Chapter 5 - Ex2: Glass.data

Cho dữ liệu glass.data.txt

Sử dụng thuật toán KNN để dự đoán loại kính dựa trên các thông tin được cung cấp

- 1. Đọc dữ liệu và gán cho biến data. Tiền xử lý dữ liệu (nếu cần)
- 2. Tạo inputs data với các cột trừ cột type of class, và outputs data với 1 cột là type of class
- 3. Từ inputs data và outputs data => Tạo X_train, X_test, y_train, y_test với tỷ lệ 70-30
- 4. Thực hiện KNN với X train, y train
- 5. Dự đoán y từ X test => so sánh với y test
- 6. Đánh giá mô hình => Nhận xét
- 7. Ghi mô hình (nếu mô hình tốt sau khi đánh giá)

Attribute Information:

- 1. Id number: 1 to 214
- 2. RI: refractive index
- 3. Na: Sodium (unit measurement: weight percent in corresponding oxide, as are attributes 4-10)
- 4. Mg: Magnesium
- 5. Al: Aluminum
- 6. Si: Silicon
- 7. K: Potassium
- 8. Ca: Calcium
- 9. Ba: Barium
- 10. Fe: Iron
- 11. Type of glass: (class attribute) -- 1 building_windows_float_processed -- 2 building_windows_non_float_processed -- 3 vehicle_windows_float_processed -- 4 vehicle_windows_non_float_processed (none in this database) -- 5 containers -- 6 tableware -- 7 headlamps
- In [1]: # from google.colab import drive
 # drive.mount("/content/gdrive", force_remount=True)
 # %cd '/content/gdrive/My Drive/LDS6_MachineLearning/practice/Chapter5_KNN/'
- In [2]: import numpy as np
 import pandas as pd
 import matplotlib.pyplot as plt
 from sklearn.model_selection import train_test_split

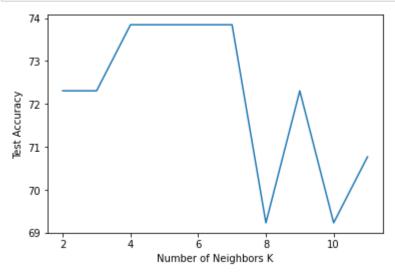
```
In [3]: # import some data to play with
        data = pd.read_csv("glass.data.txt", sep=",", header=None)
        data.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 214 entries, 0 to 213
        Data columns (total 11 columns):
               214 non-null int64
        1
               214 non-null float64
               214 non-null float64
        2
        3
               214 non-null float64
               214 non-null float64
        4
        5
               214 non-null float64
        6
               214 non-null float64
        7
               214 non-null float64
               214 non-null float64
        8
               214 non-null float64
        10
               214 non-null int64
        dtypes: float64(9), int64(2)
        memory usage: 18.5 KB
In [4]:
        data.shape
Out[4]: (214, 11)
In [5]:
        data.head()
Out[5]:
            0
                   1
                         2
                              3
                                         5
                                              6
                                                   7
                                                       8
                                                           9
                                                             10
         0 1 1.52101 13.64 4.49 1.10 71.78 0.06 8.75 0.0 0.0
         1 2 1.51761 13.89 3.60 1.36 72.73 0.48 7.83 0.0 0.0
           3 1.51618 13.53 3.55 1.54
                                     72.99 0.39 7.78 0.0
           4 1.51766 13.21 3.69 1.29 72.61 0.57 8.22 0.0 0.0
                                                              1
         4 5 1.51742 13.27 3.62 1.24 73.08 0.55 8.07 0.0 0.0
        # data.tail()
In [6]:
In [7]: # thống kê số lượng các lớp
        data.groupby(10).count()[0]
Out[7]: 10
        1
              70
        2
              76
              17
        3
        5
              13
        6
               9
              29
        Name: 0, dtype: int64
```

```
In [8]: # The columns that we will be making predictions with.
         inputs = data.iloc[:,1:-1]
         inputs.shape
 Out[8]: (214, 9)
 In [9]:
         inputs.head()
 Out[9]:
                                                   8
                                                       9
          0 1.52101 13.64 4.49 1.10 71.78 0.06 8.75 0.0
                                                      0.0
          1 1.51761 13.89 3.60 1.36 72.73 0.48 7.83
                                                      0.0
          2 1.51618 13.53 3.55 1.54 72.99 0.39 7.78 0.0
                                                      0.0
            1.51766 13.21 3.69 1.29
                                  72.61 0.57 8.22 0.0
                                                      0.0
            1.51742 13.27 3.62 1.24 73.08 0.55 8.07 0.0 0.0
In [10]:
         # The column that we want to predict.
         outputs = data[10]
         outputs = np.array(outputs)
         outputs.shape
Out[10]: (214,)
In [11]: from sklearn.model selection import train test split
         X_train, X_test, y_train, y_test = train_test_split(inputs, outputs,
                                                              test size=0.30,
                                                              random state=1)
         from sklearn.neighbors import KNeighborsClassifier
In [12]:
         from sklearn.metrics import accuracy score
         list k = []
         list acc = []
         for K_value in range(2,int(y_train.shape[0]**0.5)):
             list k.append(K value)
             neigh = KNeighborsClassifier(n neighbors = K value)
             neigh.fit(X train, y train)
             y_pred = neigh.predict(X_test)
             acc = accuracy_score(y_test,y_pred)*100
             list acc.append(acc)
             print("k = ", K_value,": Accuracy is ", accuracy_score(y_test,y_pred))
         k = 2: Accuracy is 0.7230769230769231
         k = 3: Accuracy is 0.7230769230769231
         k = 4: Accuracy is 0.7384615384615385
         k = 5: Accuracy is 0.7384615384615385
         k = 6: Accuracy is 0.7384615384615385
         k = 7: Accuracy is 0.7384615384615385
         k = 8 : Accuracy is 0.6923076923076923
         k = 9: Accuracy is 0.7230769230769231
         k = 10 : Accuracy is 0.6923076923076923
         k = 11 : Accuracy is 0.7076923076923077
```

```
In [13]: vi_tri = list_acc.index(max(list_acc))
    k = list_k[vi_tri]
    print("The optimal number of neighbors is", k,"with", list_acc[vi_tri])
```

The optimal number of neighbors is 4 with 73.84615384615385

```
In [14]: plt.plot(list_k, list_acc)
    plt.xlabel('Number of Neighbors K')
    plt.ylabel('Test Accuracy')
    plt.show()
```



In [15]: from sklearn.neighbors import KNeighborsClassifier

```
k= 4 : The Train prediction accuracy is: 76.51006711409396\% ----- The Test prediction accuracy is: 73.84615384615385\% k= 5 : The Train prediction accuracy is: 72.48322147651007\% ----- The Test prediction accuracy is: 73.84615384615385\% k= 6 : The Train prediction accuracy is: 71.14093959731544\% ----- The Test prediction accuracy is: 73.84615384615385\% k= 7 : The Train prediction accuracy is: 66.44295302013423\% ----- The Test prediction accuracy is: 73.84615384615385\%
```

```
In [17]: knn = KNeighborsClassifier(n neighbors=5)
         knn.fit(X_train, y_train)
Out[17]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                              metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                              weights='uniform')
In [18]:
         # Kiểm tra độ chính xác
         print("The Train prediction accuracy is: ",
               knn.score(X train,y train)*100,"%")
         print("The Test prediction accuracy is: ",
               knn.score(X_test,y_test)*100,"%")
         The Train prediction accuracy is: 72.48322147651007 %
         The Test prediction accuracy is: 73.84615384615385 %
In [19]:
         y pred = knn.predict(X test)
         # y_pred
In [20]: | df = pd.DataFrame({'Actual': pd.DataFrame(y test)[0].values,
                             'Prediction': pd.DataFrame(y_pred)[0].values})
         df.head()
Out[20]:
            Actual Prediction
          0
                2
                          5
                7
                         7
          1
          2
                2
                          2
                2
                          2
                1
                          1
In [21]: # Đánh giá model
         from sklearn.metrics import confusion_matrix, classification_report
In [22]: confusion_matrix(y_test, y_pred)
Out[22]: array([[22, 3,
                          0,
                              0,
                                  0,
                                      0],
                                     0],
                [ 3, 15, 0, 2,
                                  1,
                [6, 1, 0, 0,
                                  0, 0],
                                0,
                [ 0,
                     0, 0, 2,
                                     0],
                [ 0,
                      0, 0, 0, 1, 0],
                      0, 0,
                              0,
                                  0, 8]], dtype=int64)
                [ 1,
```

In [23]: print(classification_report(y_test, y_pred))

	precision	recall	f1-score	support	
1	0.69	0.88	0.77	25	
2	0.79	0.71	0.75	21	
3	0.00	0.00	0.00	7	
5	0.50	1.00	0.67	2	
6	0.50	1.00	0.67	1	
7	1.00	0.89	0.94	9	
accuracy			0.74	65	
macro avg	0.58	0.75	0.63	65	
weighted avg	0.68	0.74	0.70	65	

c:\program files\python36\lib\site-packages\sklearn\metrics\classification.py:1
437: UndefinedMetricWarning: Precision and F-score are ill-defined and being se
t to 0.0 in labels with no predicted samples.

'precision', 'predicted', average, warn for)

 Quan sát kết quả và đánh giá: Mô hình có độ chính xác chưa cao, còn có class dự đoán không chính xác do số lượng trong các class còn ít và chưa cân bằng => ??? co cach nao khac tot hon khong???

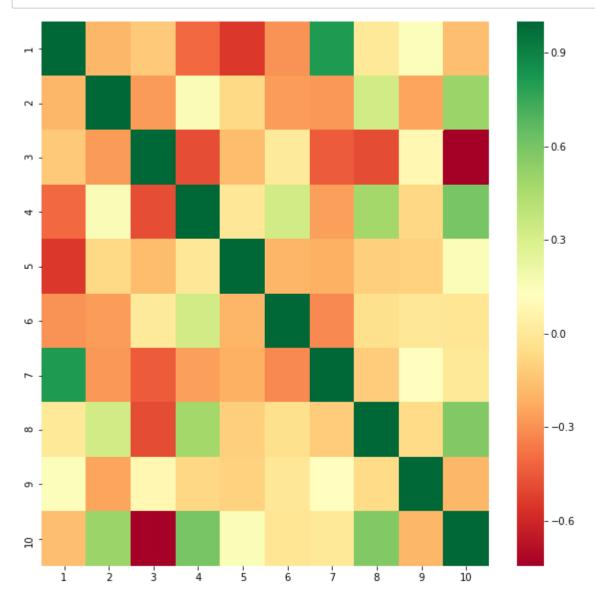
```
In [24]: # Feature Selection
#get correlations of each features in dataset
data_sub = data.iloc[:,1:]
corrmat = data_sub.corr()
top_corr_features = corrmat.index
```

In [25]: data_sub.corr()

Out[25]:

	1	2	3	4	5	6	7	8	ţ
1	1.000000	-0.191885	-0.122274	-0.407326	-0.542052	-0.289833	0.810403	-0.000386	0.143010
2	-0.191885	1.000000	-0.273732	0.156794	-0.069809	-0.266087	-0.275442	0.326603	-0.241346
3	-0.122274	-0.273732	1.000000	-0.481799	-0.165927	0.005396	-0.443750	-0.492262	0.083060
4	-0.407326	0.156794	-0.481799	1.000000	-0.005524	0.325958	-0.259592	0.479404	-0.074402
5	-0.542052	-0.069809	-0.165927	-0.005524	1.000000	-0.193331	-0.208732	-0.102151	-0.094201
6	-0.289833	-0.266087	0.005396	0.325958	-0.193331	1.000000	-0.317836	-0.042618	-0.007719
7	0.810403	-0.275442	-0.443750	-0.259592	-0.208732	-0.317836	1.000000	-0.112841	0.124968
8	-0.000386	0.326603	-0.492262	0.479404	-0.102151	-0.042618	-0.112841	1.000000	-0.058692
9	0.143010	-0.241346	0.083060	-0.074402	-0.094201	-0.007719	0.124968	-0.058692	1.000000
10	-0.164237	0.502898	-0.744993	0.598829	0.151565	-0.010054	0.000952	0.575161	-0.188278

```
In [26]: import seaborn as sns
   plt.figure(figsize=(10,10))
   #plot heat map
   g=sns.heatmap(data[top_corr_features].corr(),cmap="RdYlGn") # annot=True: neu mue
```



```
In [27]: # 2, 3, 4, 8 have high corr

In [28]: from sklearn.feature_selection import SelectKBest
    from sklearn.feature_selection import chi2

In [29]: #apply SelectKBest class to extract all best features
    bestfeatures = SelectKBest(score_func=chi2, k='all')
    fit = bestfeatures.fit(inputs,outputs)
    dfscores = pd.DataFrame(fit.scores_)
    dfcolumns = pd.DataFrame(inputs.columns)
```

```
In [30]: #concat two dataframes for better visualization
    featureScores = pd.concat([dfcolumns,dfscores],axis=1)
    featureScores.columns = ['Specs','Score'] #naming the dataframe columns
    print(featureScores.nlargest(9,'Score')) #print 9 best features
```

```
Specs
               Score
7
       8 145.514077
2
       3 100.984212
5
           31.670632
       6
3
           16.977488
       4
1
       2
           4.311253
       7
           3.210929
6
       9
8
            2.170185
       5
            0.110449
       1
            0.000048
```

```
In [31]: # 8, 3, 6, 4, 2 have high corr
```

```
In [32]: # => select features => KNN
# ??? Tot hon ban dau hay khong
```

```
In [33]: # kiem chung lai voi cac thuat toan da hoc
# xem xet viec scale du lieu?
# xem xet viec resample du lieu: chon cach nao de nang du lieu len?
```