main

March 16, 2023

[]: import numpy as np

```
import random
     from collections import Counter
[]: #######
                      (LIBSVM )
     def load_svmfile(filename):
         X = []
         Y = \Gamma
         with open(filename, 'r') as f:
             filelines = f.readlines()
             for fileline in filelines:
                 fileline = fileline.strip().split(' ')
                 #print(fileline)
                 Y.append(int(fileline[0]))
                 tmp = []
                 for t in fileline[1:]:
                     if len(t) == 0:
                         continue
                     tmp.append(float(t.split(':')[1]))
                 X.append(tmp)
         return np.array(X), np.array(Y)
[]: #######
                   https://www.csie.ntu.edu.tw/~cjlin/libsumtools/datasets/binary.
     ⇔html#svmquide1
     #######
     #######
     dataset = 'svmguide1'
     print('Start loading dataset {}'.format(dataset))
     X, Y = load_svmfile(dataset) # train set
     X_test, Y_test = load_svmfile('{}.t'.format(dataset)) # test set
     print('trainset X shape {}, train label Y shape {}'.format(X.shape, Y.shape))
     print('testset X_test shape {}, test label Y shape {}'.format(X_test.shape,__

¬Y_test.shape))
    Start loading dataset symguide1
    trainset X shape (3089, 4), train label Y shape (3089,)
    testset X_test shape (4000, 4), test label Y shape (4000,)
```

```
[ ]: | ####### KNN
                           train, test_calculate_distances
     class KNN_model():
         def __init__(self, k=1):
             self.k = k
         def train(self, x_train, y_train):
             """Implement the training code for KNN
             Input:
                 x_{train}: Training instances of size (N, D), where N denotes the
      ⇔number of instances and D denotes the feature dimension
                 y_train: Training labels of size (N, )
             self.x_train = x_train
             self.y_train = y_train
         def test(self, x_test):
             Input: Test instances of size (N, D), where N denotes the number of \Box
      \hookrightarrow instances and D denotes the feature dimension
             Return: Predicted labels of size (N, )
             11 11 11
             distances = np.array([self._calculate_distances(x_test_sample) for_

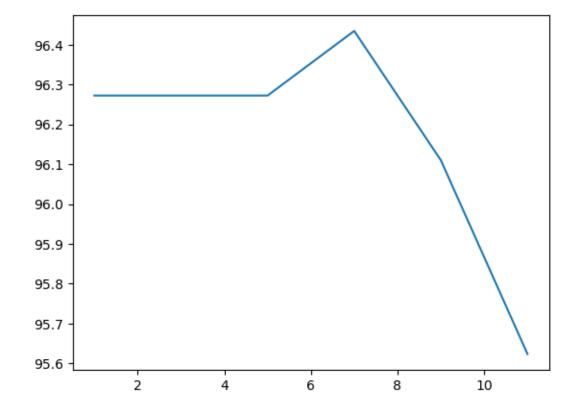
¬x_test_sample in x_test])
             #
                  k
             indices = np.argsort(distances)[:, :self.k]
             labels = self.y_train[indices]
             y_pred = np.array([Counter(labels_for_one).most_common()[0][0] for_u
      →labels_for_one in labels])
             return y_pred
         def _calculate_distances(self, point):
             """Calculate the euclidean distance between a test instance and all _{\sqcup}
      ⇒points in the training set x_train
             Input: a single point of size (D, )
             Return: distance matrix of size (N, )
             return ((self.x_train - point) ** 2).sum(axis=1) ** 0.5
     \# m = KNN_model(k=1)
     # m.train(np.array([[0, 0, 0], [1, 1, 1], [2, 2, 2]]), np.array([0, 1, 0]))
     # print(m._calculate_distances(np.array([0, 0, 0])))
     # print(m.test(np.array([[0, 0, 0], [0, 1, 1]])))
```

trainset X_train shape (2472, 4), validset X_valid shape (617, 4)

```
[]: #####
    possible_k_list = [1,3,5,7,9,11] #
    accs = [] #
                  k
    for k in possible_k_list:
        #####
                  k
        model = KNN_model(k)
        ##### , : model.train()
        model.train(X_train, Y_train)
        ##### X_valid
                         Y_pred_valid, model.test()
        Y_pred_valid = model.test(X_valid)
        acc_k = cal_accuracy(Y_pred_valid, Y_valid)
        ##### k
        accs.append(acc_k)
        print('k={}, accuracy on validation={}%'.format(k, acc_k))
    import matplotlib.pyplot as plt
    plt.plot(possible k list, accs) # k
```

```
k=1, accuracy on validation=96.27228525121556%
k=3, accuracy on validation=96.27228525121556%
k=5, accuracy on validation=96.27228525121556%
k=7, accuracy on validation=96.43435980551054%
k=9, accuracy on validation=96.11021069692059%
k=11, accuracy on validation=95.62398703403565%
```

[]: [<matplotlib.lines.Line2D at 0x257cefacdf0>]



```
[]: ##### k k k
best_k = 7

##### k
best_model = KNN_model(best_k)

#####
best_model.train(X, Y)

##### Y_pred_test
Y_pred_test = best_model.test(X_test)
print('Test Accuracy={}%'.format(cal_accuracy(Y_pred_test, Y_test)))
```

Test Accuracy=96.575%

```
[]: ##### 5
    folds = 5
     #####(k, , )
    k_mean_std_list = []
    for k in possible_k_list: #
        print('*****k={}*****'.format(k))
        valid accs = []
        ########
        random.seed(777777) #
        N = X.shape[0]
        valid_frac = 1 / folds # 1/folds
        valid_size = int(N * valid_frac)
                 random shuffle
        shuffle_index = [i for i in range(N)]
        random.shuffle(shuffle_index)
        shuffle_X, shuffle_Y = X[shuffle_index], Y[shuffle_index]
        for i in range(folds): # i
                       X\_train\_i, Y\_train\_i X\_valid\_i, Y\_valid\_i;
             ##### i
                                                                         random
      ⇔shuffle
               index
            X_valid_i, Y_valid_i = X[i * valid_size: (i+1) * valid_size], Y[i *_
      →valid_size: (i+1) * valid_size]
            X_train_i = np.vstack((X[:i * valid_size], X[(i+1) * valid_size:]))
            Y_train_i = np.append(Y[:i * valid_size], Y[(i+1) * valid_size:])
             #####
            model = KNN_model(k)
             ##### Fold-i
            model.train(X_train_i, Y_train_i)
             ##### Fold-i X_valid_i
                                       Y_pred_valid_i
            Y_pred_valid_i = model.test(X_valid_i)
            acc = cal_accuracy(Y_pred_valid_i, Y_valid_i)
            valid_accs.append(acc)
            print('Valid Accuracy on Fold-{}: {}%'.format(i+1, acc))
        k mean_std_list.append((k, np.mean(valid_accs), np.std(valid_accs)))
        print('k={}, Accuracy {}+-{}\".format(*k_mean_std_list[len(k_mean_std_list)_u
      → 1]))
    print('k_mean_std_list:', k_mean_std_list)
    *****k=1*****
```

Valid Accuracy on Fold-1: 96.11021069692059% Valid Accuracy on Fold-2: 95.78606158833063% Valid Accuracy on Fold-3: 96.75850891410049%

```
Valid Accuracy on Fold-4: 88.49270664505673%
    Valid Accuracy on Fold-5: 92.70664505672609%
    k=1, Accuracy 93.9708265802269+-3.0741232335892827%
    *****k=3*****
    Valid Accuracy on Fold-1: 96.27228525121556%
    Valid Accuracy on Fold-2: 95.78606158833063%
    Valid Accuracy on Fold-3: 97.24473257698541%
    Valid Accuracy on Fold-4: 90.76175040518638%
    Valid Accuracy on Fold-5: 93.67909238249594%
    k=3, Accuracy 94.74878444084278+-2.3094344415632944%
    *****k=5*****
    Valid Accuracy on Fold-1: 96.75850891410049%
    Valid Accuracy on Fold-2: 96.27228525121556%
    Valid Accuracy on Fold-3: 97.08265802269044%
    Valid Accuracy on Fold-4: 91.24797406807131%
    Valid Accuracy on Fold-5: 93.03079416531604%
    k=5, Accuracy 94.87844408427875+-2.320780851820909%
    *****k=7*****
    Valid Accuracy on Fold-1: 96.5964343598055%
    Valid Accuracy on Fold-2: 96.5964343598055%
    Valid Accuracy on Fold-3: 97.24473257698541%
    Valid Accuracy on Fold-4: 92.05834683954619%
    Valid Accuracy on Fold-5: 93.354943273906%
    k=7, Accuracy 95.17017828200972+-2.06643467753766%
    *****k=9*****
    Valid Accuracy on Fold-1: 96.5964343598055%
    Valid Accuracy on Fold-2: 96.27228525121556%
    Valid Accuracy on Fold-3: 97.08265802269044%
    Valid Accuracy on Fold-4: 92.05834683954619%
    Valid Accuracy on Fold-5: 93.03079416531604%
    k=9, Accuracy 95.00810372771474+-2.051123762665333%
    *****k=11*****
    Valid Accuracy on Fold-1: 96.5964343598055%
    Valid Accuracy on Fold-2: 96.43435980551054%
    Valid Accuracy on Fold-3: 96.92058346839546%
    Valid Accuracy on Fold-4: 92.22042139384116%
    Valid Accuracy on Fold-5: 92.86871961102106%
    k=11, Accuracy 95.00810372771474+-2.0279406573247405%
    k_mean_std_list: [(1, 93.9708265802269, 3.0741232335892827), (3,
    94.74878444084278, 2.3094344415632944), (5, 94.87844408427875,
    2.320780851820909), (7, 95.17017828200972, 2.06643467753766), (9,
    95.00810372771474, 2.051123762665333), (11, 95.00810372771474,
    2.0279406573247405)]
[]: #####
     best_k = 7
     ##### k
```

Test Accuracy chosing k using cross-validation=96.575%

```
[]: ##### /
     #####
                        1
     N_{\text{test}} = int(X_{\text{test.shape}}[0]*0.7)
     X_test, Y_test = X_test[:N_test], Y_test[:N_test]
     print(Counter(Y_test)) #
     model = KNN_model(k=7) #
     model.train(X, Y)
     Y_pred_test = model.test(X_test)
     # percision recall F1 score
     def cal_prec_recall_f1(Y_pred, Y_gt):
         Input: predicted labels y_pred, ground truth labels Y_gt
         Retur: precision, recall, and F1 score
         TP = np.bitwise_and(Y_pred == 1, Y_gt == 1).sum()
         FP = np.bitwise_and(Y_pred == 1, Y_gt == 0).sum()
         FN = np.bitwise_and(Y_pred == 0, Y_gt == 1).sum()
         TN = np.bitwise_and(Y_pred == 0, Y_gt == 0).sum()
         precision = TP / (TP + FP) if (TP + FP) != 0 else 1
         recall = TP / (TP + FN) if (TP + FN) != 0 else 1
         f1 = 2 * precision * recall / (precision + recall)
         return precision, recall, f1
     print(cal_prec_recall_f1(Y_pred_test, Y_test))
```

```
Counter({0: 2000, 1: 800})
(0.910271546635183, 0.96375, 0.936247723132969)
```

0.1

0.1.1 Precision Recall

 0.1.2 Numpy

Numpy , , .

0.2