Kmeans

February 27, 2019

In [1]:
```
#"Decomment for install"
#!pip install kmeans
#!pip install seaborn
```

In [2]:
```
#Modules to install via pip pandas,ipynb
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import json
from pprint import pprint
import os
import import_ipynb
import sys
import kmeans
sys.path.append('../')
from functions import *
from pandas.plotting import scatter_matrix
import cmath as math
from mpl_toolkits.mplot3d import Axes3D
from sklearn import cluster
from sklearn.metrics import confusion_matrix
from sklearn.metrics.cluster import normalized_mutual_info_score
from sklearn.metrics.cluster import adjusted_rand_score
from sklearn.cluster import KMeans
# scipy
from scipy.cluster.vq import kmeans,vq,whiten
import sklearn.metrics as sm
import seaborn as sns
from sklearn.decomposition import PCA
%matplotlib inline
import random
random.seed(6666)
```

In [3]:
```
dataList=coojaJsonImporter("./traces")
data=[]
cases=[
      "BH1",
        "BH2",
```

```
    "normal"
      ]

BlackHole=[-1,4,5+8]
for nodeList in dataList:
    data.append(createNodes(nodeList))

#All data collection is in variable node that is a list of list of nodes
#3 nets input x 9 nodes by net
data[0][0].pkts[1:5]

d={ "label":[],
    "count":[],
    "std":  [],
    "mean": [],
    "var":  [],
    "25%":  [],
   "50%":[],
   "75%":[],
   "min":[],
   "max":[],
   "hop":[],
   "missing": []
   #"rtt/pkt":[]
}
count=[]
labels=[]
var=[]
window=100
#stats=pd.DataFrame(columns=columns)
rows=[count,labels]
for i in range(len(data)):
    for j in range(len(data[i])):
            #df1 = df1.assign(e=p.Series(np.random.randn(sLength)).values)
            node=data[i][j].pkts
            name=str(j)+" "+cases[i]
            nodeWindow=node["rtt"]
            #current=data[i][j].pkts['rtt'][z:z+window]
            #print(nodeWindow.shape)
            d["count"].append(nodeWindow.count())
            d["std"].append(nodeWindow.std())
            d["mean"].append(nodeWindow.mean())
            d["var"].append(nodeWindow.var())
            d["label"].append(cases[i])
            #print(nodeWindow.describe()["25%"])
            d["25%"].append(nodeWindow.describe()["25%"])
            d["50%"].append(nodeWindow.describe()["50%"])
            d["75%"].append(nodeWindow.describe()["75%"])
```

```
                    d["min"].append(nodeWindow.describe()["min"])
                    d["max"].append(nodeWindow.describe()["max"])
                    d["hop"].append(data[i][j].hop)

                    missing=window-nodeWindow.count()
                    d["missing"].append(missing)



        stats=pd.DataFrame(d)

        stats
        correction=[]
        correction2=[] #for 3 cluster 0:normal net 1:bh net 2:bh
        correction3=[] #for 3 cluster 0:normal net 1:bh net 2:bh net
        for i in range(len(d["label"])):
            el=d["label"][i]
            if el=="normal":
                correction.append(1)
                correction2.append(1)

            else:
                #print(el=="BH2" and i==BlackHole[2])
                correction.append(0)
                if ((el=="BH1" and i==BlackHole[1]) or
                    (el=="BH2" and i==BlackHole[2])):

                    correction2.append(2)
                else:
                    correction2.append(0)


        correction=np.array(correction)
        correction2=np.array(correction2)

        stats.head()
```

```
Importing test_1BH_2018-11-09_12_31_25.json
Importing test_1BH_2018-11-09_14_37_46.json
Importing test_nom_2018-11-09_08_55_11.json
```

Out[3]:

	label	count	std	mean	var	25%	50%	\
0	BH1	98	1403.775442	1868.816327	1.970585e+06	1035.75	1404.5	
1	BH1	99	1812.662114	2139.282828	3.285744e+06	1094.00	1430.0	
2	BH1	91	1873.889033	3916.604396	3.511460e+06	2471.00	3067.0	
3	BH1	97	1308.893667	1815.742268	1.713203e+06	1035.00	1313.0	
4	BH1	25	2220.932875	4667.000000	4.932543e+06	3024.00	3943.0	

```
          75%     min     max  hop  missing
0  1883.75   498.0  8170.0    1        2
1  2435.50   615.0  9112.0    1        1
2  4722.00  1236.0  9972.0    2        9
3  2029.00   258.0  6985.0    1        3
4  6051.00  2004.0  9803.0    3       75
```

```
In [4]: data=stats.drop(["label","25%","var","mean","75%","50%","min","max"],axis=1)

        dataC=stats["label"]
        print(data.head())
        #Y = data[['var']]
        #X = data[['std']]
```

```
   count          std  hop  missing
0     98  1403.775442    1        2
1     99  1812.662114    1        1
2     91  1873.889033    2        9
3     97  1308.893667    1        3
4     25  2220.932875    3       75
```

Kmeans with 2 clusters, using just count, mean and hop feature we can get 85% of understanding probability

```
In [5]: data.head()
```

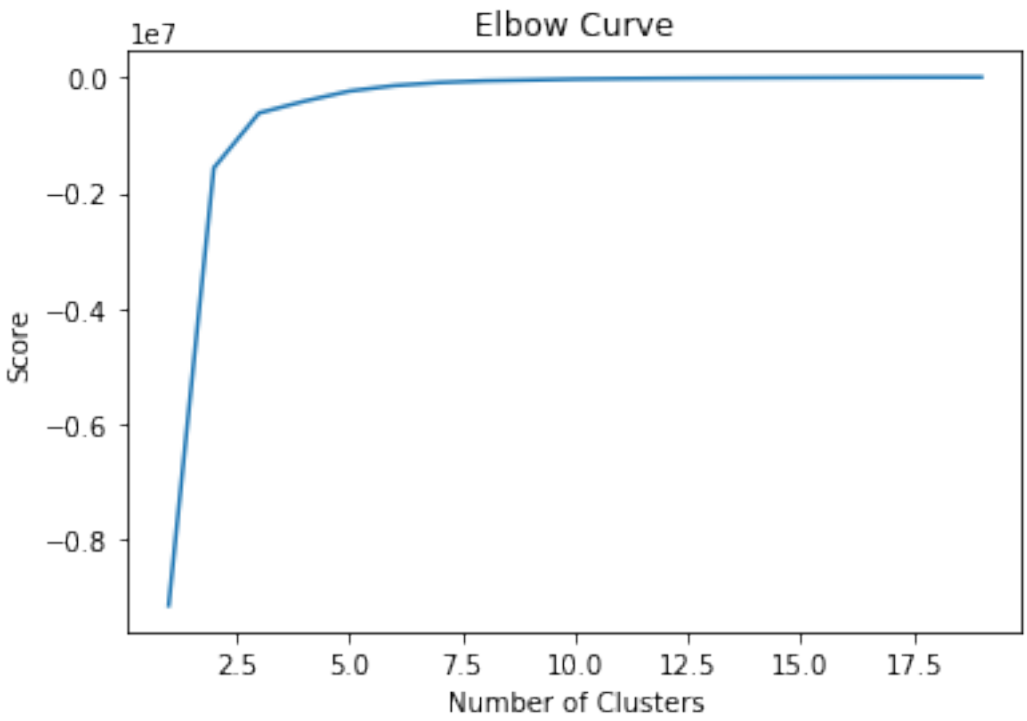
```
Out[5]:    count          std  hop  missing
        0     98  1403.775442    1        2
        1     99  1812.662114    1        1
        2     91  1873.889033    2        9
        3     97  1308.893667    1        3
        4     25  2220.932875    3       75
```

```
In [6]: kmeans = KMeans(n_clusters=2)
        kmeans.fit(data)
        labels = kmeans.predict(data)
        centroids = kmeans.cluster_centers_


        print(labels)
        print(correction)

        # Performance Metrics
        accuracy=sm.accuracy_score(correction, labels)

        # Confusion Matrix
        confusionMatrix=sm.confusion_matrix(correction, labels)
```

```
        print(accuracy)
        print(confusionMatrix)
```

```
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1]
0.0
[[ 0 18]
 [ 9  0]]
```

In [7]:
```
Y=data
Nc = range(1, 20)

kmeans = [KMeans(n_clusters=i) for i in Nc]

kmeans

score = [kmeans[i].fit(Y).score(Y) for i in range(len(kmeans))]

score

plt.plot(Nc,score)

plt.xlabel('Number of Clusters')

plt.ylabel('Score')

plt.title('Elbow Curve')

plt.show()
```




```
In [8]: dataplus=stats.drop(["label"],axis=1)
        data=dataplus
        data.head()
```

Out[8]:

	count	std	mean	var	25%	50%	75%	\
0	98	1403.775442	1868.816327	1.970585e+06	1035.75	1404.5	1883.75	
1	99	1812.662114	2139.282828	3.285744e+06	1094.00	1430.0	2435.50	
2	91	1873.889033	3916.604396	3.511460e+06	2471.00	3067.0	4722.00	
3	97	1308.893667	1815.742268	1.713203e+06	1035.00	1313.0	2029.00	
4	25	2220.932875	4667.000000	4.932543e+06	3024.00	3943.0	6051.00	

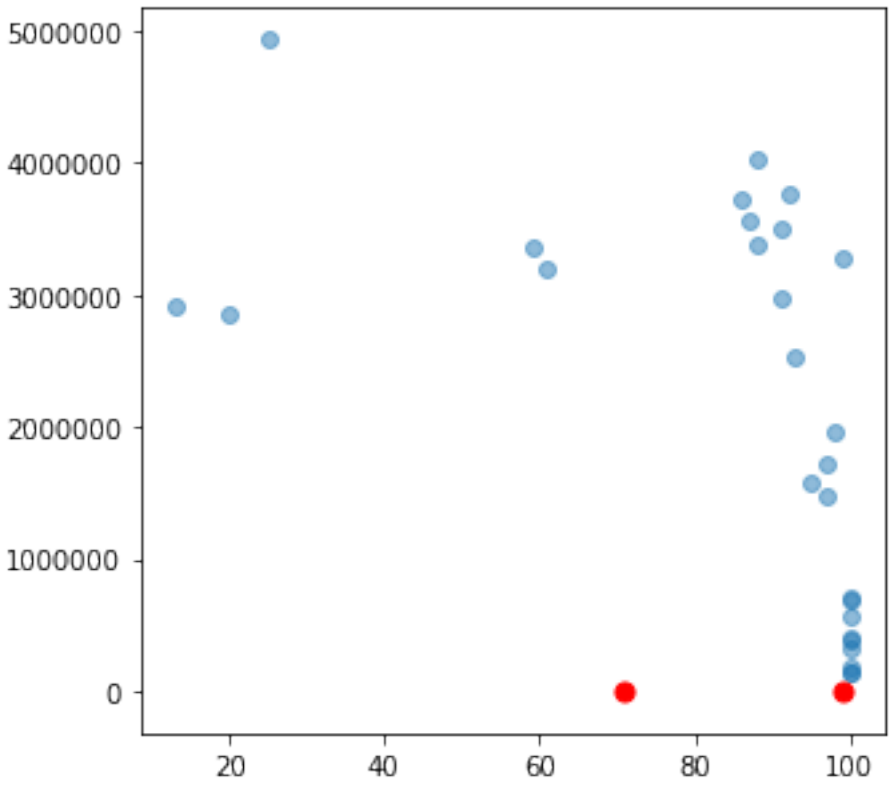
	min	max	hop	missing
0	498.0	8170.0	1	2
1	615.0	9112.0	1	1
2	1236.0	9972.0	2	9
3	258.0	6985.0	1	3
4	2004.0	9803.0	3	75

```
In [9]: kmeans = KMeans(n_clusters=2)
        kmeans.fit(data)
        labels = kmeans.predict(data)
        centroids = kmeans.cluster_centers_
```

```
        print(labels)
        print(correction)

        # Performance Metrics
        accuracy=sm.accuracy_score(correction, labels)

        # Confusion Matrix
        confusionMatrix=sm.confusion_matrix(correction, labels)

        print(accuracy)
        print(confusionMatrix)
```

```
[1 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1]
0.8518518518518519
[[14  4]
 [ 0  9]]
```

```
In [10]: fig = plt.figure(figsize=(5, 5))

         colors = map(lambda x: colmap[x+1], labels)


         plt.scatter(data['count'], data['var'], alpha=0.5)
         plt.scatter(centroids[:, 0], centroids[:, 1], c='red', s=50)

         plt.show()
```



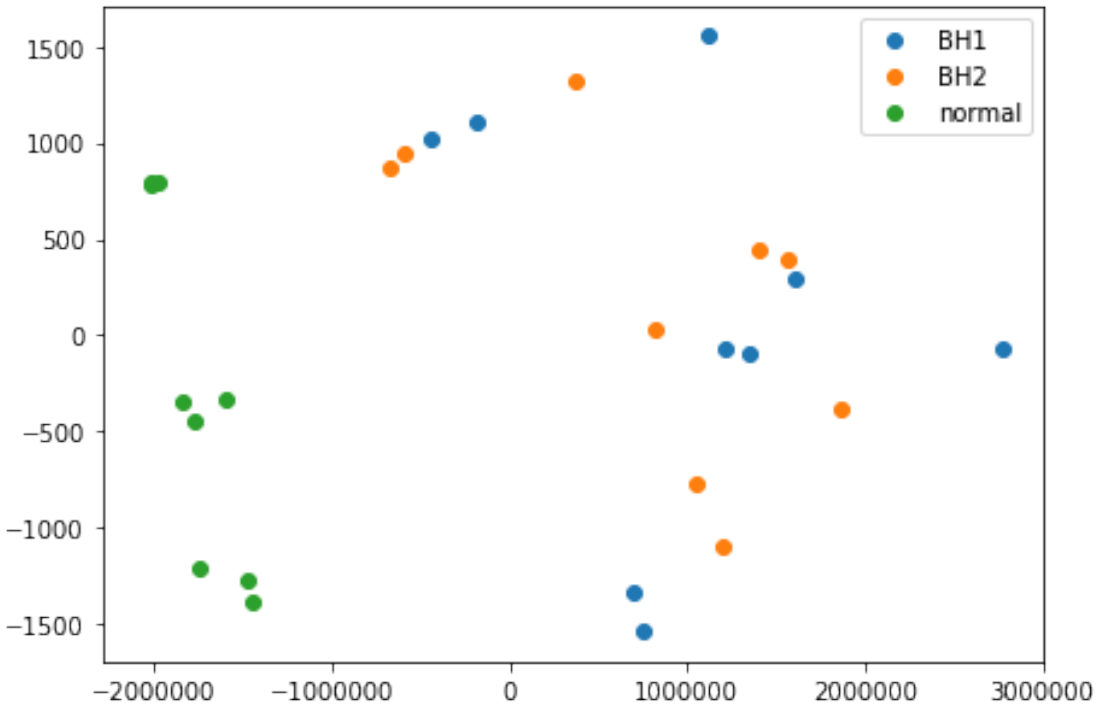

```
In [11]: #https://www.learndatasci.com/tutorials/k-means-clustering-algorithms-python-intro/
         #df=np.array(X,Y)

In [12]: X = dataplus.iloc[:,0:4]
         pca = PCA(n_components=2)
         pca.fit(X)
         X_ = pca.transform(X)

         dfPCA = pd.DataFrame({'x1': X_[:,0], 'x2': X_[:,1]})
         dfPCA['labels'] = stats['label']
         dfPCA.head()
```

Out[12]:

	x1	x2	labels
0	-1.906469e+05	1109.374349	BH1
1	1.124512e+06	1558.013436	BH1
2	1.350229e+06	-95.831043	BH1
3	-4.480298e+05	1021.728477	BH1
4	2.771312e+06	-69.901685	BH1

```
In [13]: labels = stats['label'].unique().tolist()
         plt.figure(figsize=(7,5))
         for lab in labels:
```

```
        plt.scatter(dfPCA.loc[dfPCA['labels'] == lab, 'x1'],  dfPCA.loc[dfPCA['labels'] ==
        plt.legend()
```



Experiment with 3 clusters trying also to find the black Hole node, 0.74% of probability finding a black hole in the network

```
In [14]: kmeans = KMeans(n_clusters=3)
         kmeans.fit(dataplus)
         labels = kmeans.predict(dataplus)
         centroids = kmeans.cluster_centers_


         print(labels)
         print(correction2)


         # Performance Metrics
         accuracy=sm.accuracy_score(correction2, labels)

         # Confusion Matrix
         confusionMatrix=sm.confusion_matrix(correction2, labels)

         print(accuracy)
         print(confusionMatrix)
```

```
[2 0 0 2 0 0 0 0 0 2 2 0 2 0 0 0 0 0 1 1 1 1 1 1 1 1 1]
[0 0 0 0 2 0 0 0 0 0 0 0 0 2 0 0 0 0 0 1 1 1 1 1 1 1 1 1]
0.7407407407407407
[[11  0  5]
 [ 0  9  0]
 [ 2  0  0]]
```

```
In [15]: for i in range(len(labels)):
             if labels[i]==2:
                 labels[i]=0

             if correction2[i]==2:
                 correction2[i]=0
         print(labels)
         print(correction2)
         # Performance Metrics
         accuracy=sm.accuracy_score(correction2, labels)

         # Confusion Matrix
         confusionMatrix=sm.confusion_matrix(correction2, labels)

         print(accuracy)
         print(confusionMatrix)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1]
1.0
[[18  0]
 [ 0  9]]
```

#Last experiment
using windows so we can have virtually more data to work

```
In [16]: dataList=coojaJsonImporter("./traces")
         data=[]
         cases=[
               "BH1",
                 "BH2",
             "normal"
               ]

         for nodeList in dataList:
             data.append(createNodes(nodeList))

         d={ "label":[],
             "count":[],
             "std":  [],
```

```
            "mean": [],
            "var":  [],
            "25%":  [],
            "50%":[],
            "75%":[],
           "min":[],
           "max":[],
           "hop":[],
           "missing":[]
           #"rtt/pkt":[]
        }

        window=75
        for i in range(len(data)):
            for j in range(len(data[i])):
                n=len(data[i][j].pkts["rtt"])
                #print(n)
                for z in range(0,n,window):
                    #print(z)

                    #df1 = df1.assign(e=p.Series(np.random.randn(sLength)).values)
                    node=data[i][j].pkts
                    name=str(j)+" "+cases[i]
                    nodeWindow=node[(node["pkt"]<z+window) & (node["pkt"]>=z)]["rtt"]
                    #current=data[i][j].pkts['rtt'][z:z+window]
                    #print(nodeWindow.shape)
                    d["count"].append(nodeWindow.count())
                    d["std"].append(nodeWindow.std())
                    d["mean"].append(nodeWindow.mean())
                    d["var"].append(nodeWindow.var())
                    d["label"].append(cases[i])
                    #print(nodeWindow.describe()["25%"])
                    d["25%"].append(nodeWindow.describe()["25%"])
                    d["50%"].append(nodeWindow.describe()["50%"])
                    d["75%"].append(nodeWindow.describe()["75%"])
                    d["min"].append(nodeWindow.describe()["min"])
                    d["max"].append(nodeWindow.describe()["max"])
                    d["hop"].append(data[i][j].hop)

                    missing=window-nodeWindow.count()
                    d["missing"].append(missing)
```

```
Importing test_1BH_2018-11-09_12_31_25.json
Importing test_1BH_2018-11-09_14_37_46.json
Importing test_nom_2018-11-09_08_55_11.json
```

```
In [17]: stats=pd.DataFrame(d)
```

```
stats.head()
```

Out[17]:

	label	count	std	mean	var	25%	50%	75%	min	max	hop	missing
0	BH1	73	1581.838750	1982.575342	2.502214e+06	1017.00	1403.0	2406.0	709.0	8170.0	1	2
1	BH1	25	550.914685	1536.640000	3.035070e+05	1229.00	1495.0	1790.0	498.0	3430.0	1	50
2	BH1	74	1985.449426	2177.121622	3.942009e+06	1047.50	1385.5	2053.0	615.0	9112.0	1	1
3	BH1	25	1187.024484	2027.280000	1.409027e+06	1253.00	1431.0	2484.0	935.0	5528.0	1	50
4	BH1	66	1956.142049	3845.909091	3.826492e+06	2427.75	2952.0	4627.0	1236.0	9972.0	2	9

In [18]:
```
print(stats.shape)
stats=stats.dropna()
print(stats.shape)
print(stats.columns)
```

```
(49, 12)
(49, 12)
Index(['label', 'count', 'std', 'mean', 'var', '25%', '50%', '75%', 'min',
       'max', 'hop', 'missing'],
      dtype='object')
```

In [19]:
```
data=stats.drop(["label","25%","75%","50%","min","max","mean","var"],axis=1)
data.head()
```

Out[19]:

	count	std	hop	missing
0	73	1581.838750	1	2
1	25	550.914685	1	50
2	74	1985.449426	1	1
3	25	1187.024484	1	50
4	66	1956.142049	2	9

In [20]:
```
#dataplus=stats.drop(["label"],axis=1)

#data=dataplus
kmeans = KMeans(n_clusters=2)
kmeans.fit(data)
labels = kmeans.predict(data)
centroids = kmeans.cluster_centers_

data.columns
```

Out[20]: Index(['count', 'std', 'hop', 'missing'], dtype='object')

In [21]:
```
correction=[]
#stats=stats.dropna()

col=np.array(stats["label"])

for i in range(len(col)):
    el=col[i]
    if el=="normal":
        correction.append(0)


    else:

        correction.append(1)


correction=np.array(correction)
print(len(correction))
print(len(labels))
```

```
49
49
```

In [22]:
```
#print(labels)
#print(correction)

# Performance Metrics
accuracy=sm.accuracy_score(correction, labels)

# Confusion Matrix
confusionMatrix=sm.confusion_matrix(correction, labels)

print(correction)
print(labels)
print(accuracy)
print(confusionMatrix)
```

```
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0]
[1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0]
0.9183673469387755
[[18  0]
 [ 4 27]]
```

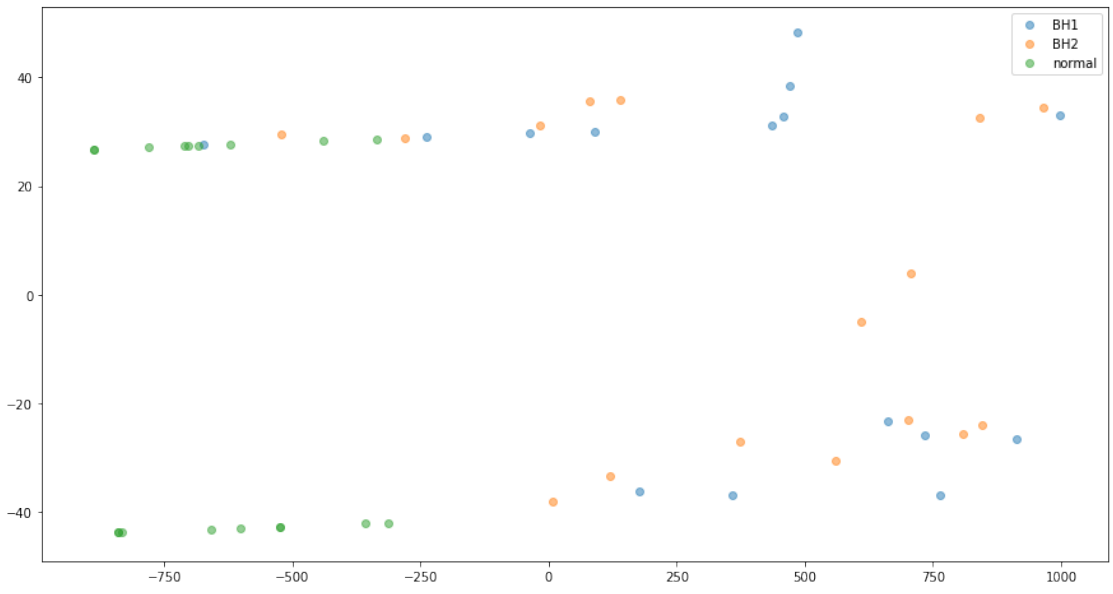
In [23]:
```
X = data.iloc[:,0:4]
pca = PCA(n_components=2)
```

```
pca.fit(X)
X_ = pca.transform(X)

dfPCA = pd.DataFrame({'x1': X_[:,0], 'x2': X_[:,1]})
dfPCA['labels'] = stats['label']
dfPCA.head()
```

Out[23]:

	x1	x2	labels
0	359.154533	-36.931972	BH1
1	-671.990054	27.513671	BH1
2	762.767654	-37.001013	BH1
3	-35.883832	29.633703	BH1
4	733.423084	-25.781852	BH1

In [24]:
```
labels = stats['label'].unique().tolist()
plt.figure(figsize=(15,8))
for lab in labels:
    plt.scatter(dfPCA.loc[dfPCA['labels'] == lab, 'x1'],  dfPCA.loc[dfPCA['labels'] ==
    plt.legend()
```



In [ ]:

In [ ]:

In [ ]:

In [ ]:

Example adding also the 16 nodes, clearly the accuracy goes down as we dont have many data

In [25]:
```
dataList=coojaJsonImporter("../cooja-16nodes/traces/")

data=[]
cases=[
    "1BH",
       "1BH","1BH","Norm"]
"""
Importing test_1BH_P8_16nodes_2002019-01-29_21_40_55.json
Importing test_1BH_16nodes2018-11-09_19_46_22.json
Importing test_1BH_P8_16nodes_2002019-01-29_23_27_48.json
Importing test_norm_16nodes_5002019-01-29_18_56_03.json
Importing test_1BH_2018-11-09_12_31_25.json
Importing test_1BH_2018-11-09_14_37_46.json
Importing test_nom_2018-11-09_08_55_11.json
"""



BlackHole=[-1,4,5+8,-1]
#cases=["1BH","1BH","Norm"]
for nodeList in dataList:
    data.append(createNodes(nodeList))
#dataList=coojaJsonImporter("../cooja-9nodes/traces/")
#for nodeList in dataList:
#    data.append(createNodes(nodeList))

d={ "label":[],
    "count":[],
    "std":  [],
    "mean": [],
    "var":  [],
    "25%":  [],
    "50%":[],
    "75%":[],
   "min":[],
   "max":[],
   "hop":[],
   "missing":[]
   #"rtt/pkt":[]
}

window=10
for i in range(len(data)):
    for j in range(len(data[i])):
        n=len(data[i][j].pkts["rtt"])
        #print(n)
        for z in range(0,n,window):
            #print(z)
```

```
            #df1 = df1.assign(e=p.Series(np.random.randn(sLength)).values)
            node=data[i][j].pkts
            name=str(j)+" "+cases[i]
            nodeWindow=node[(node["pkt"]<z+window) & (node["pkt"]>=z)]["rtt"]
            #current=data[i][j].pkts['rtt'][z:z+window]
            #print(nodeWindow.shape)
            d["count"].append(nodeWindow.count())
            d["std"].append(nodeWindow.std())
            d["mean"].append(nodeWindow.mean())
            d["var"].append(nodeWindow.var())
            d["label"].append(cases[i])
            #print(nodeWindow.describe()["25%"])
            d["25%"].append(nodeWindow.describe()["25%"])
            d["50%"].append(nodeWindow.describe()["50%"])
            d["75%"].append(nodeWindow.describe()["75%"])
            d["min"].append(nodeWindow.describe()["min"])
            d["max"].append(nodeWindow.describe()["max"])
            d["hop"].append(data[i][j].hop)

            missing=window-nodeWindow.count()
            d["missing"].append(missing)

stats=pd.DataFrame(d)
stats=stats.dropna()
data=stats.drop(["label","25%","75%","50%","min","max","mean","var"],axis=1)
print(data.shape)

print(data.shape)
print(data.columns)
correction=[]
correction2=[] #for 3 cluster 0:normal net 1:bh net 2:bh
for i in range(len(stats["label"])):
    el=d["label"][i]
    if el=="1BH":
        correction.append(1)
        correction2.append(1)

    else:
        #print(el=="BH2" and i==BlackHole[2])
        correction.append(0)
        if ((el=="BH1" and i==BlackHole[1]) or
            (el=="BH2" and i==BlackHole[2])):

            correction2.append(2)
        else:
            correction2.append(0)
```

```python
correction=np.array(correction)
correction2=np.array(correction2)


kmeans = KMeans(n_clusters=2)
kmeans.fit(data)
labels = kmeans.predict(data)
centroids = kmeans.cluster_centers_


print(labels)

print(correction)

# Performance Metrics
accuracy=sm.accuracy_score(correction, labels)

# Confusion Matrix
confusionMatrix=sm.confusion_matrix(correction, labels)

print(accuracy)
print(confusionMatrix)
```

```
Importing test_1BH_P8_16nodes_2002019-01-29_21_40_55.json
Importing test_1BH_16nodes2018-11-09_19_46_22.json
Importing test_1BH_P8_16nodes_2002019-01-29_23_27_48.json
Importing test_norm_16nodes_5002019-01-29_18_56_03.json
(770, 4)
(770, 4)
Index(['count', 'std', 'hop', 'missing'], dtype='object')
[0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0
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0.38701298701298703
[[228  21]
 [451  70]]
```

```
In [26]: stats.head()
```

Out[26]:

	label	count	std	mean	var	25%	50%	75%	\
0	1BH	10	151.314243	1038.0	22896.000000	927.50	1034.5	1082.75	
1	1BH	10	343.852762	1096.5	118234.722222	940.50	955.0	1053.75	
2	1BH	10	192.830265	1045.2	37183.511111	917.75	999.5	1124.25	
3	1BH	10	94.293867	1007.0	8891.333333	943.00	974.0	1068.75	
4	1BH	10	141.277347	1031.2	19959.288889	931.50	1024.5	1102.50	

	min	max	hop	missing
0	821.0	1287.0	3	0
1	872.0	1998.0	3	0
2	825.0	1444.0	3	0
3	904.0	1199.0	3	0
4	801.0	1255.0	3	0

```
In [27]: X = data
         pca = PCA(n_components=2)
```

```
pca.fit(X)
X_ = pca.transform(X)

dfPCA = pd.DataFrame({'x1': X_[:,0], 'x2': X_[:,1]})
dfPCA['labels'] = stats['label']
dfPCA.head()
labels = stats['label'].unique().tolist()
plt.figure(figsize=(15,8))
for lab in labels:
    plt.scatter(dfPCA.loc[dfPCA['labels'] == lab, 'x1'],  dfPCA.loc[dfPCA['labels'] ==
    plt.legend()
```