In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
data = pd.read_csv('E:/New folder/sonar.all-data.csv')
data.head()
```

Out[2]:

	0.0200	0.0371	0.0428	0.0207	0.0954	0.0986	0.1539	0.1601	0.3109	0.2111	...	0.0027	0.0065	0.015
0	0.0453	0.0523	0.0843	0.0689	0.1183	0.2583	0.2156	0.3481	0.3337	0.2872	...	0.0084	0.0089	0.004
1	0.0262	0.0582	0.1099	0.1083	0.0974	0.2280	0.2431	0.3771	0.5598	0.6194	...	0.0232	0.0166	0.009
2	0.0100	0.0171	0.0623	0.0205	0.0205	0.0368	0.1098	0.1276	0.0598	0.1264	...	0.0121	0.0036	0.015
3	0.0762	0.0666	0.0481	0.0394	0.0590	0.0649	0.1209	0.2467	0.3564	0.4459	...	0.0031	0.0054	0.010
4	0.0286	0.0453	0.0277	0.0174	0.0384	0.0990	0.1201	0.1833	0.2105	0.3039	...	0.0045	0.0014	0.003

5 rows × 61 columns

In [3]:
```
data.isna().sum()
```

Out[3]:
```
0.0200    0
0.0371    0
0.0428    0
0.0207    0
0.0954    0
         ..
0.0180    0
0.0084    0
0.0090    0
0.0032    0
R         0
Length: 61, dtype: int64
```

There are 60 features, from which we can predict whether the object is rock or mine

In [4]:
```
data['R'].value_counts()
```

Out[4]:
```
M    111
R     96
Name: R, dtype: int64
```

In [5]:
```
data_R = data[data['R']=='R']
data_M = data[data['R']=='M']
```

In [6]:
```
data_R.head(5)
```

Out[6]:

	0.0200	0.0371	0.0428	0.0207	0.0954	0.0986	0.1539	0.1601	0.3109	0.2111	...	0.0027	0.0065	0.015
0	0.0453	0.0523	0.0843	0.0689	0.1183	0.2583	0.2156	0.3481	0.3337	0.2872	...	0.0084	0.0089	0.004
1	0.0262	0.0582	0.1099	0.1083	0.0974	0.2280	0.2431	0.3771	0.5598	0.6194	...	0.0232	0.0166	0.009
2	0.0100	0.0171	0.0623	0.0205	0.0205	0.0368	0.1098	0.1276	0.0598	0.1264	...	0.0121	0.0036	0.015
3	0.0762	0.0666	0.0481	0.0394	0.0590	0.0649	0.1209	0.2467	0.3564	0.4459	...	0.0031	0.0054	0.010
4	0.0286	0.0453	0.0277	0.0174	0.0384	0.0990	0.1201	0.1833	0.2105	0.3039	...	0.0045	0.0014	0.003

5 rows × 61 columns

In [7]:
```
data_M.head(5)
```

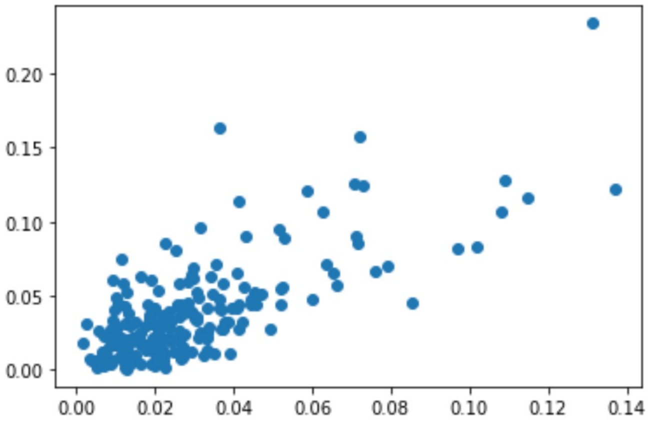
Out[7]:

	0.0200	0.0371	0.0428	0.0207	0.0954	0.0986	0.1539	0.1601	0.3109	0.2111	...	0.0027	0.0065	0.0
96	0.0491	0.0279	0.0592	0.1270	0.1772	0.1908	0.2217	0.0768	0.1246	0.2028	...	0.0081	0.0129	0.0
97	0.1313	0.2339	0.3059	0.4264	0.4010	0.1791	0.1853	0.0055	0.1929	0.2231	...	0.0362	0.0210	0.0
98	0.0201	0.0423	0.0554	0.0783	0.0620	0.0871	0.1201	0.2707	0.1206	0.0279	...	0.0191	0.0182	0.0
99	0.0629	0.1065	0.1526	0.1229	0.1437	0.1190	0.0884	0.0907	0.2107	0.3597	...	0.0089	0.0262	0.0
100	0.0335	0.0134	0.0696	0.1180	0.0348	0.1180	0.1948	0.1607	0.3036	0.4372	...	0.0244	0.0232	0.0

5 rows × 61 columns

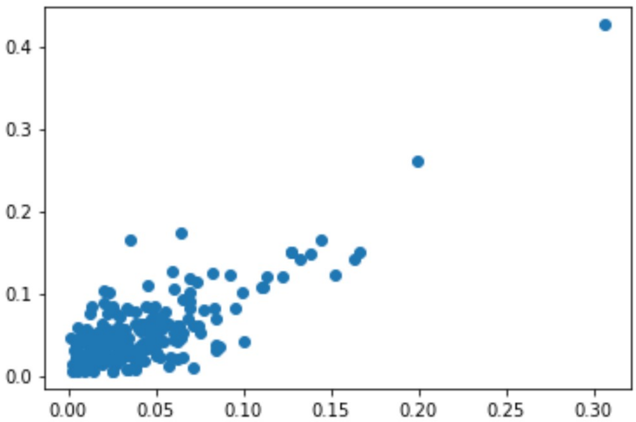
In [8]:
```
plt.scatter(data['0.0200'],data['0.0371'])
```

Out[8]: <matplotlib.collections.PathCollection at 0x2339a312fc8>



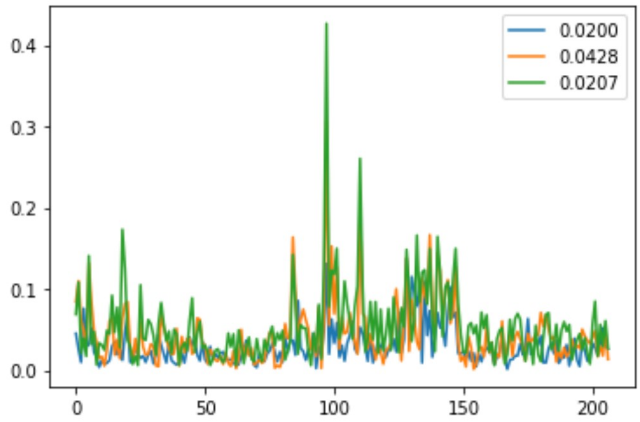
In [9]:
```
plt.scatter(data['0.0428'],data['0.0207'])
```

Out[9]: <matplotlib.collections.PathCollection at 0x2339a312b48>



In [10]:
```
plt.plot(data['0.0200'], label='0.0200')
plt.plot(data['0.0428'], label='0.0428')
plt.plot(data['0.0207'], label='0.0207')
plt.legend()
```

Out[10]: <matplotlib.legend.Legend at 0x2339a44b908>



In [11]:
```
from sklearn.model_selection import train_test_split
X=data.drop('R', axis=1)
y=data['R']
```

In [12]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.8, random_
state=29)
```

In [13]:
```
print(X_train.shape)
print(X_test.shape)
```

```
(165, 60)
(42, 60)
```

Classification

KNN

In [14]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [15]:
```
knn = KNeighborsClassifier()
```

In [16]:
```
knn.fit(X=X_train, y=y_train)
```

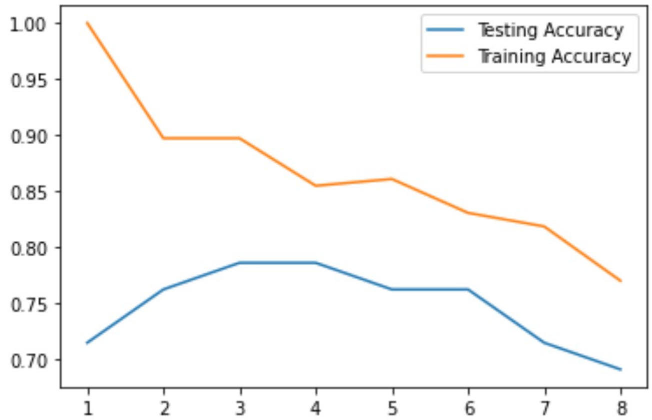
Out[16]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='uniform')
```

In [17]:
```
knn.score(X_test, y_test)
```

Out[17]: 0.7619047619047619

Accuracy: 76.2%

In [18]:
```
neighbors = np.arange(1,9)
train_accuracy = np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

for i,k in enumerate(neighbors):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    train_accuracy[i] = knn.score(X_train,y_train)
    test_accuracy[i] = knn.score(X_test, y_test)

plt.plot(neighbors, test_accuracy, label='Testing Accuracy')
plt.plot(neighbors, train_accuracy, label='Training Accuracy')
plt.legend()
plt.show()
```



Maximum accuracy is obtained when k=3 or 4

In [19]:
```
knn = KNeighborsClassifier(n_neighbors=4)
knn.fit(X=X_train, y=y_train)
knn.score(X_test, y_test)
```

Out[19]:
```
0.7857142857142857
```

Accuracy: 78.57%

In [20]:
```
from sklearn.metrics import confusion_matrix
y_pred = knn.predict(X_test)
confusion_matrix(y_test, y_pred)
```

Out[20]:
```
array([[23,  5],
       [ 4, 10]], dtype=int64)
```

9 wrong predictions out of 42

In [21]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           M       0.85      0.82      0.84        28
           R       0.67      0.71      0.69        14

    accuracy                           0.79        42
   macro avg       0.76      0.77      0.76        42
weighted avg       0.79      0.79      0.79        42
```

Decision Tree

In [22]:
```
from sklearn.tree import DecisionTreeClassifier
clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)
clf.score(X_test, y_test)
```

Out[22]:
```
0.9047619047619048
```

Accuracy: 90.47%

In [23]:
```
from sklearn.metrics import confusion_matrix
y_pred = clf.predict(X_test)
confusion_matrix(y_test, y_pred)
```

Out[23]:
```
array([[27,  1],
       [ 3, 11]], dtype=int64)
```

4 out of 42 were predicted wrong

In [24]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           M       0.90      0.96      0.93        28
           R       0.92      0.79      0.85        14

    accuracy                           0.90        42
   macro avg       0.91      0.88      0.89        42
weighted avg       0.91      0.90      0.90        42
```

SVM

In [25]:
```
from sklearn.svm import SVC
svm = SVC()
svm.fit(X_train, y_train)
svm.score(X_test, y_test)
```

```
C:\Users\SR1407SM1106\AppData\Local\Continuum\anaconda3\lib\site-packages\skle
arn\svm\base.py:193: FutureWarning: The default value of gamma will change fro
m 'auto' to 'scale' in version 0.22 to account better for unscaled features. S
et gamma explicitly to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

Out[25]:
```
0.6428571428571429
```

In [26]:
```
from sklearn.metrics import confusion_matrix
y_pred = svm.predict(X_test)
confusion_matrix(y_test, y_pred)
```

Out[26]:
```
array([[21,  7],
       [ 8,  6]], dtype=int64)
```

In [27]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           M       0.72      0.75      0.74        28
           R       0.46      0.43      0.44        14

    accuracy                           0.64        42
   macro avg       0.59      0.59      0.59        42
weighted avg       0.64      0.64      0.64        42
```

Accuracy: 64.28%

15 were predicted wrong out of 42

Standardising data

In [42]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_p = scaler.fit_transform(X)
X_p
```

Out[42]:
```
array([[ 0.70018948,  0.42042142,  1.0529498 , ..., -0.4709383 ,
        -0.44268846, -0.42246083],
       [-0.13089402,  0.59942737,  1.71912994, ...,  1.30656071,
         0.25299833,  0.25405324],
       [-0.83579208, -0.64754631,  0.48045125, ..., -0.54822087,
        -0.63683361,  1.03005467],
       ...,
       [ 1.00042384,  0.15949749, -0.67235266, ...,  0.90469137,
        -0.0382194 , -0.68112798],
       [ 0.0475061 , -0.09535845,  0.13434985, ..., -0.00724291,
        -0.70154866, -0.34287094],
       [-0.13959647, -0.06501846, -0.78685237, ..., -0.67187297,
        -0.2970796 ,  0.99025973]])
```

PCA

In [43]:
```
from sklearn.decomposition import PCA
pca = PCA()
X_pca = pca.fit_transform(X_p)
```

In [44]:
```
print(pca.explained_variance_ratio_)
```

```
[2.03897950e-01 1.89405455e-01 8.56018085e-02 5.68862840e-02
 5.01317021e-02 4.05567677e-02 3.27272864e-02 3.03529373e-02
 2.57210787e-02 2.49016628e-02 2.07971452e-02 1.90546557e-02
 1.75405558e-02 1.54132664e-02 1.43177628e-02 1.35130771e-02
 1.23002112e-02 1.11555925e-02 1.03282502e-02 9.79584100e-03
 9.31755378e-03 8.82245274e-03 8.41377607e-03 7.75326916e-03
 7.24358160e-03 6.98525179e-03 6.05789229e-03 5.32915402e-03
 5.25475666e-03 4.92103776e-03 4.77289354e-03 4.36932921e-03
 3.68829839e-03 3.26860405e-03 3.09930505e-03 3.03922888e-03
 2.87559886e-03 2.44611335e-03 2.19463709e-03 2.06394408e-03
 1.85188563e-03 1.58641602e-03 1.34933280e-03 1.24743835e-03
 1.01715873e-03 9.48405524e-04 9.01965543e-04 7.07573125e-04
 5.59258464e-04 5.23852009e-04 4.82666208e-04 4.46857015e-04
 3.80233202e-04 3.55950060e-04 3.20623754e-04 2.68355115e-04
 2.48356050e-04 1.92144557e-04 1.87217896e-04 1.08340357e-04]
```

In [45]:
```
print(pca.singular_values_)
```

```
[50.32308163 48.50170877 32.60635616 26.5805878  24.95266999 22.44359719
 20.16117301 19.41606247 17.87332641 17.58632002 16.0717312  15.38371942
 14.759868   13.83592313 13.33516455 12.95501516 12.35996051 11.77083084
 11.32593784 11.03015617 10.75750984 10.46780125 10.22248007  9.8130323
  9.48500308  9.3143345   8.67404301  8.13560648  8.07861856  7.81788264
  7.69930762  7.36661855  6.76820996  6.37150393  6.20430244  6.14387685
  5.97619761  5.51187153  5.22086129  5.06302138  4.79587526  4.43883847
  4.09374076  3.93613825  3.55430885  3.43208342  3.34700046  2.96446592
  2.63552464  2.55073361  2.44841057  2.35583618  2.17313055  2.10259357
  1.99553176  1.8256425   1.75629785  1.54480918  1.52487582  1.1599945 ]
```

KNN

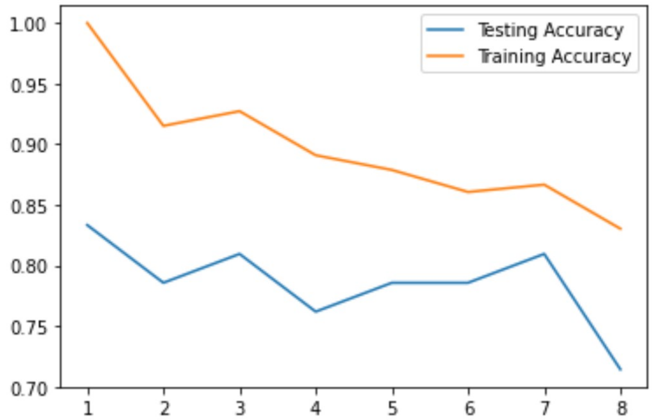
In [46]:
```
from sklearn.model_selection import train_test_split
X_train_pca, X_test_pca, y_train_pca, y_test_pca = train_test_split(X_pca, y, te
st_size=0.2, random_state=1)
X_train_pca.shape
```

Out[46]: (165, 60)

In [47]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
knn.fit(X=X_train_pca, y=y_train_pca)
knn.score(X_test_pca, y_test_pca)
```

Out[47]: 0.7857142857142857

In [48]:
```
neighbors = np.arange(1,9)
train_accuracy = np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

for i,k in enumerate(neighbors):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_pca, y_train_pca)
    train_accuracy[i] = knn.score(X_train_pca,y_train_pca)
    test_accuracy[i] = knn.score(X_test_pca, y_test_pca)

plt.plot(neighbors, test_accuracy, label='Testing Accuracy')
plt.plot(neighbors, train_accuracy, label='Training Accuracy')
plt.legend()
plt.show()
```



High accuracy when k=1

In [49]:
```
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X=X_train_pca, y=y_train_pca)
knn.score(X_test_pca, y_test_pca)
```

Out[49]:
```
0.8333333333333334
```

In [50]:
```
from sklearn.metrics import confusion_matrix
y_pred_pca = knn.predict(X_test_pca)
confusion_matrix(y_test_pca, y_pred_pca)
```

Out[50]:
```
array([[18,  2],
       [ 5, 17]], dtype=int64)
```

In [51]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test_pca, y_pred_pca))
```

```
              precision    recall  f1-score   support

           M       0.78      0.90      0.84        20
           R       0.89      0.77      0.83        22

    accuracy                           0.83        42
   macro avg       0.84      0.84      0.83        42
weighted avg       0.84      0.83      0.83        42
```

Accuracy: 83.3%

7 out of 42 wrong predictions

Decision Tree

In [52]:
```
from sklearn.tree import DecisionTreeClassifier
clf = DecisionTreeClassifier()
clf.fit(X_train_pca, y_train_pca)
clf.score(X_test_pca, y_test_pca)
```

Out[52]:
```
0.7619047619047619
```

In [53]:
```
from sklearn.metrics import confusion_matrix
y_pred_pca = clf.predict(X_test_pca)
confusion_matrix(y_test_pca, y_pred_pca)
```

Out[53]:
```
array([[15,  5],
       [ 5, 17]], dtype=int64)
```

In [54]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test_pca, y_pred_pca))
```

```
              precision    recall  f1-score   support

           M       0.75      0.75      0.75        20
           R       0.77      0.77      0.77        22

    accuracy                           0.76        42
   macro avg       0.76      0.76      0.76        42
weighted avg       0.76      0.76      0.76        42
```

Accuracy: 76.19%

10 out of 42 wrong predictions

SVM

In [55]:
```
from sklearn.svm import SVC
svm = SVC()
svm.fit(X_train_pca, y_train_pca)
svm.score(X_test_pca, y_test_pca)
```

```
C:\Users\SR1407SM1106\AppData\Local\Continuum\anaconda3\lib\site-packages\skle
arn\svm\base.py:193: FutureWarning: The default value of gamma will change fro
m 'auto' to 'scale' in version 0.22 to account better for unscaled features. S
et gamma explicitly to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

Out[55]:
```
0.7857142857142857
```

In [56]:
```
from sklearn.metrics import confusion_matrix
y_pred_pca = svm.predict(X_test_pca)
confusion_matrix(y_test_pca, y_pred_pca)
```

Out[56]:
```
array([[18,  2],
       [ 7, 15]], dtype=int64)
```

In [57]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test_pca, y_pred_pca))
```

```
              precision    recall  f1-score   support

           M       0.72      0.90      0.80        20
           R       0.88      0.68      0.77        22

    accuracy                           0.79        42
   macro avg       0.80      0.79      0.78        42
weighted avg       0.81      0.79      0.78        42
```

Accuracy: 78.57%

9 out of 42 wrong predictions

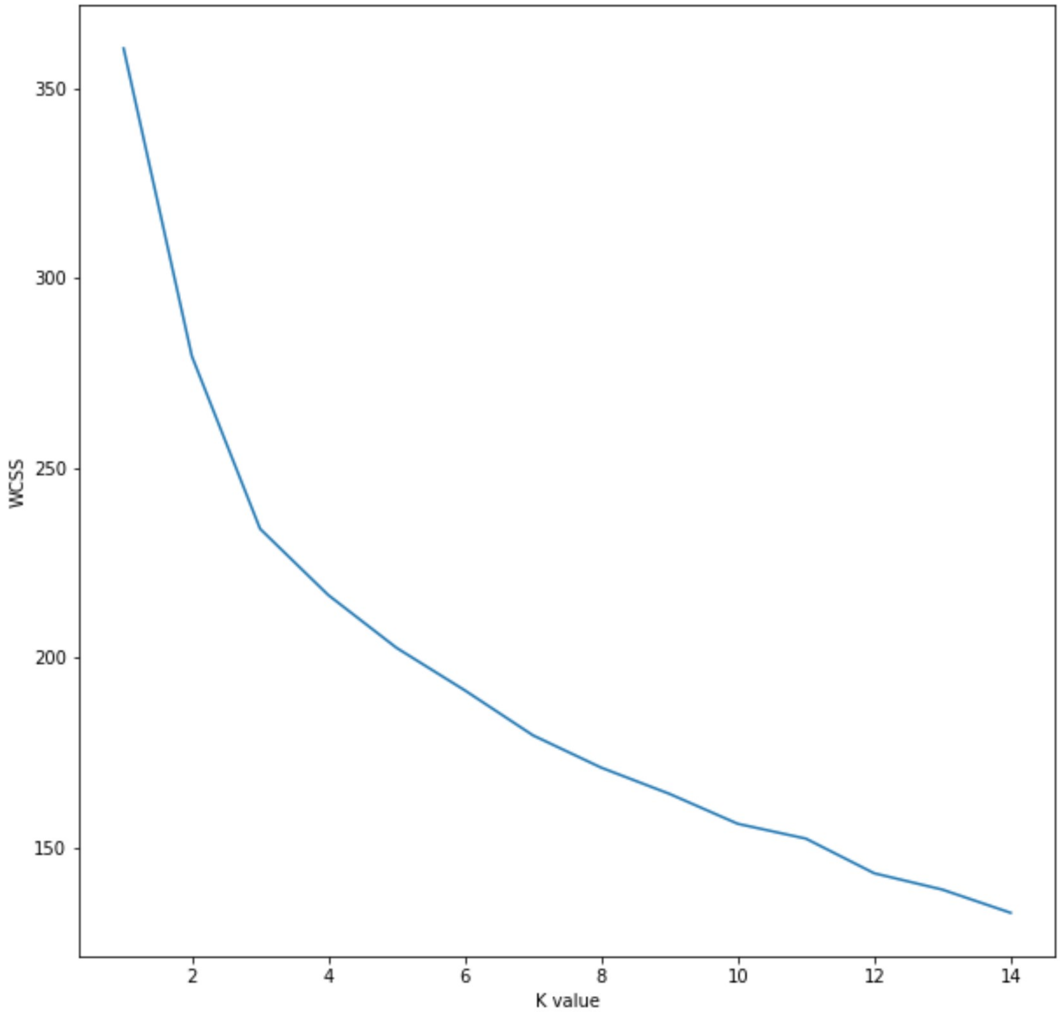
Algorithm	Accuracy (Normal)	Accuracy (PCA)	Wrong Predictions (Normal)	Wrong Predictions (PCA)
KNN	78.5	83.3	9	7
DT	90.47	76.19	4	10
SVM	64.28	78.57	15	9

PCA worked well for KNN and SVM. Decision Tree gave highest accuracy

Clustering:

K means clustering

In [90]:
```
from sklearn.cluster import KMeans
wcss = []

for k in range(1, 15):
    kmeansForLoop = KMeans(n_clusters = k)
    kmeansForLoop.fit(X)
    wcss.append(kmeansForLoop.inertia_)

plt.figure(figsize = (10, 10))
plt.plot(range(1, 15), wcss)
plt.xlabel("K value")
plt.ylabel("WCSS")
plt.show()
```



In [76]:
```
from sklearn.cluster import KMeans
df = data
df.head()
```

Out[76]:

	0.0200	0.0371	0.0428	0.0207	0.0954	0.0986	0.1539	0.1601	0.3109	0.2111	...	0.0027	0.0065	0.015
0	0.0453	0.0523	0.0843	0.0689	0.1183	0.2583	0.2156	0.3481	0.3337	0.2872	...	0.0084	0.0089	0.004
1	0.0262	0.0582	0.1099	0.1083	0.0974	0.2280	0.2431	0.3771	0.5598	0.6194	...	0.0232	0.0166	0.009
2	0.0100	0.0171	0.0623	0.0205	0.0205	0.0368	0.1098	0.1276	0.0598	0.1264	...	0.0121	0.0036	0.015
3	0.0762	0.0666	0.0481	0.0394	0.0590	0.0649	0.1209	0.2467	0.3564	0.4459	...	0.0031	0.0054	0.010
4	0.0286	0.0453	0.0277	0.0174	0.0384	0.0990	0.1201	0.1833	0.2105	0.3039	...	0.0045	0.0014	0.003

5 rows × 61 columns

In [77]:
```
kmeans = KMeans(n_clusters=2)
```

In [78]:
```
kmeans.fit(df.drop('R',axis=1))
```

Out[78]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=2, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

In [80]:
```
kmeans.cluster_centers_
```

Out[80]:
```
array([[0.03000612, 0.03953673, 0.04685204, 0.06019796, 0.08832143,
        0.11321122, 0.13089592, 0.14420918, 0.18996531, 0.23429592,
        0.2737102 , 0.28927551, 0.33128163, 0.38904796, 0.44173878,
        0.5304    , 0.60288469, 0.65269592, 0.70914184, 0.74849388,
        0.78412755, 0.79563673, 0.77186939, 0.74666939, 0.7076602 ,
        0.69397857, 0.67020816, 0.60677653, 0.51466837, 0.44462653,
        0.37925102, 0.32470408, 0.30264796, 0.28699694, 0.28031735,
        0.27957857, 0.28383265, 0.26861122, 0.26827755, 0.26862653,
        0.23407653, 0.22373673, 0.20443673, 0.18207449, 0.15821122,
        0.12247857, 0.1053    , 0.07932959, 0.04807551, 0.0196898 ,
        0.01580306, 0.01308776, 0.01093571, 0.01158673, 0.0095898 ,
        0.00877041, 0.00800408, 0.0085    , 0.00769082, 0.00622041],
       [0.02849083, 0.03745963, 0.04112661, 0.04852752, 0.06322202,
        0.09685596, 0.11322569, 0.12610642, 0.16602844, 0.18482385,
        0.20280917, 0.21595229, 0.22163394, 0.21555046, 0.21326147,
        0.24329083, 0.2489156 , 0.27356055, 0.32107431, 0.3970789 ,
        0.4519422 , 0.47128165, 0.53664954, 0.60718807, 0.64647982,
        0.70569541, 0.73080183, 0.7714211 , 0.75628257, 0.70526514,
        0.62049174, 0.54347706, 0.51935872, 0.50451468, 0.48926606,
        0.47521927, 0.43290826, 0.40105596, 0.37597064, 0.34982752,
        0.34104495, 0.32729725, 0.28406789, 0.2409055 , 0.23170183,
        0.19513578, 0.13803394, 0.10190459, 0.05551835, 0.02097431,
        0.0162422 , 0.01381743, 0.01054404, 0.01031468, 0.00904037,
        0.00765046, 0.00756147, 0.00744954, 0.00815688, 0.00679541]])
```

In [84]:
```
def converter(cluster):
    if cluster=='R':
        return 1
    else:
        return 0
```

In [85]:
```
df['Cluster'] = df['R'].apply(converter)
df.head()
```

Out[85]:

	0.0200	0.0371	0.0428	0.0207	0.0954	0.0986	0.1539	0.1601	0.3109	0.2111	...	0.0065	0.0159	0.007
0	0.0453	0.0523	0.0843	0.0689	0.1183	0.2583	0.2156	0.3481	0.3337	0.2872	...	0.0089	0.0048	0.009
1	0.0262	0.0582	0.1099	0.1083	0.0974	0.2280	0.2431	0.3771	0.5598	0.6194	...	0.0166	0.0095	0.018
2	0.0100	0.0171	0.0623	0.0205	0.0205	0.0368	0.1098	0.1276	0.0598	0.1264	...	0.0036	0.0150	0.008
3	0.0762	0.0666	0.0481	0.0394	0.0590	0.0649	0.1209	0.2467	0.3564	0.4459	...	0.0054	0.0105	0.011
4	0.0286	0.0453	0.0277	0.0174	0.0384	0.0990	0.1201	0.1833	0.2105	0.3039	...	0.0014	0.0038	0.001

5 rows × 62 columns

In [88]:
```
kmeans.labels_
```

Out[88]:
```
array([0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1,
       1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       0, 0, 1, 1, 1, 1, 1, 0, 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, 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, 0, 0, 0, 0, 1, 1,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0,
       1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0,
       0, 0, 0, 1, 1, 1, 1, 1, 1])
```

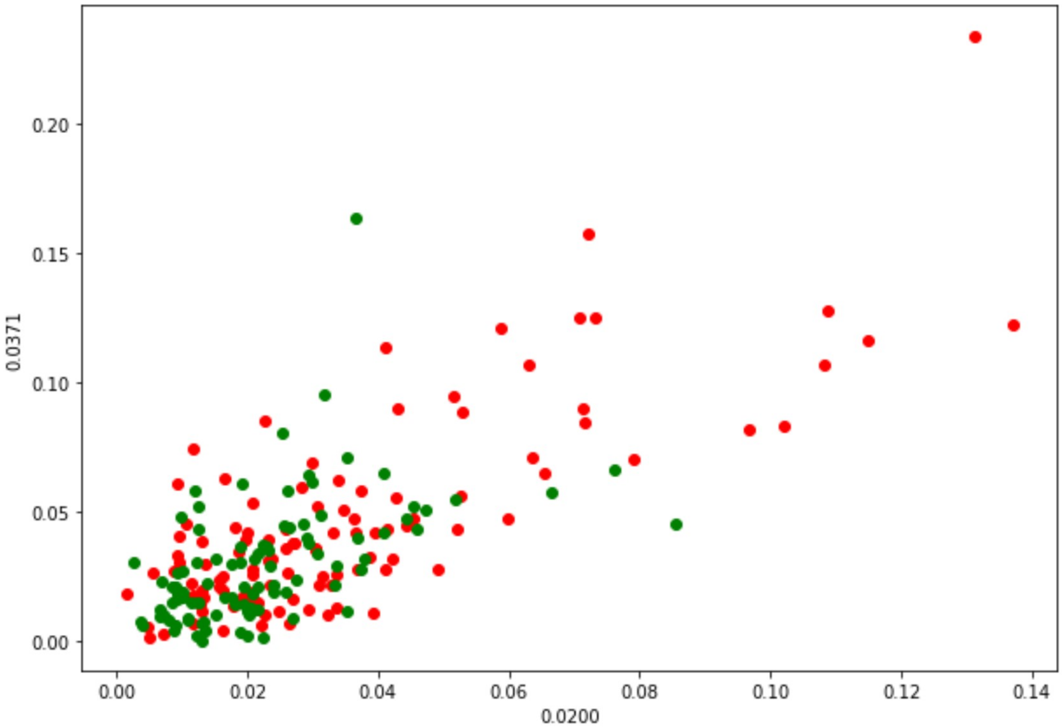
In [89]:
```python
from sklearn.metrics import confusion_matrix,classification_report
print(confusion_matrix(df['Cluster'],kmeans.labels_))
print(classification_report(df['Cluster'],kmeans.labels_))
```

```
[[58 53]
 [40 56]]
              precision    recall  f1-score   support

           0       0.59      0.52      0.56       111
           1       0.51      0.58      0.55        96

    accuracy                           0.55       207
   macro avg       0.55      0.55      0.55       207
weighted avg       0.56      0.55      0.55       207
```

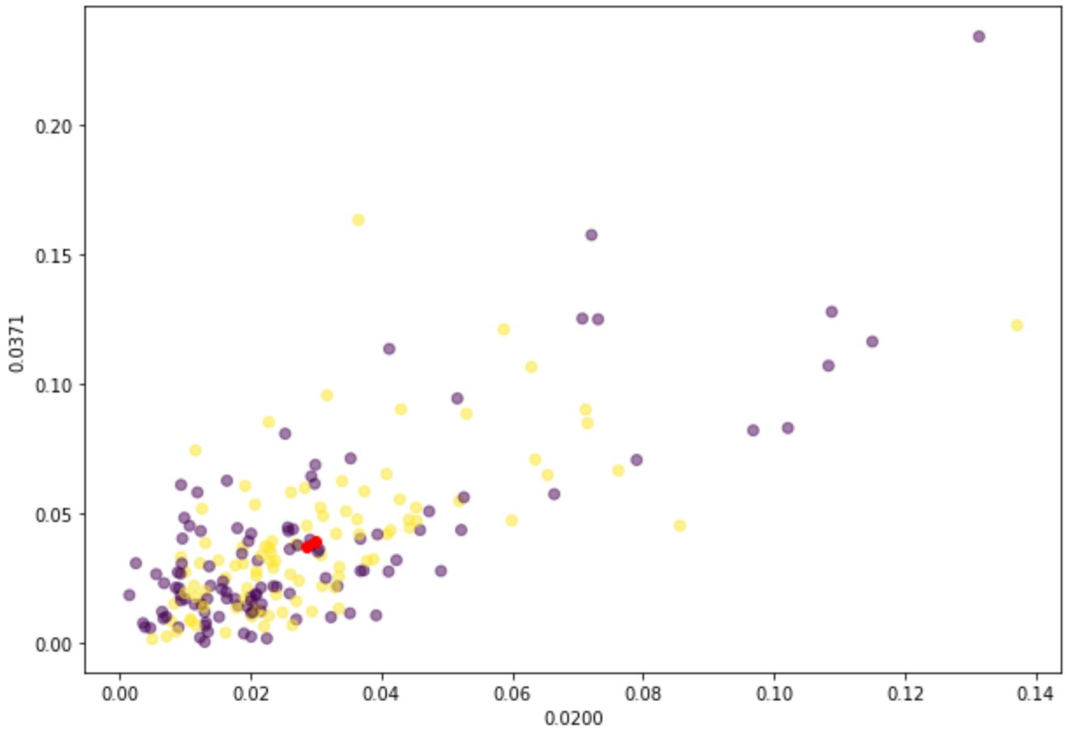
Accuracy: 55%

93 wrong predictions out of 207

In [92]:
```
plt.figure(figsize = (10, 7))
plt.scatter(df['0.0200'][df["Cluster"] == 0], df["0.0371"][df["Cluster"] == 0],
color = "red")
plt.scatter(df["0.0200"][df["Cluster"] == 1], df["0.0371"][df["Cluster"] == 1],
color = "green")
plt.xlabel('0.0200')
plt.ylabel('0.0371')
plt.show()
```

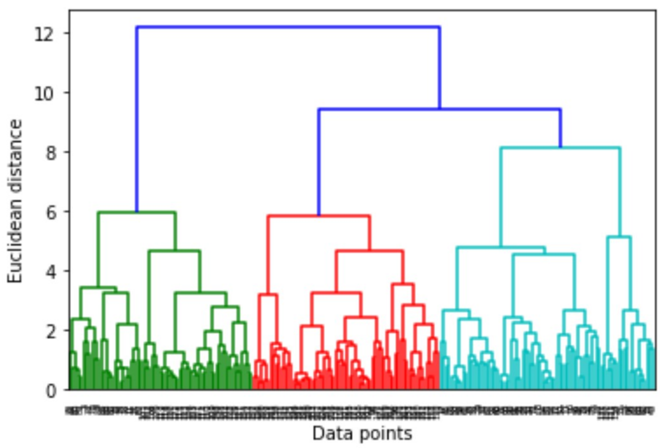


In [95]:
```
# plotting centroids
clusters = kmeans.fit_predict(X)
plt.figure(figsize = (10, 7))
plt.scatter(df["0.0200"], df["0.0371"], c = clusters, alpha = 0.5)
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], color
= "red", alpha = 1)
plt.xlabel('0.0200')
plt.ylabel('0.0371')
plt.show()
```



Hierarchical Clustering

In [97]:
```
df_X = df.drop('R', axis=1)
from scipy.cluster.hierarchy import linkage, dendrogram
merg = linkage(df_X, method='ward')
dendrogram(merg, leaf_rotation = 90)
plt.xlabel('Data points')
plt.ylabel('Euclidean distance')
plt.show()
```

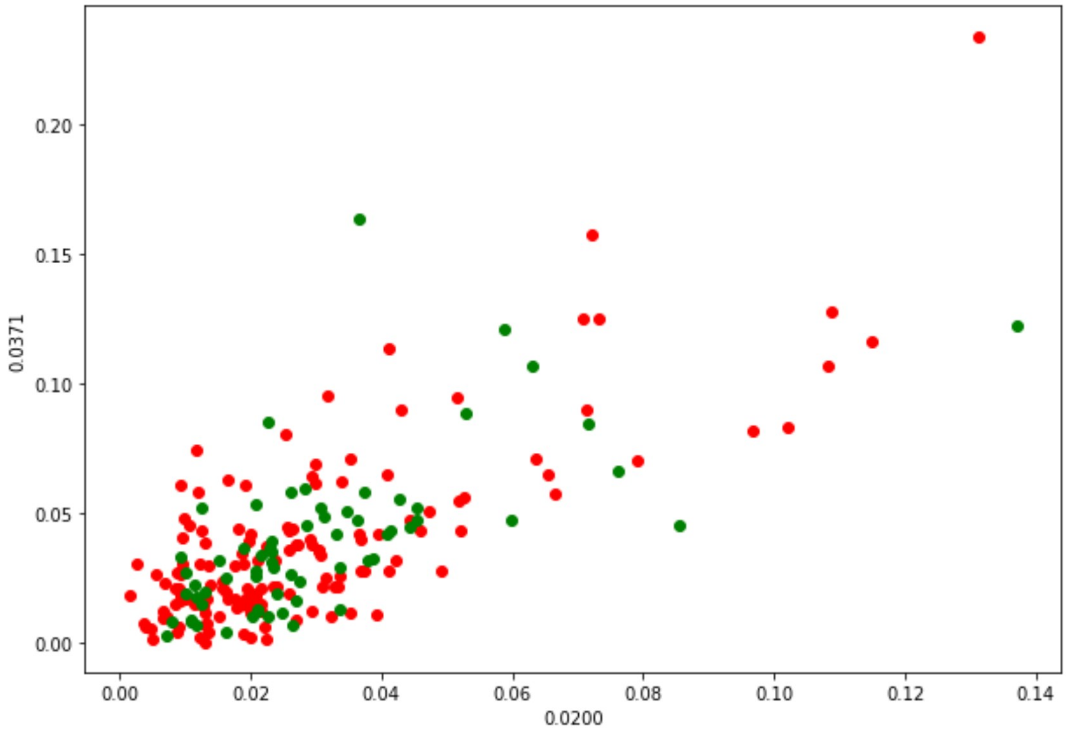


In [98]:
```
from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering(n_clusters = 2, affinity = "euclidean", linkage = "
ward")
cluster = hc.fit_predict(df_X)
df_X["label"] = cluster
```

In [102]:
```
df_X.label.value_counts()
```

Out[102]:
```
0    142
1     65
Name: label, dtype: int64
```

In [104]:
```
plt.figure(figsize = (10, 7))
plt.scatter(df_X['0.0200'][df_X["label"] == 0], df_X["0.0371"][df_X["label"] ==
0], color = "red")
plt.scatter(df_X["0.0200"][df_X["label"] == 1], df_X["0.0371"][df_X["label"] ==
1], color = "green")
plt.xlabel('0.0200')
plt.ylabel('0.0371')
plt.show()
```



In [107]:
```
def converter(cluster):
    if cluster=='R':
        return 1
    else:
        return 0

df_X['Cluster'] = df['R'].apply(converter)

from sklearn.metrics import confusion_matrix,classification_report
print(confusion_matrix(df_X['Cluster'],hc.labels_))
print(classification_report(df_X['Cluster'],hc.labels_))
```

```
[[72 39]
 [70 26]]
              precision    recall  f1-score   support

           0       0.51      0.65      0.57       111
           1       0.40      0.27      0.32        96

    accuracy                           0.47       207
   macro avg       0.45      0.46      0.45       207
weighted avg       0.46      0.47      0.45       207
```

Accuracy: 47%

109 wrong predictions out of 207

DBSCAN

In [113]:
```
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler
X.head()
```

Out[113]:

	0.0200	0.0371	0.0428	0.0207	0.0954	0.0986	0.1539	0.1601	0.3109	0.2111	...	0.0232	0.0027	0.006!
0	0.0453	0.0523	0.0843	0.0689	0.1183	0.2583	0.2156	0.3481	0.3337	0.2872	...	0.0125	0.0084	0.008!
1	0.0262	0.0582	0.1099	0.1083	0.0974	0.2280	0.2431	0.3771	0.5598	0.6194	...	0.0033	0.0232	0.016(
2	0.0100	0.0171	0.0623	0.0205	0.0205	0.0368	0.1098	0.1276	0.0598	0.1264	...	0.0241	0.0121	0.003(
3	0.0762	0.0666	0.0481	0.0394	0.0590	0.0649	0.1209	0.2467	0.3564	0.4459	...	0.0156	0.0031	0.005‹
4	0.0286	0.0453	0.0277	0.0174	0.0384	0.0990	0.1201	0.1833	0.2105	0.3039	...	0.0104	0.0045	0.001‹

5 rows × 60 columns

In [109]:
```
X_ss = StandardScaler().fit_transform(X)
```

In [110]:
```
db = DBSCAN().fit(X_ss)
cluster_labels = db.labels_
num_clusters = len(set(cluster_labels))
```

In [111]:
```
cluster_labels
```

Out[111]:
```
array([-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, -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, -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, -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, -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, -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, -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, -1,
       -1, -1, -1], dtype=int64)
```

In [112]:
```
num_clusters
```

Out[112]:
```
1
```

Getting only 1 label in DBSCAN

In [ ]:
```

```