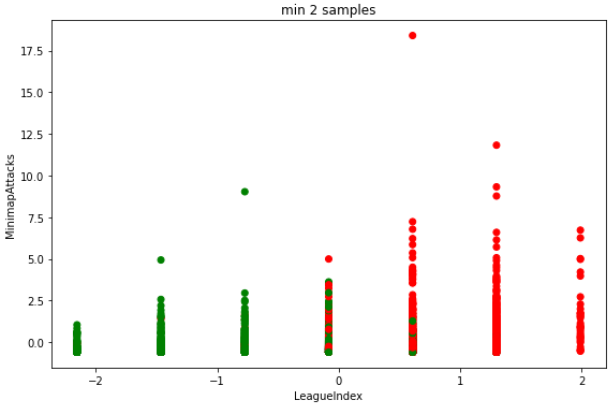
```
<Figure size 432x288 with 0 Axes>
```

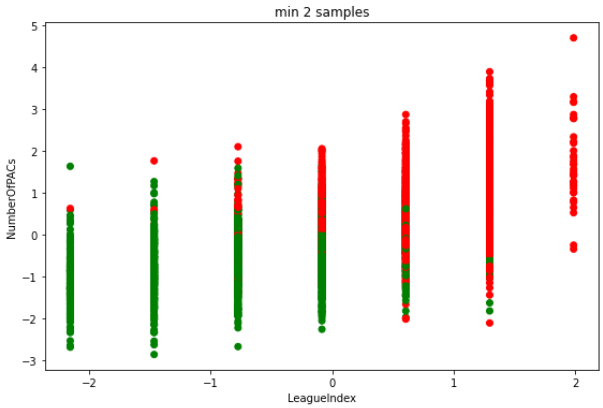


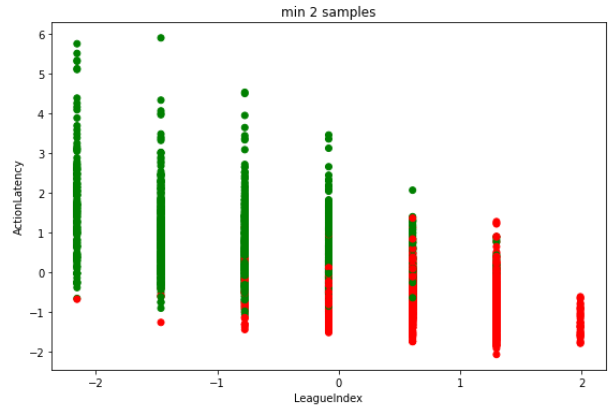

APM
LeagueIndex

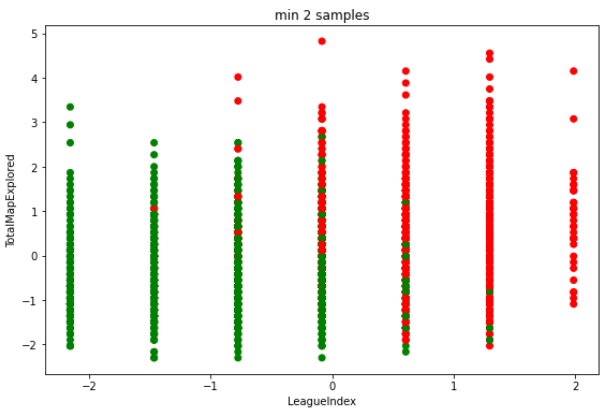

SelectByHotkeys
LeagueIndex

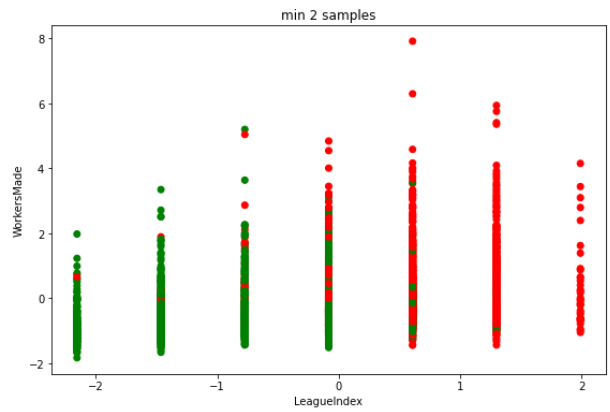

min 2 samples
UniqueHotkeys
LeagueIndex

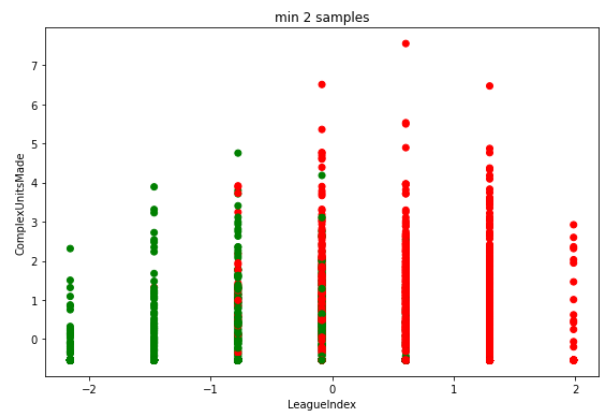

min 2 samples
MinimapAttacks
LeagueIndex

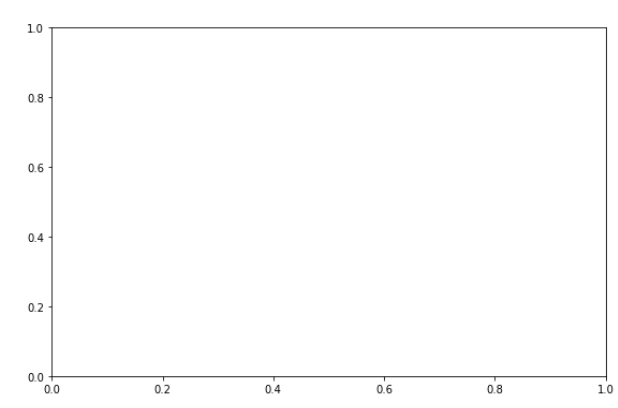

min 2 samples
NumberOfPACs
LeagueIndex


min 2 samples
ActionLatency
LeagueIndex


min 2 samples
TotalMapExplored
LeagueIndex


min 2 samples
WorkersMade
LeagueIndex


min 2 samples
ComplexUnitsMade
LeagueIndex

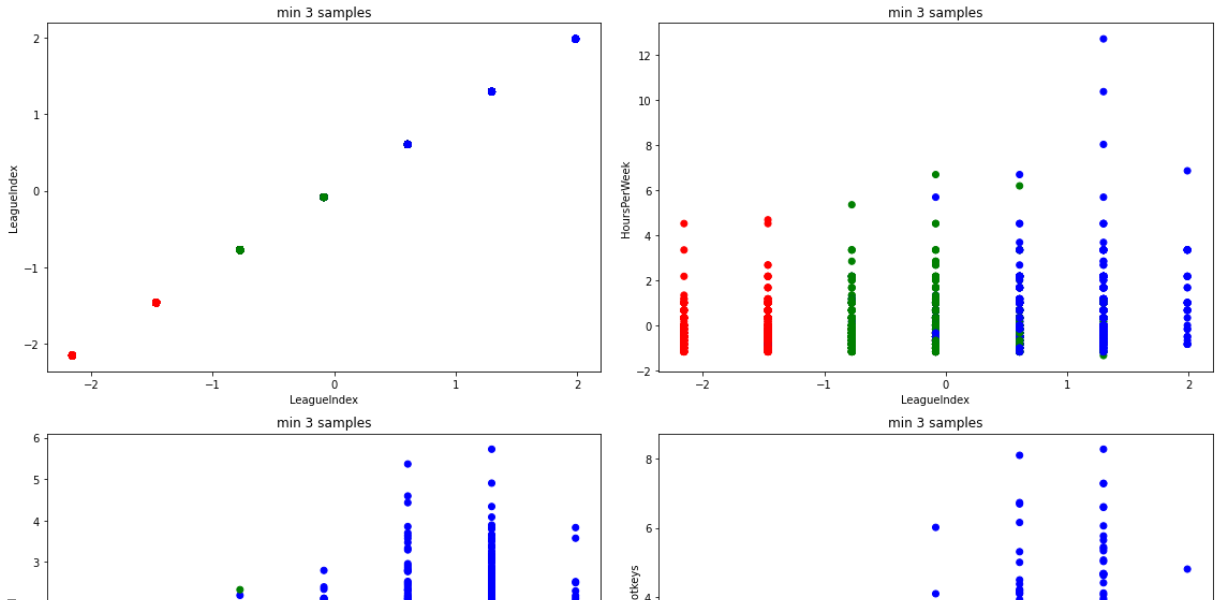


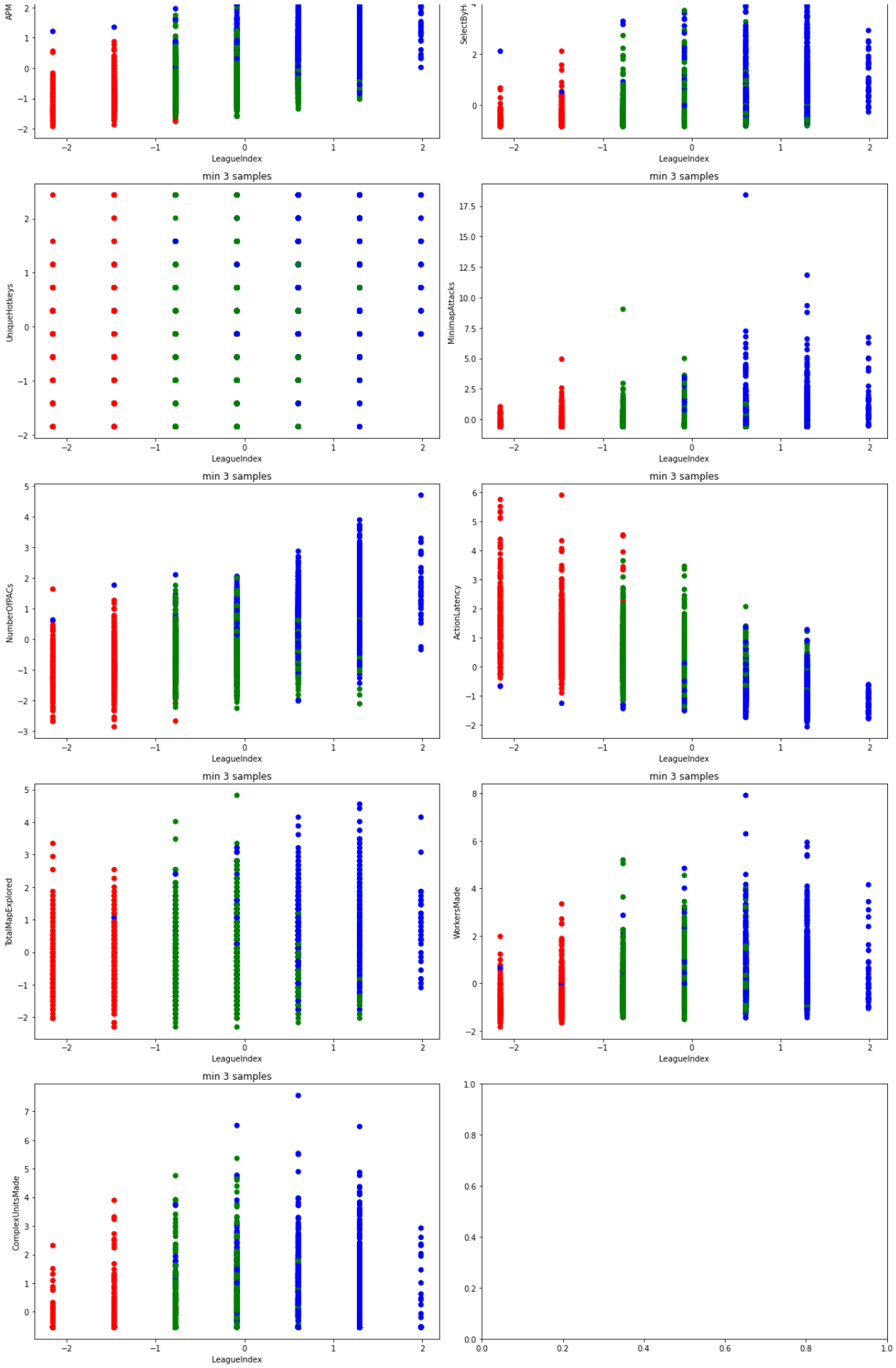
KMeans clustering with 2 groups seems to be separating players by skill level

In [24]:

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

plot_against=7

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6],[ax7,ax8],[ax9,ax10],[ax11,ax12]] = plt.
axes = [ax1,ax2,ax3,ax4,ax5,ax6,ax7,ax8,ax9,ax10,ax11]

dbs = KM(init='k-means++', n_clusters=3, n_init=10)
dbs.fit(data)
color_no = np.array(dbs.labels_)
colors_dict = ['r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
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[:,plot_against], data.iloc[:,interestin

for i in range(1,12):
    addSubPlot(i-1, reduced_data, i+2)
idx = 0
for ax in axes:
    ax.set(xlabel=var[plot_against], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()

```

```
        Using KMeans clustering on the data

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





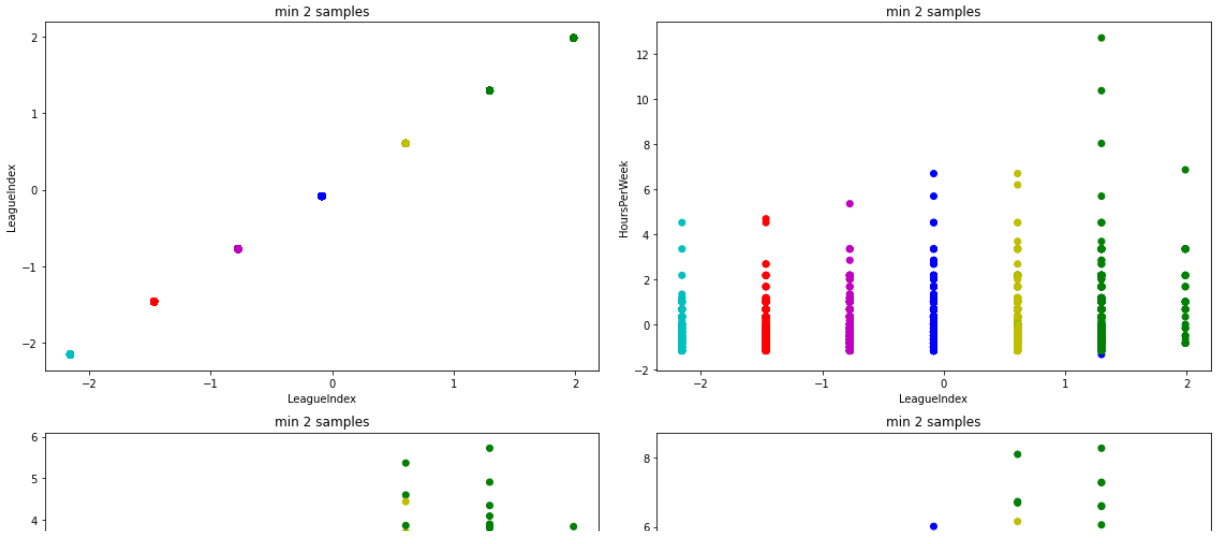
The same as before, it seems to be separating players by skill level

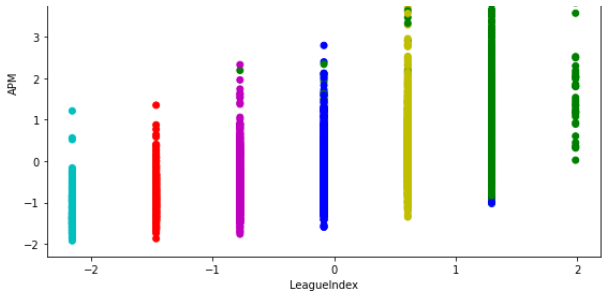
The same as before, it seems to be separating players by skill level

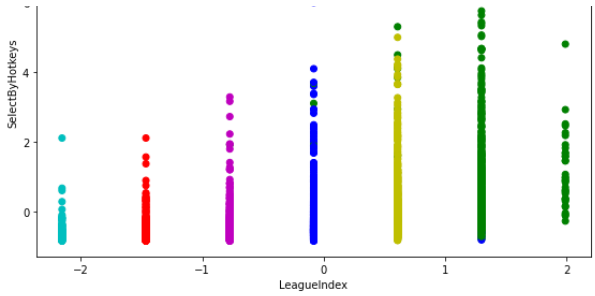
In [27]:

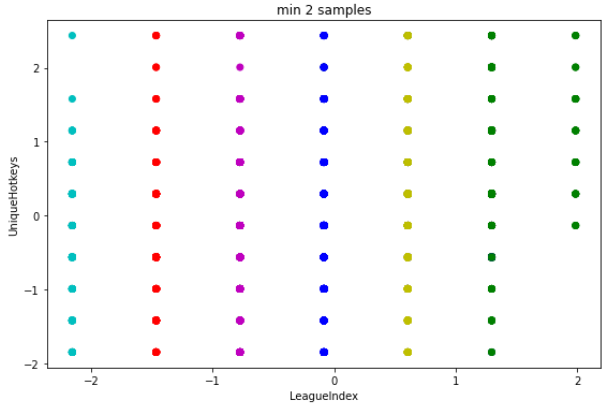
```
print("\tUsing KMeans clustering on the data\n")
plt.clf()
#reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

plot_against=7

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6],[ax7,ax8],[ax9,ax10],[ax11,ax12]] = plt.
axes = [ax1,ax2,ax3,ax4,ax5,ax6,ax7,ax8,ax9,ax10,ax11]


clusters = 6
dbs = KM(init='k-means++', n_clusters=clusters, n_init=10)
dbs.fit(data)
color_no = np.array(dbs.labels_)
colors_dict = ['r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
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(clusters)

    axes[subplt_n].scatter(data.iloc[:,plot_against], data.iloc[:,interestin

for i in range(1,12):
    addSubPlot(i-1, reduced_data, i+2)
idx = 0
for ax in axes:
    ax.set(xlabel=var[plot_against], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()
```

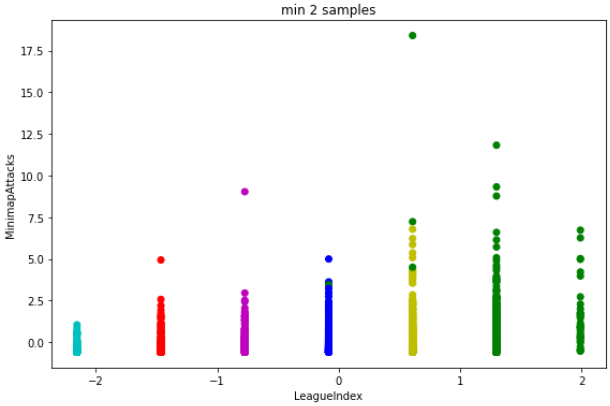
```
        Using KMeans clustering on the data

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

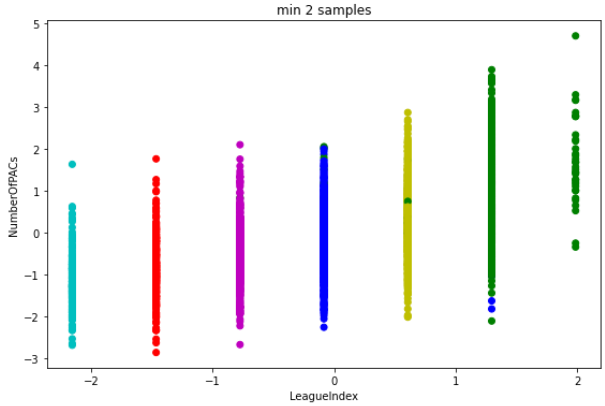


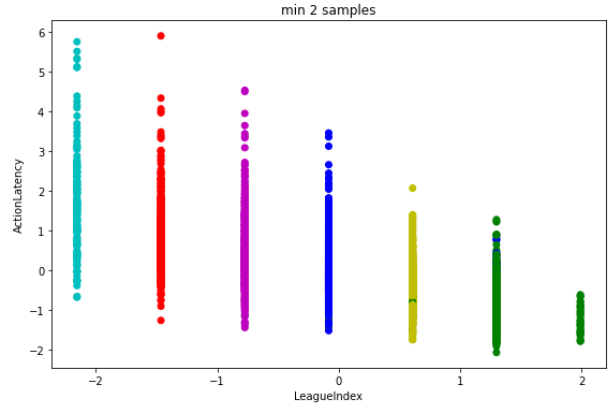

APM
LeagueIndex

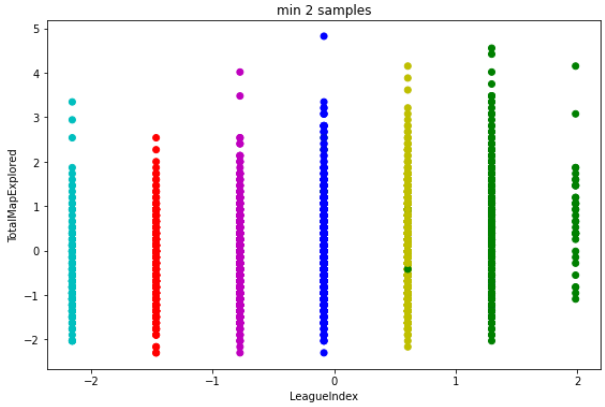

SelectByHotkeys
LeagueIndex

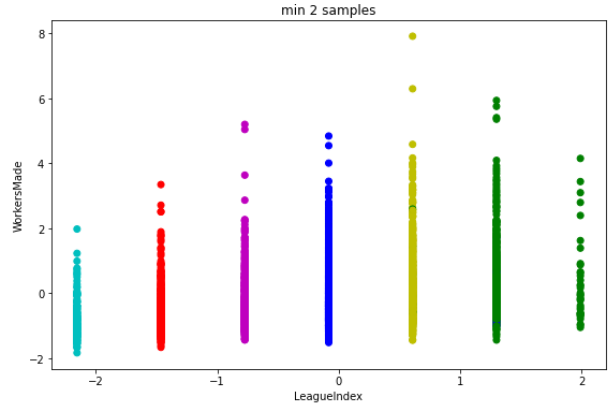

min 2 samples
UniqueHotkeys
LeagueIndex

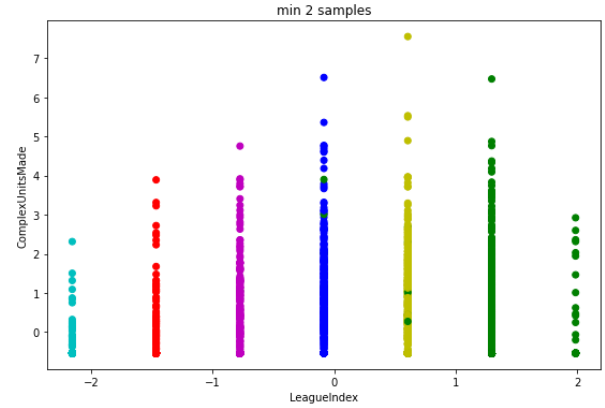

min 2 samples
MinimapAttacks
LeagueIndex

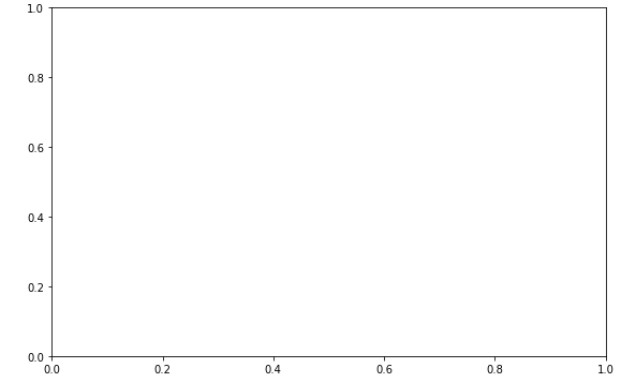

min 2 samples
NumberOfPACs
LeagueIndex


min 2 samples
ActionLatency
LeagueIndex


min 2 samples
TotalMapExplored
LeagueIndex


min 2 samples
WorkersMade
LeagueIndex


min 2 samples
ComplexUnitsMade
LeagueIndex

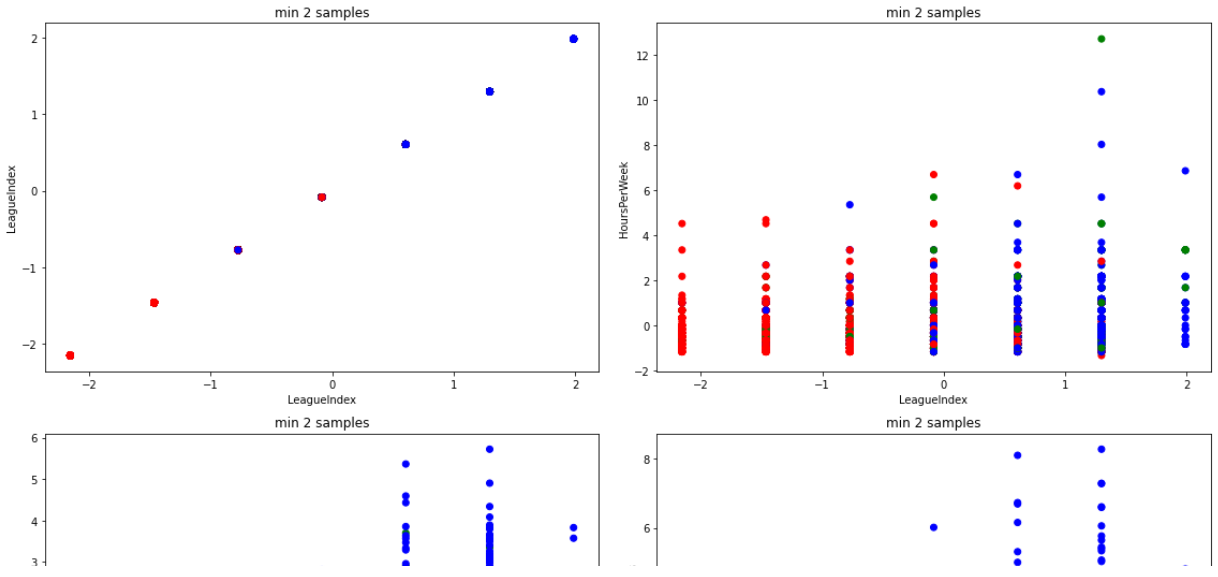


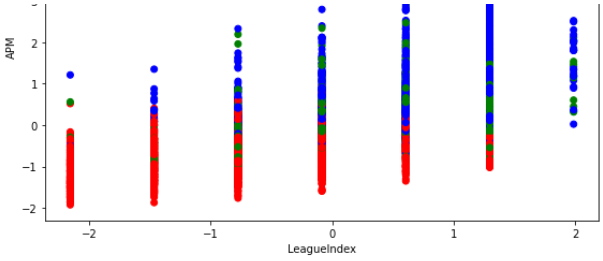
KMeans seems to want to split the players based on skill level. Now lets see if it does the same if a player's league is excluded

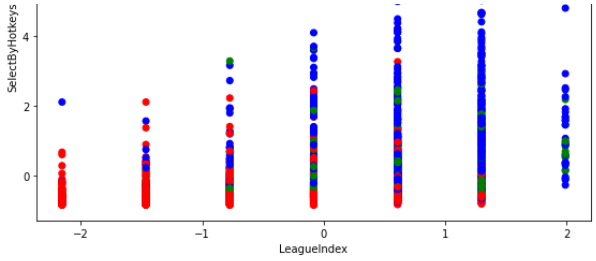
In [28]:

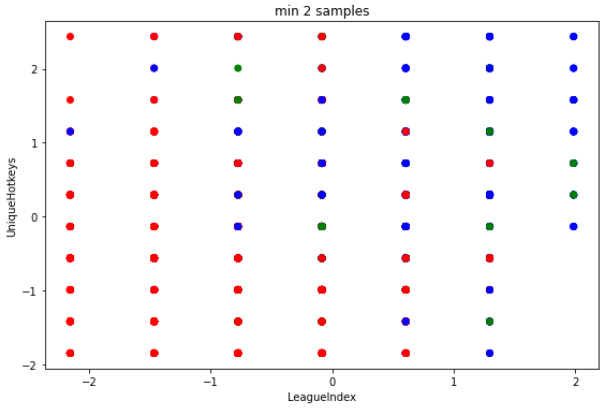
```
print("\tUsing KMeans clustering on the data\n")
plt.clf()
#reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

plot_against=7

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6],[ax7,ax8],[ax9,ax10],[ax11,ax12]] = plt.
axes = [ax1,ax2,ax3,ax4,ax5,ax6,ax7,ax8,ax9,ax10,ax11]

dbs = KM(init='k-means++', n_clusters=3, n_init=10)
dataX = data.iloc[:,8:]
dbs.fit(dataX)
color_no = np.array(dbs.labels_)
colors_dict = ['r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
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(2))

    axes[subplt_n].scatter(data.iloc[:,plot_against], data.iloc[:,interestin

for i in range(1,12):
    addSubPlot(i-1, reduced_data, i+2)
idx = 0
for ax in axes:
    ax.set(xlabel=var[plot_against], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()

```

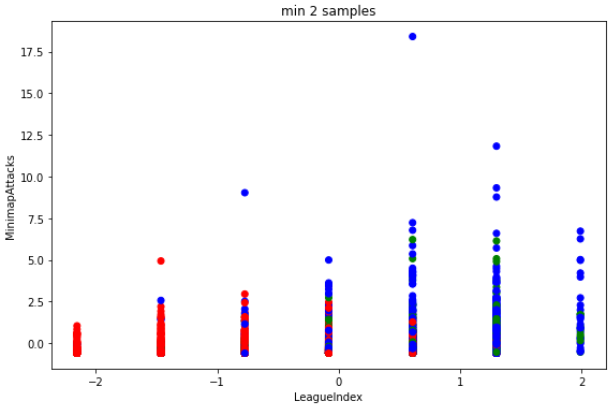
```
	Using KMeans clustering on the data

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

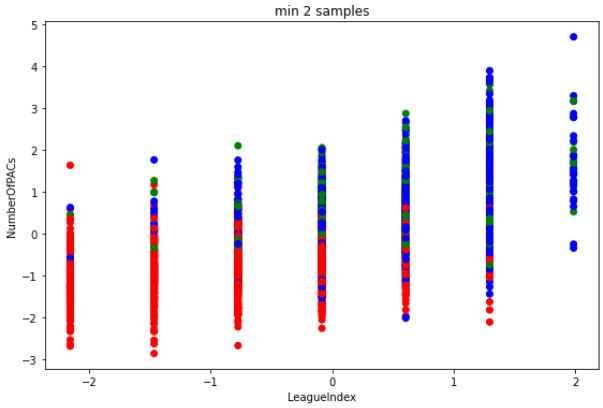


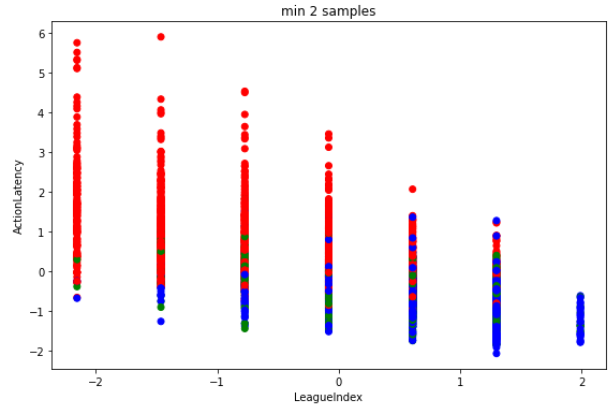

APM
LeagueIndex

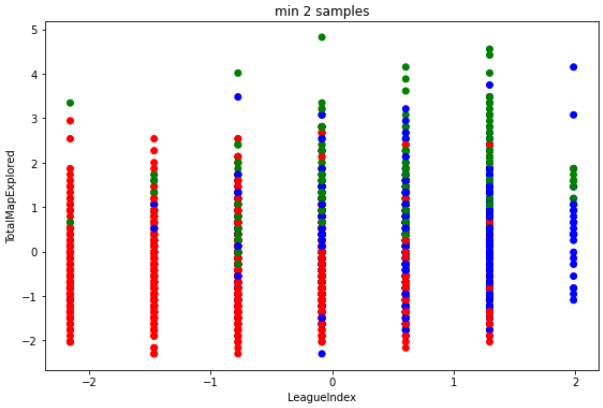

SelectByHotkeys
LeagueIndex

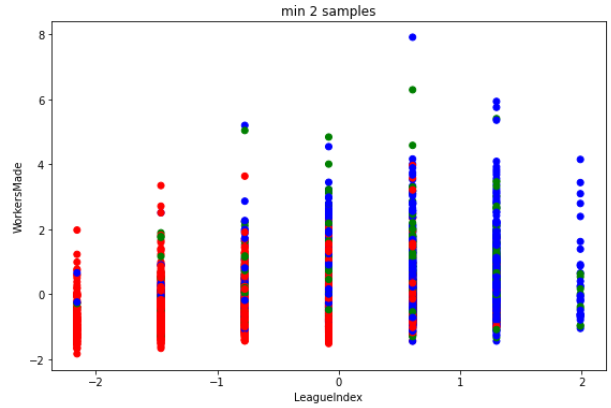

min 2 samples
UniqueHotkeys
LeagueIndex

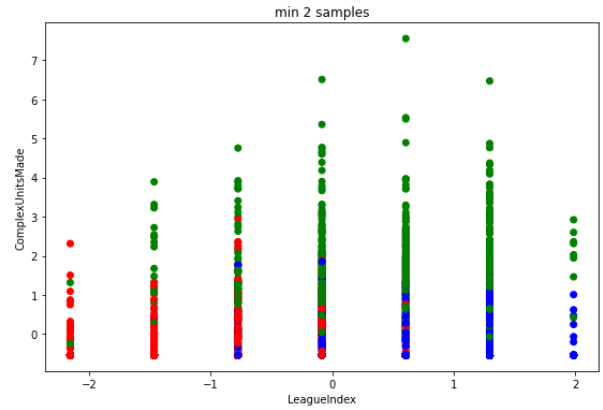

min 2 samples
MinimapAttacks
LeagueIndex

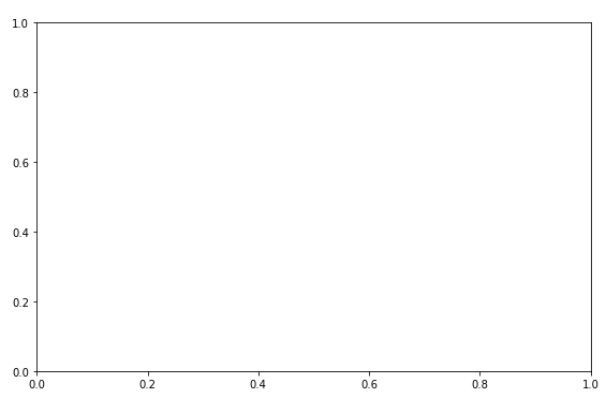

min 2 samples
NumberOfPACs
LeagueIndex


min 2 samples
ActionLatency
LeagueIndex


min 2 samples
TotalMapExplored
LeagueIndex


min 2 samples
WorkersMade
LeagueIndex

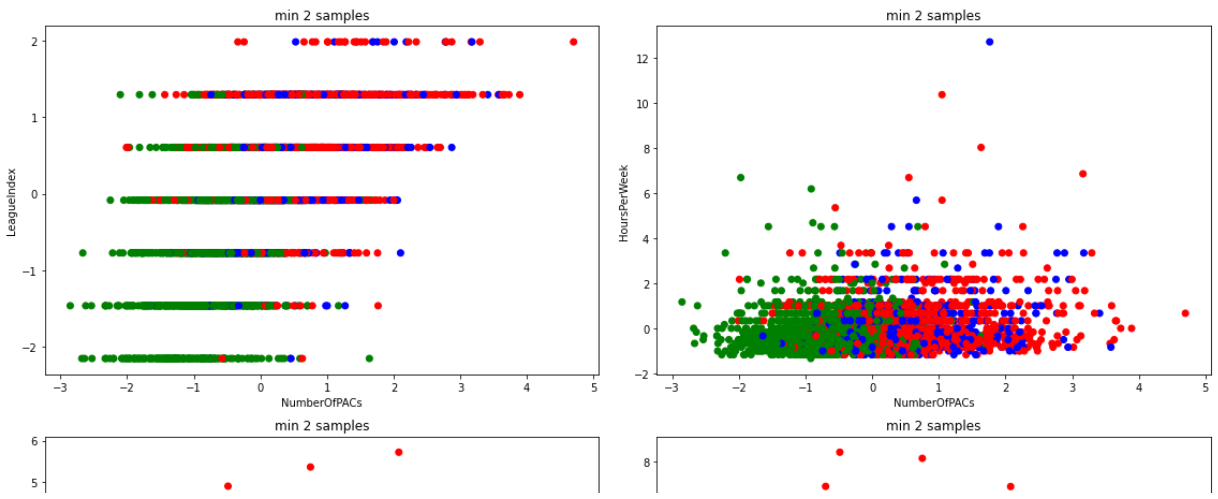

min 2 samples
ComplexUnitsMade
LeagueIndex

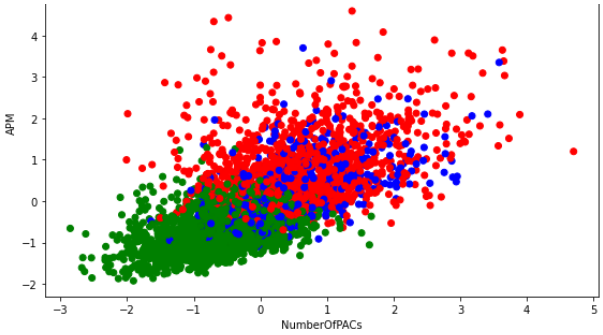


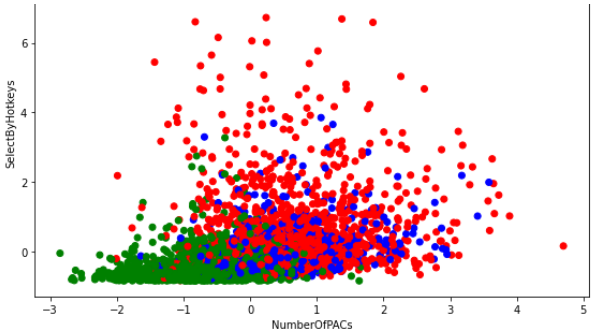
In [30]:

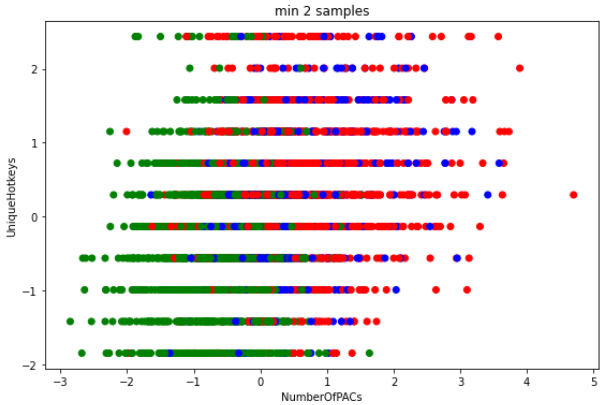
```
print("\tUsing KMeans clustering on the data\n")
plt.clf()
#reduced_data = pd.DataFrame(PCA(n_components=2).fit_transform(data))

plot_against=17

fig, [[ax1,ax2],[ax3,ax4],[ax5,ax6],[ax7,ax8],[ax9,ax10],[ax11,ax12]] = plt.
axes = [ax1,ax2,ax3,ax4,ax5,ax6,ax7,ax8,ax9,ax10,ax11]

dbs = KM(init='k-means++', n_clusters=3, n_init=10)
dataX = data.iloc[:,8:]
dbs.fit(dataX)
color_no = np.array(dbs.labels_)
colors_dict = ['r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
               'r','g','b','m','y','c','k','slategrey','forestgreen','brown'
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(2))

    axes[subplt_n].scatter(data.iloc[:,plot_against], data.iloc[:,interestin

for i in range(1,12):
    addSubPlot(i-1, reduced_data, i+2)
idx = 0
for ax in axes:
    ax.set(xlabel=var[plot_against], ylabel=var[interesting_variables[idx]])
    idx += 1
plt.tight_layout()
plt.show()
```

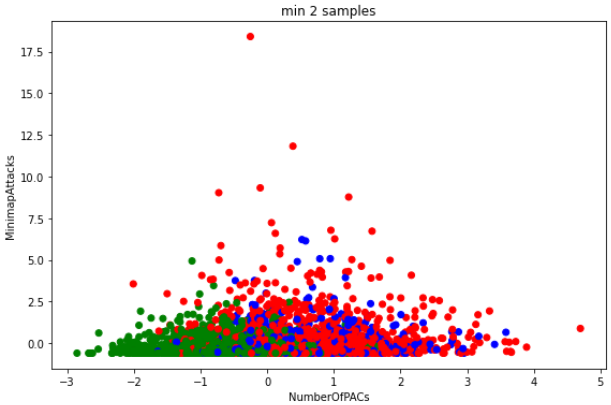
```
        Using KMeans clustering on the data

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

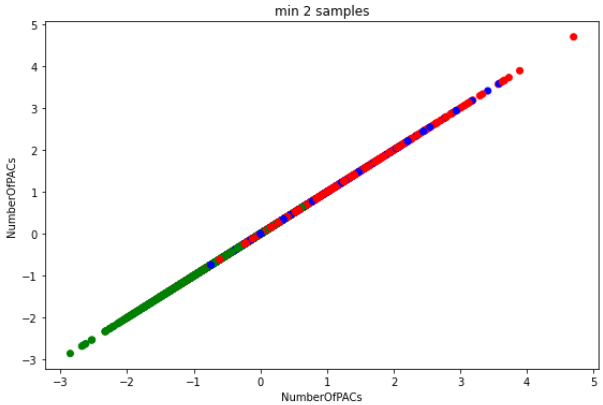


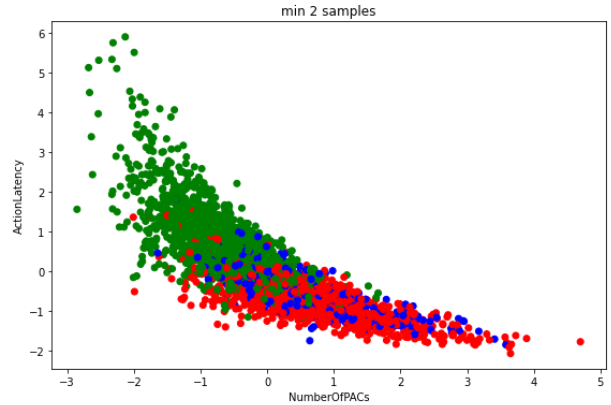

APM
NumberOfPACs

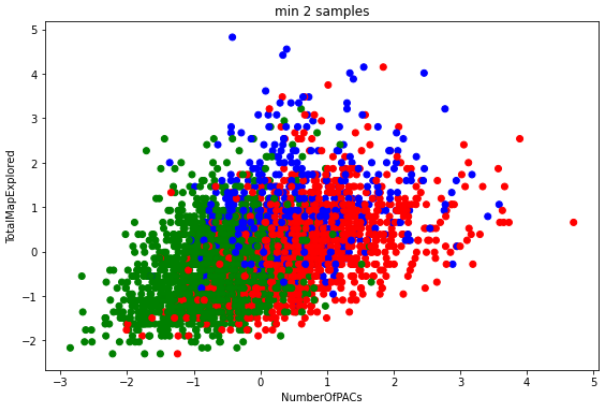

SelectByHotkeys
NumberOfPACs

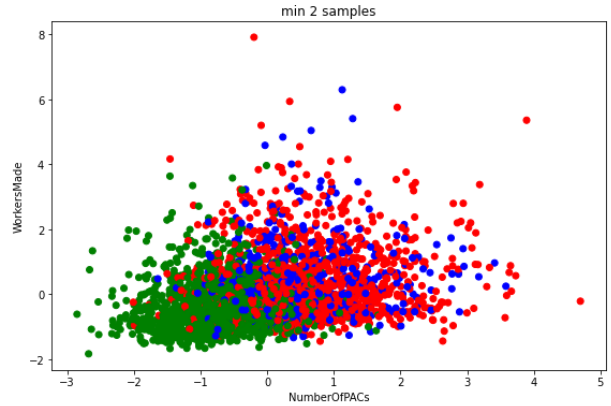

min 2 samples
UniqueHotkeys
NumberOfPACs

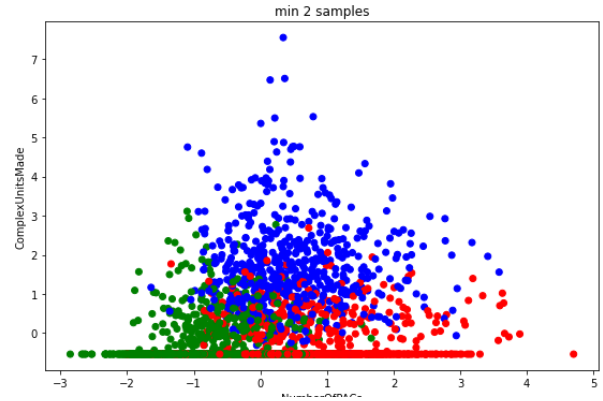

min 2 samples
MinimapAttacks
NumberOfPACs

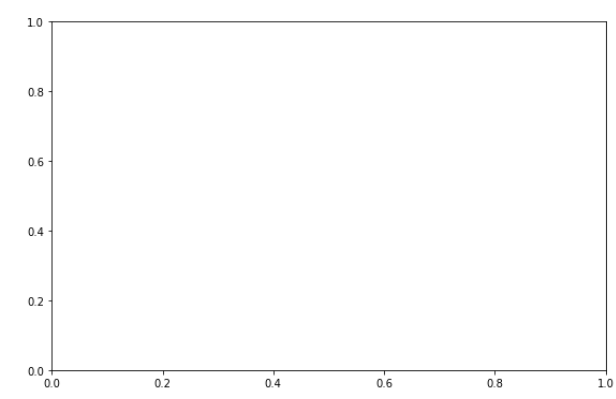

min 2 samples
NumberOfPACs
NumberOfPACs


min 2 samples
ActionLatency
NumberOfPACs


min 2 samples
TotalMapExplored
NumberOfPACs


min 2 samples
WorkersMade
NumberOfPACs


min 2 samples
ComplexUnitsMade



NumberOfPACs

Without the information on which league the player is in, it seems to be focusing on how quickly a player is acting in the game, which makes sense since there are many variables related to that in this dataset.

In [ ]:
```
1
```