KMeans + KNN

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1 Lab 8

2 K-Means Clustering and KNN

2.1 Submitted to: Prof. Sweetlin Hemlatha

2.2 Submitted by: Prateek Singh (15BCE1091)

In [1]:
```
import random
import numpy as np
import pandas as pd
import seaborn as sn

from sklearn.cluster import KMeans
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import precision_score, recall_score
from sklearn.neighbors import KNeighborsClassifier

import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
%matplotlib inline
```

In [2]:
```
red_wine_data = pd.read_csv('../Dataset/winequality-red.csv', sep=';')
white_wine_data = pd.read_csv('../Dataset/winequality-white.csv', sep=';')

wine_data = pd.concat([red_wine_data, white_wine_data])
bins = (2, 6.5, 10)
group_names = ['bad', 'good']
wine_data['quality'] = pd.cut(wine_data['quality'], bins = bins, labels = group_names)
wine_data.iloc[:, :11].describe()
```

Out[2]:
```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    6497.000000       6497.000000  6497.000000     6497.000000
mean        7.215307          0.339666     0.318633        5.443235
std         1.296434          0.164636     0.145318        4.757804
min         3.800000          0.080000     0.000000        0.600000
```

```
25%         6.400000          0.230000     0.250000        1.800000
50%         7.000000          0.290000     0.310000        3.000000
75%         7.700000          0.400000     0.390000        8.100000
max        15.900000          1.580000     1.660000       65.800000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  6497.000000          6497.000000           6497.000000  6497.000000
mean      0.056034            30.525319            115.744574     0.994697
std       0.035034            17.749400             56.521855     0.002999
min       0.009000             1.000000              6.000000     0.987110
25%       0.038000            17.000000             77.000000     0.992340
50%       0.047000            29.000000            118.000000     0.994890
75%       0.065000            41.000000            156.000000     0.996990
max       0.611000           289.000000            440.000000     1.038980

                pH    sulphates      alcohol
count  6497.000000  6497.000000  6497.000000
mean      3.218501     0.531268    10.491801
std       0.160787     0.148806     1.192712
min       2.720000     0.220000     8.000000
25%       3.110000     0.430000     9.500000
50%       3.210000     0.510000    10.300000
75%       3.320000     0.600000    11.300000
max       4.010000     2.000000    14.900000
```

In [3]:
```
scaler = StandardScaler()

data = wine_data.iloc[:,:11].values
scaled_features = scaler.fit_transform(data)

wine_data_scaled = pd.DataFrame(scaled_features, index=wine_data.index, columns=wine_da
wine_data_scaled.head()
```

Out[3]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0       0.142473          2.188833    -2.192833       -0.744778   0.569958
1       0.451036          3.282235    -2.192833       -0.597640   1.197975
2       0.451036          2.553300    -1.917553       -0.660699   1.026697
3       3.073817         -0.362438     1.661085       -0.744778   0.541412
4       0.142473          2.188833    -2.192833       -0.744778   0.569958

   free sulfur dioxide  total sulfur dioxide   density        pH  sulphates  \
0            -1.100140             -1.446359  1.034993  1.813090   0.193097
1            -0.311320             -0.862469  0.701486 -0.115073   0.999579
2            -0.874763             -1.092486  0.768188  0.258120   0.797958
3            -0.762074             -0.986324  1.101694 -0.363868   0.327510
4            -1.100140             -1.446359  1.034993  1.813090   0.193097

    alcohol
```

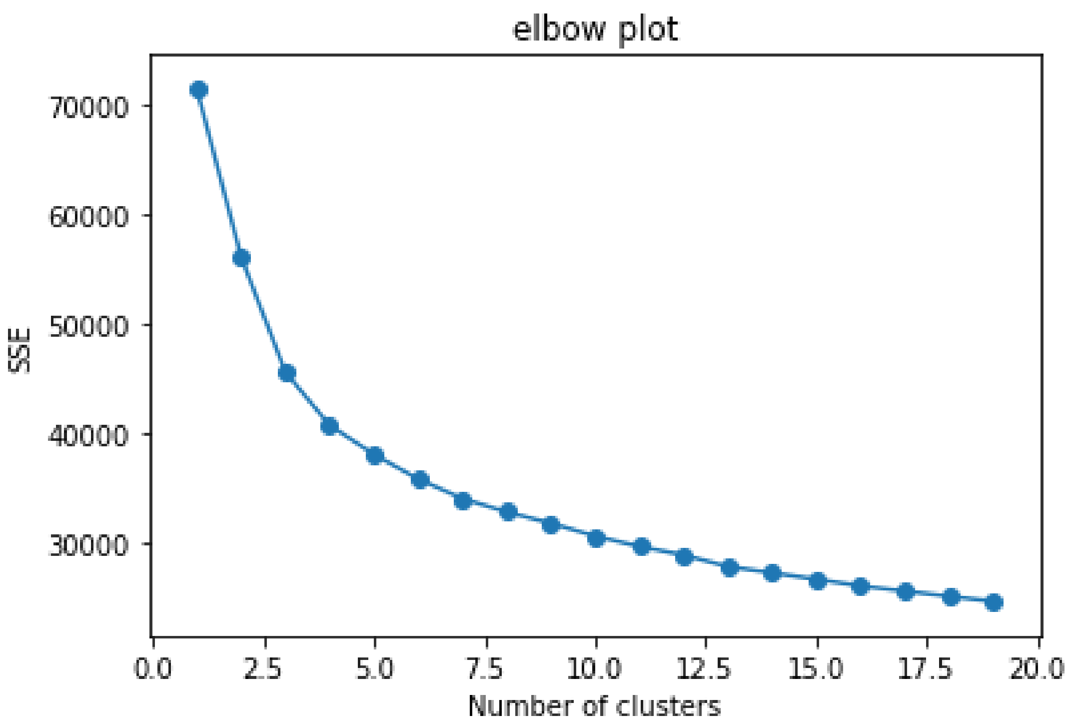
```
0 -0.915464
1 -0.580068
2 -0.580068
3 -0.580068
4 -0.915464
```

Determining the Elbow point using K means clustering

```
In [4]: sse = {}

        for k in range(1, 20):
            kmeans = KMeans(n_clusters=k, max_iter=1000).fit(wine_data_scaled)
            wine_data["clusters"] = kmeans.labels_
            sse[k] = kmeans.inertia_

        plt.figure()
        plt.plot(list(sse.keys()), list(sse.values()))
        plt.scatter(list(sse.keys()), list(sse.values()))
        plt.title('elbow plot')
        plt.xlabel("Number of clusters")
        plt.ylabel("SSE")
        plt.show()
```



From the above we can observe that K=5/6 is the perfect choice of K Thus the plot shows that the number of groups to choose is 5. Hence lets run K means algorithm for k=5 and find clusters in the data

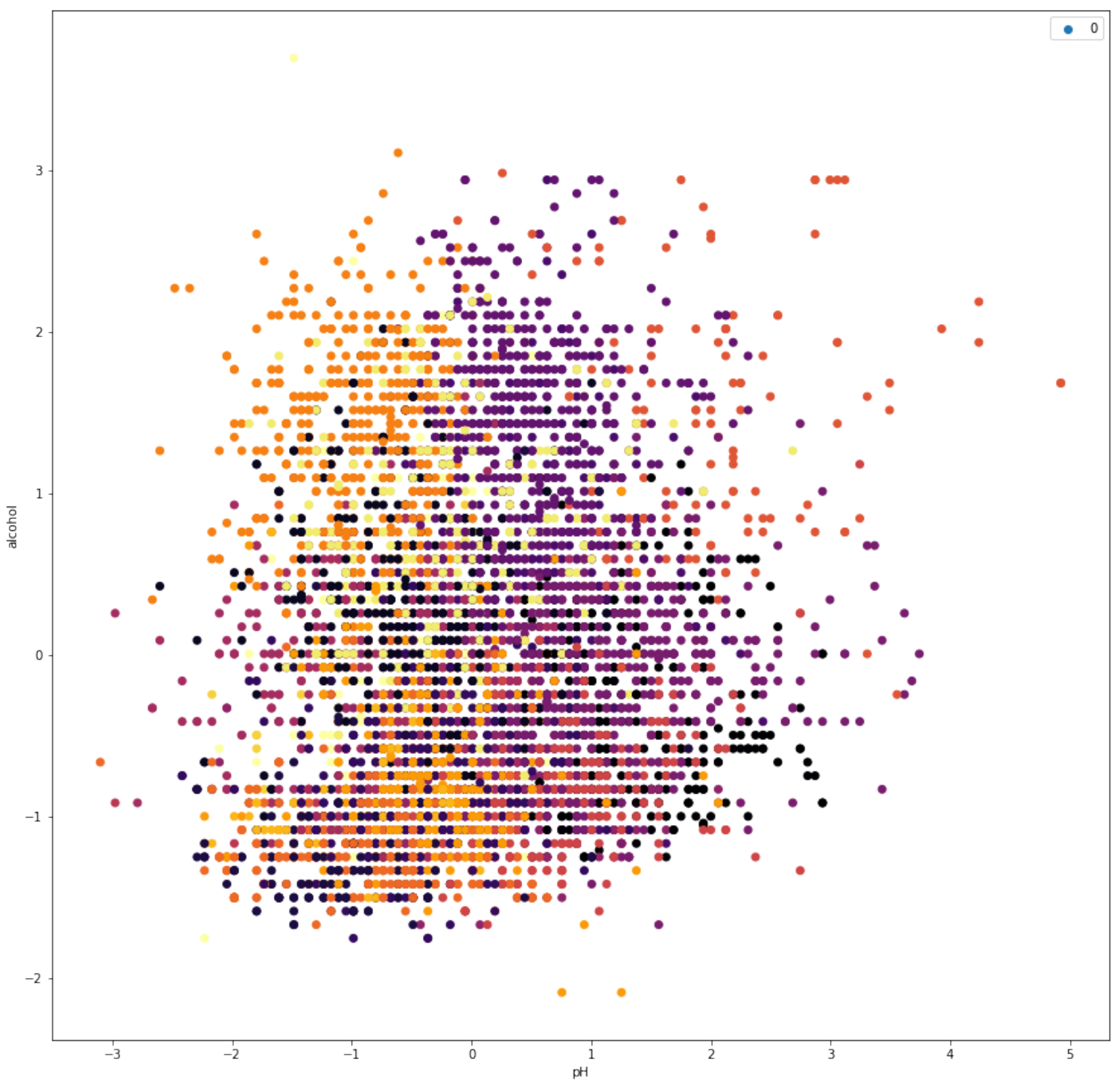
2.3 Making Pair wise profiling plots and labelling wines with respect to its ingredients

plotting alcohol vs pH clusters

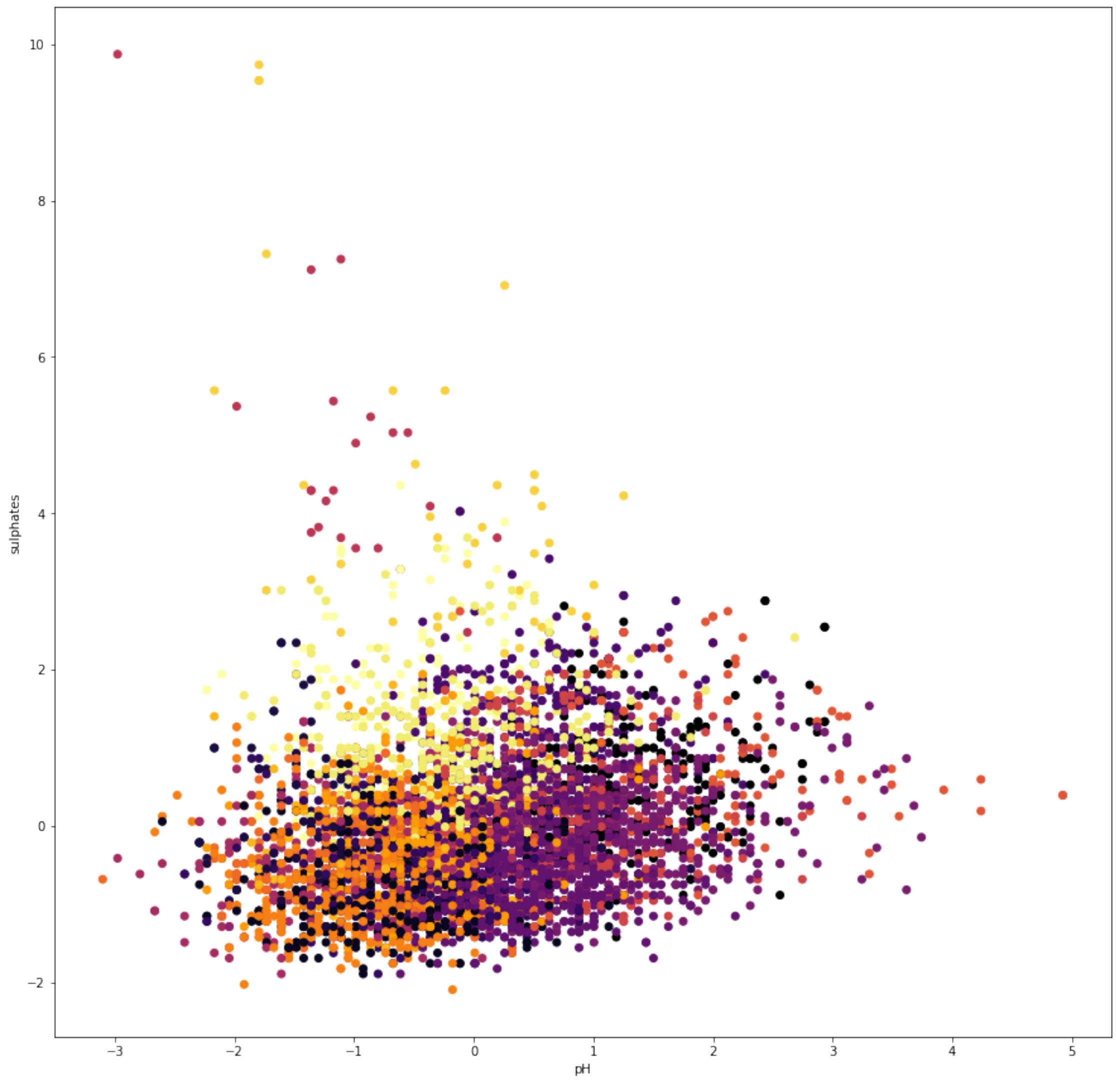
In [5]:
```
wine_data.clusters.unique()
```

Out[5]:
```
array([ 0, 18,  4, 16,  9,  7,  3, 11,  6, 15, 17,  8,  1,  5, 13,  2, 10,
       12, 14])
```

In [6]:
```
plt.figure(figsize=(15,15))
plt.scatter(wine_data_scaled.pH,
            wine_data_scaled.alcohol,
            c=wine_data.clusters,
            cmap='inferno')
plt.legend(wine_data.clusters.unique())
plt.xlabel('pH')
plt.ylabel('alcohol')
plt.show()
```

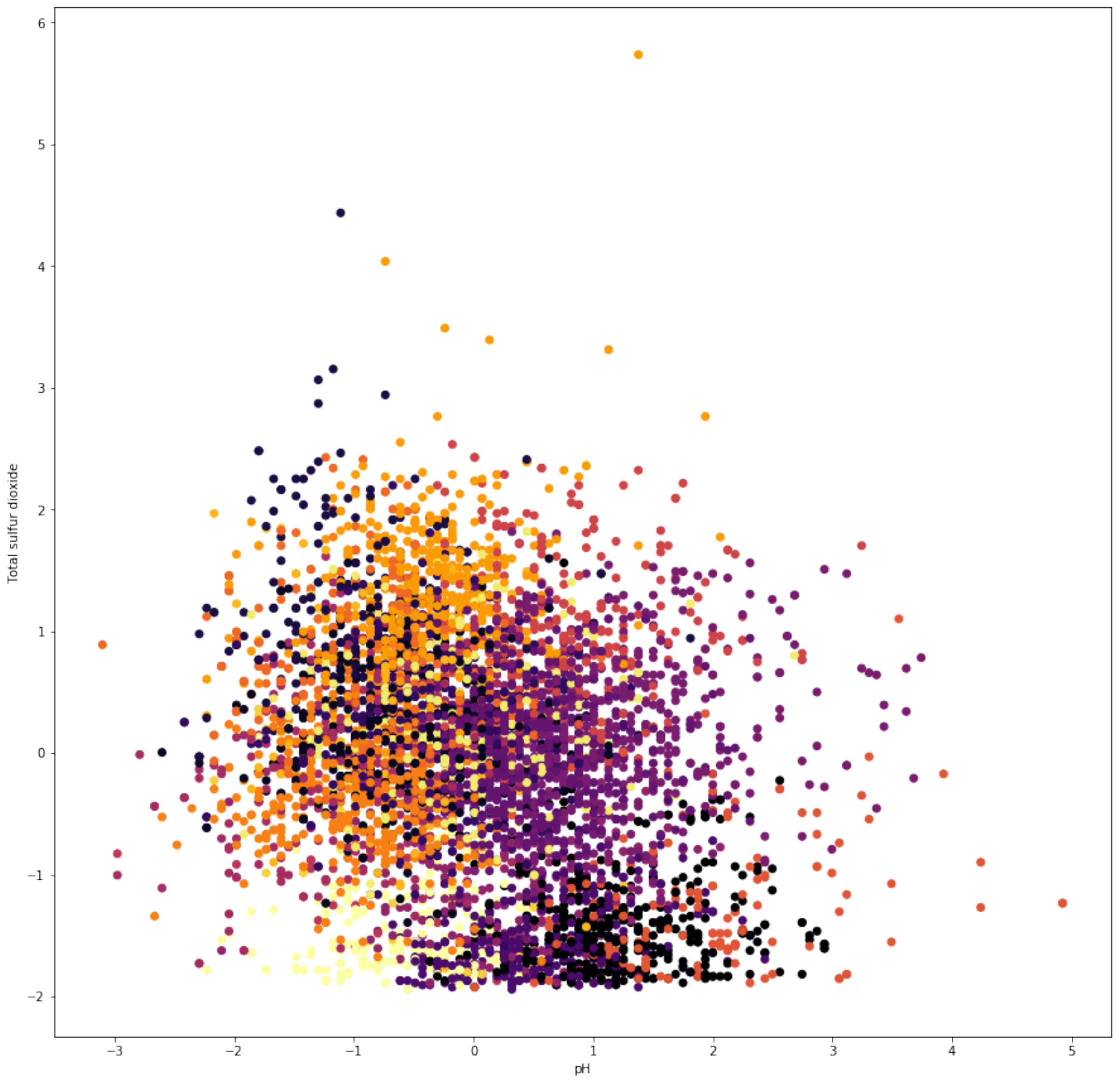


```
In [7]: plt.figure(figsize=(15,15))
        plt.scatter(wine_data_scaled.pH,
                    wine_data_scaled.sulphates,
                    c=wine_data.clusters,
                    cmap='inferno')
        plt.xlabel('pH')
        plt.ylabel('sulphates')
        plt.show()
```

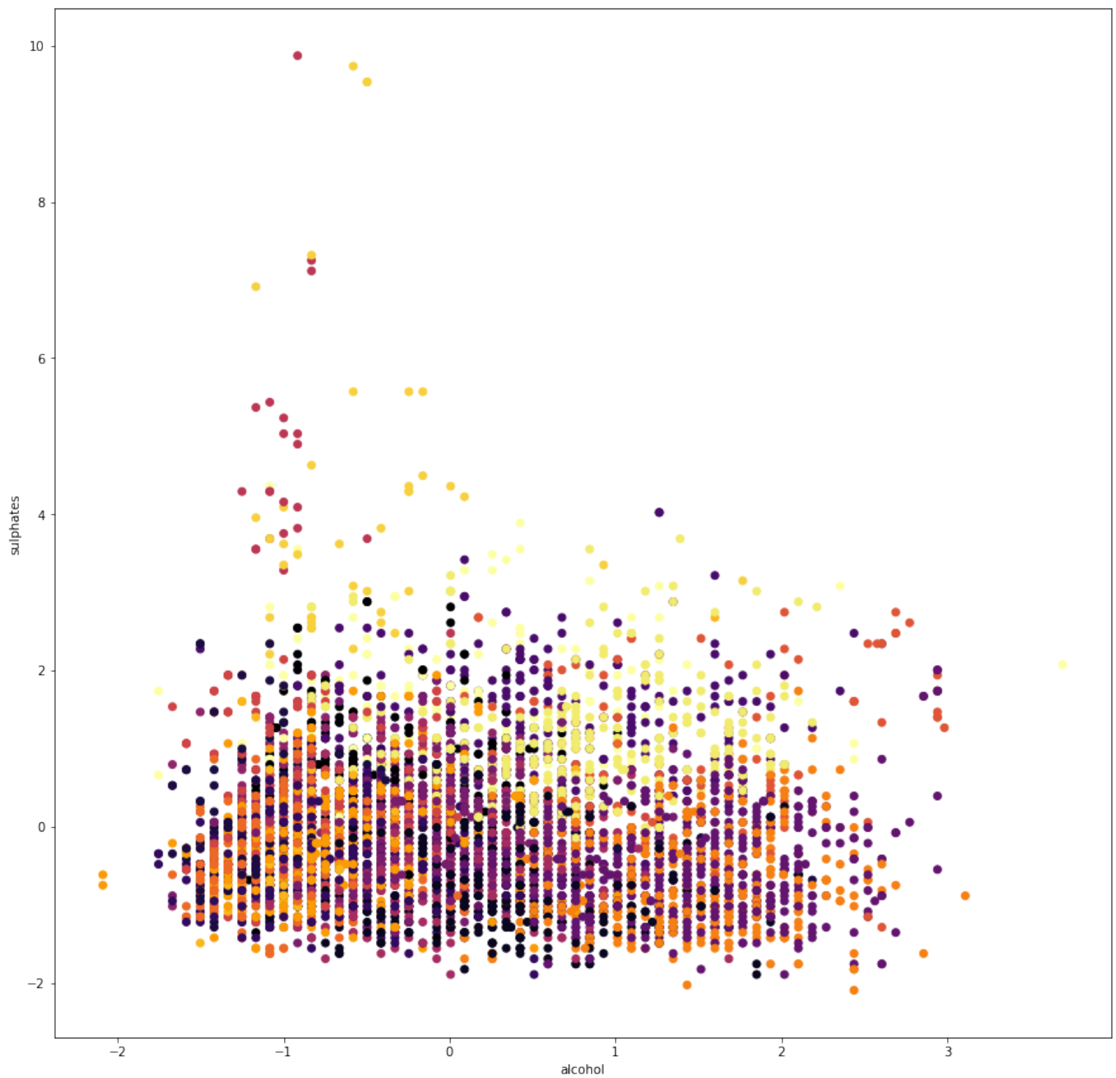



```
In [8]: plt.figure(figsize=(15,15))
        plt.scatter(wine_data_scaled.pH,
```

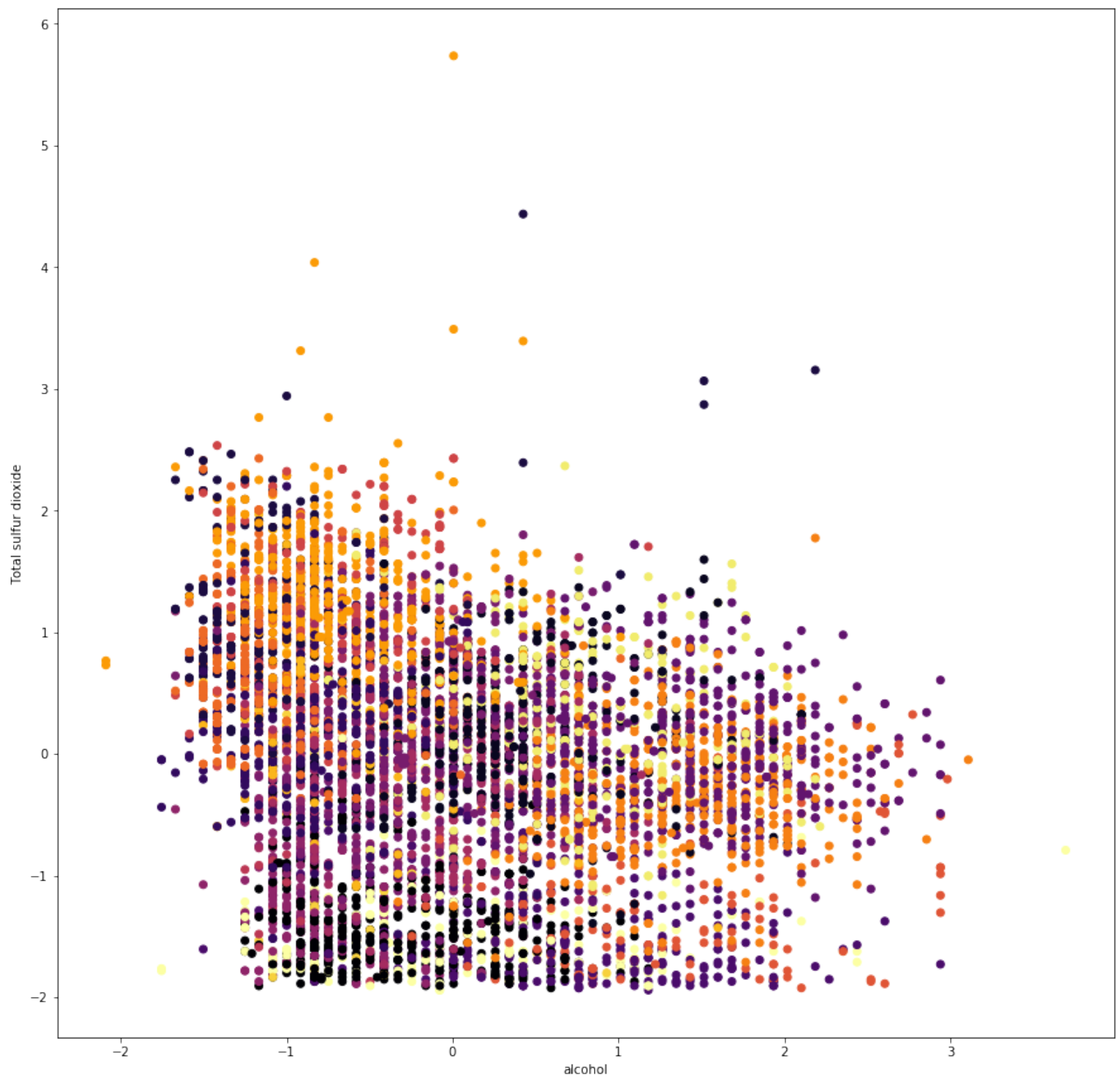
```
                 wine_data_scaled['total sulfur dioxide'],
                 c=wine_data.clusters,
                 cmap='inferno')
plt.xlabel('pH')
plt.ylabel('Total sulfur dioxide')
plt.show()
```



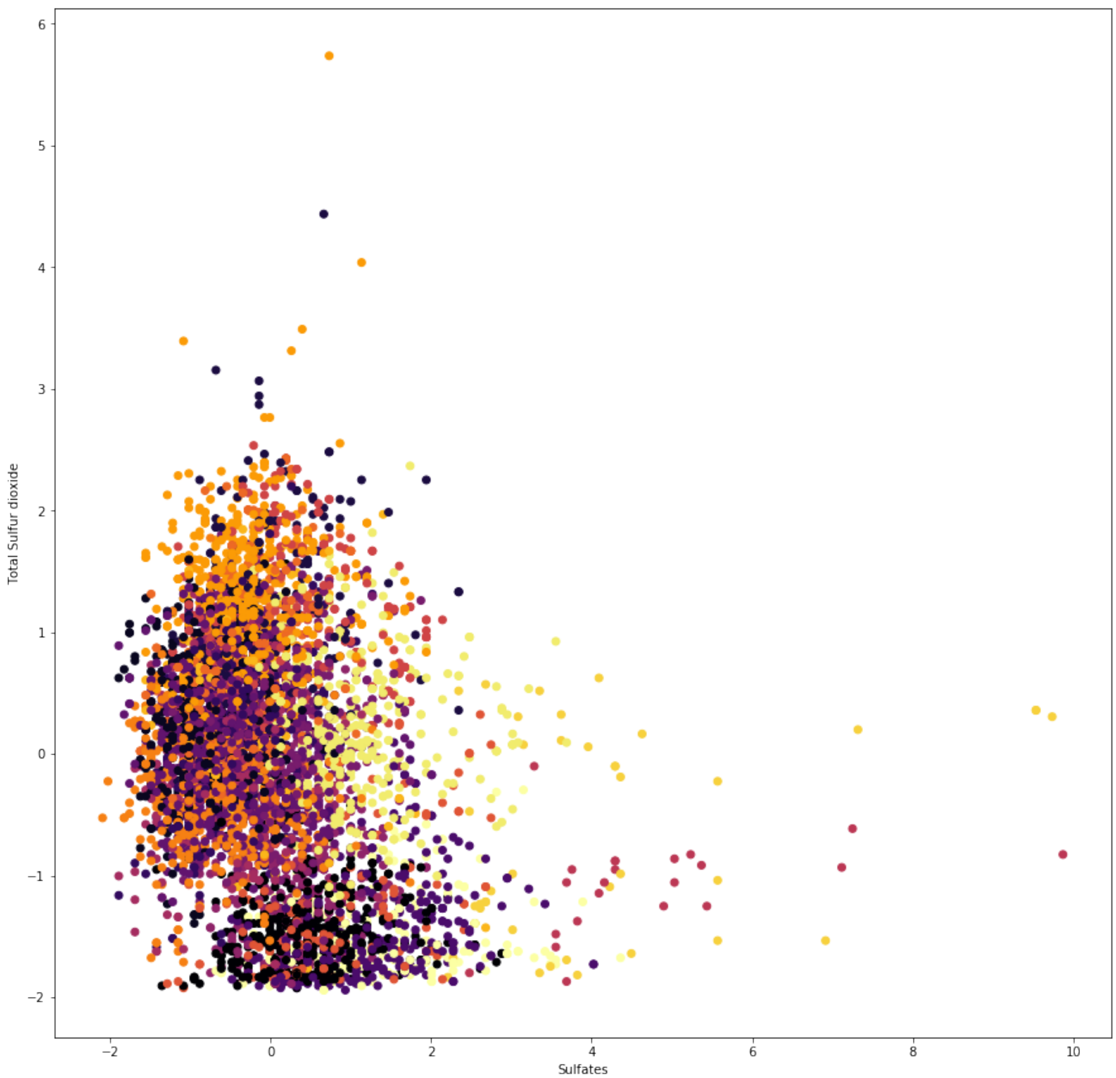
In [10]:
```
plt.figure(figsize=(15,15))
plt.scatter(wine_data_scaled.alcohol,
            wine_data_scaled.sulphates,
            c=wine_data.clusters,
            cmap='inferno')
plt.xlabel('alcohol')
plt.ylabel('sulphates')
plt.show()
```



In [11]:
```
plt.figure(figsize=(15,15))
plt.scatter(wine_data_scaled.alcohol,
            wine_data_scaled['total sulfur dioxide'],
            c=wine_data.clusters,
            cmap='inferno')
plt.xlabel('alcohol')
plt.ylabel('Total sulfur dioxide')
plt.show()
```



In [12]:
```
plt.figure(figsize=(15,15))
plt.scatter(wine_data_scaled.sulphates,
            wine_data_scaled['total sulfur dioxide'],
            c=wine_data.clusters,
            cmap='inferno')
plt.xlabel('Sulfates')
plt.ylabel('Total Sulfur dioxide')
plt.show()
```



3 KNN Classifier

In [59]:
```
red_wine_data = pd.read_csv('../Dataset/winequality-red.csv', sep=';')
white_wine_data = pd.read_csv('../Dataset/winequality-white.csv', sep=';')

wine_data = pd.concat([red_wine_data, white_wine_data])
bins = (2, 5, 6, 10)
group_names = ['bad', 'medium', 'good']
wine_data['quality'] = pd.cut(wine_data['quality'], bins = bins, labels = group_names)
wine_data.iloc[:, :11].describe()
```

Out[59]:
```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    6497.000000       6497.000000  6497.000000     6497.000000
```

```
mean        7.215307          0.339666     0.318633        5.443235
std         1.296434          0.164636     0.145318        4.757804
min         3.800000          0.080000     0.000000        0.600000
25%         6.400000          0.230000     0.250000        1.800000
50%         7.000000          0.290000     0.310000        3.000000
75%         7.700000          0.400000     0.390000        8.100000
max        15.900000          1.580000     1.660000       65.800000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  6497.000000          6497.000000           6497.000000  6497.000000
mean      0.056034            30.525319            115.744574     0.994697
std       0.035034            17.749400             56.521855     0.002999
min       0.009000             1.000000              6.000000     0.987110
25%       0.038000            17.000000             77.000000     0.992340
50%       0.047000            29.000000            118.000000     0.994890
75%       0.065000            41.000000            156.000000     0.996990
max       0.611000           289.000000            440.000000     1.038980

                pH    sulphates      alcohol
count  6497.000000  6497.000000  6497.000000
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std       0.160787     0.148806     1.192712
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25%       3.110000     0.430000     9.500000
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75%       3.320000     0.600000    11.300000
max       4.010000     2.000000    14.900000
```

In [60]:
```
scaler = StandardScaler()

data = wine_data.iloc[:,:11].values
scaled_features = scaler.fit_transform(data)

wine_data_scaled = pd.DataFrame(scaled_features, index=wine_data.index, columns=wine_d
wine_data_scaled.head()
```

Out[60]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0       0.142473          2.188833    -2.192833       -0.744778   0.569958
1       0.451036          3.282235    -2.192833       -0.597640   1.197975
2       0.451036          2.553300    -1.917553       -0.660699   1.026697
3       3.073817         -0.362438     1.661085       -0.744778   0.541412
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3            -0.762074             -0.986324  1.101694 -0.363868   0.327510
```

```
4           -1.100140            -1.446359  1.034993  1.813090   0.193097

    alcohol
0 -0.915464
1 -0.580068
2 -0.580068
3 -0.580068
4 -0.915464
```

In [83]:
```
X_train, X_test, Y_train, Y_test = train_test_split(wine_data.iloc[:, :11],
                                                     wine_data.quality,
                                                     test_size=0.2,
                                                     random_state=42)
```

In [84]:
```
knn = KNeighborsClassifier(20)
knn.fit(X_train, Y_train)
```

Out[84]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=20, p=2,
           weights='uniform')
```

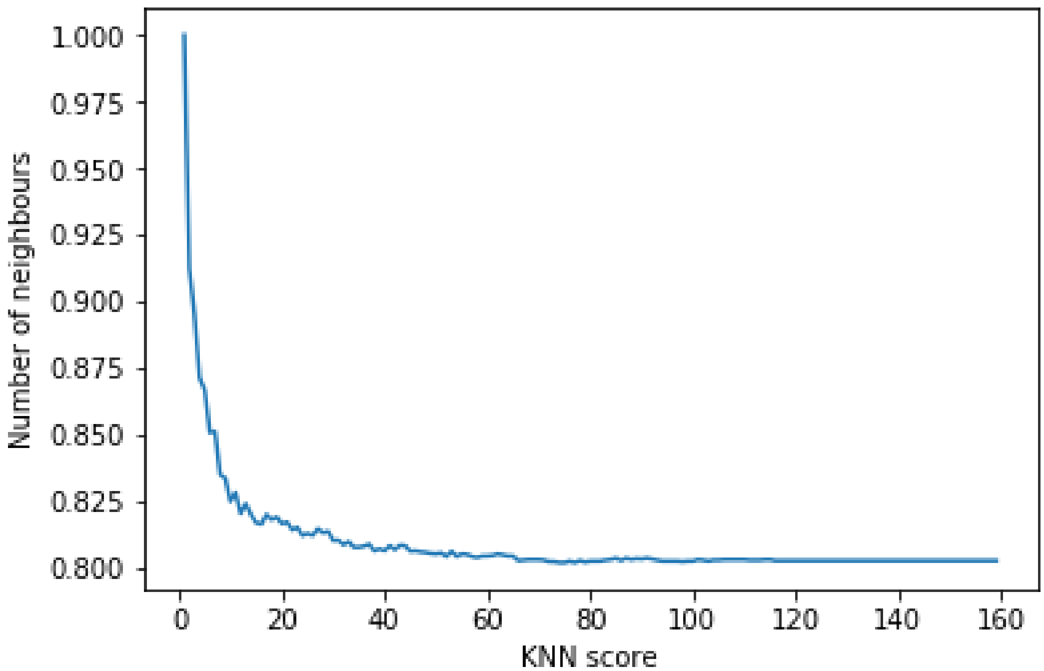
In [85]:
```
knn.score(X_train, Y_train)
```

Out[85]:
```
0.8166249759476621
```

In [89]:
```
knn_score = []

for i in range(1,160):
    knn = KNeighborsClassifier(i)
    knn.fit(X_train, Y_train)
    knn_score.append(knn.score(X_train, Y_train))

plt.plot(range(1, 160), knn_score)
plt.xlabel("KNN score")
plt.ylabel("Number of neighbours")
plt.show()
```


1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
Number of neighbours
0
20
40
60
80
100
120
140
160
KNN score