main

March 6, 2025

[1]:
```
import numpy as np
import random
from collections import Counter
```

[8]:
```
######## 读取机器学习数据集的示例代码 (LIBSVM 格式)
def load_svmfile(filename):
    X = []
    Y = []
    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)
```

[10]:
```
######## 从这个网址下载数据集: https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/
 ↪datasets/binary.html#svmguide1
######## 将数据集保存在当前目录下
######## 读取数据集
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))

print('load success!')
```

```
Start loading dataset svmguide1
```

```
trainset X shape (3089, 4), train label Y shape (3089,)
testset X_test shape (4000, 4), test label Y shape (4000,)
load success!
```

[61]:

```python
######## 实现一个 KNN 分类器的模型，需要完成的功能包括 train, test 和
_calculate_distances 三部分
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␣
↪instances and D denotes the feature dimension
        Return: Predicted labels of size (N, )
        """
        pred_labels = [self._predict(point) for point in x_test]
        return np.array(pred_labels)

    def _predict(self, point):
        distances = self._calculate_distances(point)
        # print('dis:',distances)
        k_nearest_neighbors = np.argsort(distances)[:self.k]
        # print('k:',k_nearest_neighbors)
        # print(self.y_train.shape)
        k_nearest_labels = self.y_train[k_nearest_neighbors]
        unique, counts = np.unique(k_nearest_labels, return_counts=True)
        most_common_label = unique[np.argmax(counts)]
        return most_common_label

    def _calculate_distances(self, point):
        """Calculate the euclidean distance between a test instance and all␣
↪points in the training set x_train
        Input: a single point of size (D, )
        Return: distance matrix of size (N, )
        """
        dis = np.linalg.norm(self.x_train - point, axis = 1)
```

```python
        # print(dis)
        return dis

# an easy test from problem 5
# x_train = np.array([[0, 0], [0, 1], [0, -1], [-1, 0], [1, 0], [8, 0], [8, 1], [9, 0]])
# y_train = np.array(['A', 'A', 'A', 'A', 'A', 'B', 'A', 'B'])
# x_test = np.array([[0,-2], [8, 2]])

# # k = 1 output AA
# knn = KNN_model(k=1)
# knn.train(x_train, y_train)
# predictions = knn.test(x_test)
# print(predictions)

# # k = 3 output AB
# knn = KNN_model(k=3)
# knn.train(x_train, y_train)
# predictions = knn.test(x_test)
# print(predictions)

# return
# ['A' 'A']
# ['A' 'B']
# 应该是对的，跟第五问答案一样。
```

[62]:

```python
######### 将原来的训练集划分成两部分：训练和验证
random.seed(777777) # 定下随机种子
N = X.shape[0]
valid_frac = 0.2 # 设置验证集的比例为 20%
valid_size = int(N*valid_frac)

# 出于简单起见，这里直接使用 random shuffle 来划分
shuffle_index = [i for i in range(N)]
random.shuffle(shuffle_index)
valid_index, train_index = shuffle_index[:valid_size], shuffle_index[valid_size:]
X_valid, Y_valid = X[valid_index], Y[valid_index]
X_train, Y_train = X[train_index], Y[train_index]
print('trainset X_train shape {}, validset X_valid shape {}'.format(X_train.shape, X_valid.shape))
```

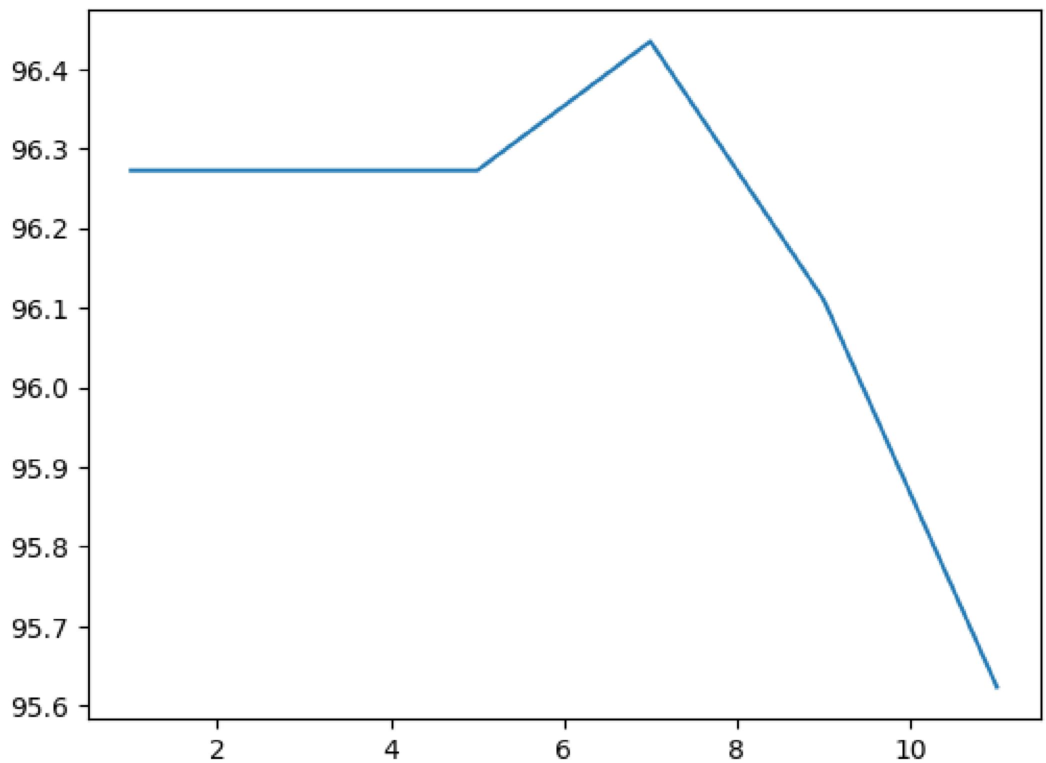
```
trainset X_train shape (2472, 4), validset X_valid shape (617, 4)
```

[63]:
```python
######### 这里需要实现计算准确率的函数，注意我们期望的输出是百分制，如准确率是 0.95，我们期望的输出是 95
def cal_accuracy(y_pred, y_gt):
    '''
    y_pred: predicted labels (N,)
    y_gt: ground truth labels (N,)
    Return: Accuracy (%)
    '''
    return np.sum(y_pred == y_gt)/y_pred.shape[0] *100

assert abs(cal_accuracy(np.zeros(Y.shape[0]), Y)-100*1089.0/3089.0)<1e-3
# print(abs(cal_accuracy(np.zeros(Y.shape[0]), Y)-100*1089.0/3089.0))
```

[64]:
```python
##### 使用验证集来选择超参数
possible_k_list = [1,3,5,7,9,11] # 在本次实验中候选的超参数取值
accs = [] # 将每个取值 k 对应的验证集准确率加入列表
for k in possible_k_list:
    ##### 模型的超参数设置为 k
    model = KNN_model(k)
    ##### 在训练集上训练，提示：model.train()
    model.train(X_train, Y_train)
    ##### 在验证集 X_valid 上给出预测结果 Y_pred_valid，提示：model.test()
    Y_pred_valid = model.test(X_valid)
    ##### 计算验证集上的准确率
    acc_k = cal_accuracy(Y_pred_valid, Y_valid)
    ##### 将每个取值 k 对应的验证集准确率加入列表
    accs.append(acc_k)
    print('k={}, accuracy on validation={}%'.format(k, acc_k))

import matplotlib.pyplot as plt
plt.plot(possible_k_list, accs) # 画出每个 k 对应的验证集准确率
```

```
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%
```

[64]:
```
[<matplotlib.lines.Line2D at 0x117a5aa10>]
```



基于上面的结果确定验证集上的最好的超参数 k，根据这个 k 最终在测试集上进行测试

定义最好的 k 对应的模型 pass

在训练集上训练，注意这里可以使用全部的训练数据 pass

在测试集上测试生成预测 Y_pred_test pass print('Test Accuracy={}%'.format(cal_accuracy(Y_pred_test, Y_test)))

以下需要实现 5 折交叉验证，可以参考之前训练集和验证集划分的方式 folds = 5

for k in possible_k_list: # 遍历所有可能的 k print('******k={}******'.format(k)) valid_accs = [] for i in range(folds): # 第 i 折的实验 ##### 生成第 i 折的训练集 X_train_i, Y_train_i 和验证集 X_valid_i, Y_valid_i; 提示：可参考之前 random shuffle 的方式来生成 index pass ##### 定义超参数设置为 k 的模型 pass ##### 在 Fold-i 上进行训练 pass ##### 给出 Fold-i 验证集 X_valid_i 上的预测结果 Y_pred_valid_i pass acc = cal_accuracy(Y_pred_valid_i, Y_valid_i) valid_accs.append(acc) print('Valid Accuracy on Fold-{}: {}%'.format(i+1, acc))

```
print('k={}, Accuracy {}+-{}%'.format(k, np.mean(valid_accs), np.std(valid_accs)))
```

[65]:
```
##### 基于交叉验证确定验证集上的最好的超参数 k，根据这个 k 最终在测试集上进行测试
##### 定义最好的 k 对应的模型
best_k = 7
##### 在训练集上训练，注意这里可以使用全部的训练数据
best_model = KNN_model(best_k)
```

```python
##### 在测试集上测试生成预测 Y_pred_test
best_model.train(X, Y)
Y_pred_test = best_model.test(X_test)
print('Test Accuracy chosing k using cross-validation={}%'.
 ↪format(cal_accuracy(Y_pred_test, Y_test)))
```

```
Test Accuracy chosing k using cross-validation=96.575%
```

[67]:
```python
##### 以下需要实现 5 折交叉验证，可以参考之前训练集和验证集划分的方式
folds = 5

for k in possible_k_list: # 遍历所有可能的 k
    print('******k={}******'.format(k))
    valid_accs = []
    for i in range(folds): # 第 i 折的实验
        ##### 生成第 i 折的训练集 X_train_i, Y_train_i 和验证集 X_valid_i,␣
 ↪Y_valid_i; 提示：可参考之前 random shuffle 的方式来生成 index
        random.seed(777777) # 定下随机种子
        N = X.shape[0]
        indices = np.random.permutation(N)
        valid_frac = 1/folds
        valid_size = int(N*valid_frac)

        valid_indices = indices[i * valid_size: (i + 1) * valid_size]
        train_indices = np.setdiff1d(indices, valid_indices)

        X_train_i, Y_train_i = X[train_indices], Y[train_indices]
        X_valid_i, Y_valid_i = X[valid_indices], Y[valid_indices]

        ##### 定义超参数设置为 k 的模型
        model = KNN_model(k=k)
        model.train(X_train_i, Y_train_i)

        ##### 在 Fold-i 上进行训练
        model.train(X_train_i, Y_train_i)

        ##### 给出 Fold-i 验证集 X_valid_i 上的预测结果 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))

    print('k={}, Accuracy {}+-{}%'.format(k, np.mean(valid_accs), np.
 ↪std(valid_accs)))
```

```
******k=1******
Valid Accuracy on Fold-1: 95.46191247974069%
Valid Accuracy on Fold-2: 95.9481361426256%
```

```
Valid Accuracy on Fold-3: 94.6515397082658%
Valid Accuracy on Fold-4: 94.97568881685575%
Valid Accuracy on Fold-5: 94.6515397082658%
k=1, Accuracy 95.13776337115071+-0.5021696397027438%
******k=3******
Valid Accuracy on Fold-1: 96.11021069692059%
Valid Accuracy on Fold-2: 96.27228525121556%
Valid Accuracy on Fold-3: 96.27228525121556%
Valid Accuracy on Fold-4: 96.75850891410049%
Valid Accuracy on Fold-5: 96.27228525121556%
k=3, Accuracy 96.33711507293356+-0.21984862181929446%
******k=5******
Valid Accuracy on Fold-1: 97.24473257698541%
Valid Accuracy on Fold-2: 98.05510534846029%
Valid Accuracy on Fold-3: 96.75850891410049%
Valid Accuracy on Fold-4: 98.05510534846029%
Valid Accuracy on Fold-5: 97.24473257698541%
k=5, Accuracy 97.47163695299838+-0.5084080110650905%
******k=7******
Valid Accuracy on Fold-1: 95.2998379254457%
Valid Accuracy on Fold-2: 96.5964343598055%
Valid Accuracy on Fold-3: 97.56888168557536%
Valid Accuracy on Fold-4: 97.40680713128039%
Valid Accuracy on Fold-5: 96.27228525121556%
k=7, Accuracy 96.62884927066452+-0.8225982198022385%
******k=9******
Valid Accuracy on Fold-1: 95.46191247974069%
Valid Accuracy on Fold-2: 95.9481361426256%
Valid Accuracy on Fold-3: 95.46191247974069%
Valid Accuracy on Fold-4: 96.5964343598055%
Valid Accuracy on Fold-5: 95.9481361426256%
k=9, Accuracy 95.88330632090761+-0.4176369117252798%
******k=11******
Valid Accuracy on Fold-1: 95.78606158833063%
Valid Accuracy on Fold-2: 97.08265802269044%
Valid Accuracy on Fold-3: 96.27228525121556%
Valid Accuracy on Fold-4: 95.62398703403565%
Valid Accuracy on Fold-5: 97.24473257698541%
k=11, Accuracy 96.40194489465154+-0.6595458654578893%
```

[68]:

```
##### 基于交叉验证确定验证集上的最好的超参数 k，根据这个 k 最终在测试集上进行测试
##### 定义最好的 k 对应的模型
best_k = 7
##### 在训练集上训练，注意这里可以使用全部的训练数据
best_model = KNN_model(best_k)
##### 在测试集上测试生成预测 Y_pred_test
best_model.train(X, Y)
```

```
Y_pred_test = best_model.test(X_test)
print('Test Accuracy chosing k using cross-validation={}%'.
 ↪format(cal_accuracy(Y_pred_test, Y_test)))
```

```
Test Accuracy chosing k using cross-validation=96.575%
```

[69]:
```
##### 如果训练/测试集不均衡如果评估模型呢？
##### 生成一个不均衡的测试集，由于示例数据集中所有的标签 1 都在后面所以出于方便直接
这样来生成一个不均衡的测试集
N_test = int(X_test.shape[0]*0.7)
X_test, Y_test = X_test[:N_test], Y_test[:N_test]
print(Counter(Y_test)) # 输出新的测试集中的标签分布

model = KNN_model(k=best_k) # 此处请填入交叉验证确定的最好的 k
model.train(X, Y)
Y_pred_test = model.test(X_test)

# 实现计算 percision， recall 和 F1 score 的函数
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.sum((Y_pred == 1) & (Y_gt == 1))
    FP = np.sum((Y_pred == 1) & (Y_gt == 0))
    FN = np.sum((Y_pred == 0) & (Y_gt == 1))
    TN = np.sum((Y_pred == 0) & (Y_gt == 0))

    precision = TP / (TP + FP) if (TP + FP) != 0 else 0
    recall = TP / (TP + FN) if (TP + FN) != 0 else 0
    f1 = 2 * (precision * recall) / (precision + recall) if (precision +␣
 ↪recall) != 0 else 0


    return precision, recall, f1

print(cal_prec_recall_f1(Y_pred_test, Y_test))
```

```
Counter({np.int64(0): 2000, np.int64(1): 800})
(np.float64(0.910271546635183), np.float64(0.96375),
np.float64(0.936247723132969))
```

1 问题和思考

问题是一开始做 knn 的时候查了一些 numpy 的用法，然后就是 jupyter 不支持补全，所以导致我有个地方写错了一直没有纠正，然后查了 1 个小时才发现是写错了一个字母.... 还有就是 precision 和 recall 要考虑分母为 0 的情况。思考就是，完整的过了一遍机器学习的流程，挺好的感觉，就是可以用 py 可能比 notebook 方便 QAQ...

[ ]:

```
# 221300079 王俊童 人工智能学院

# 由于发现这个东西不支持中文，我就在这里直接说好了，用 python 注释的形式来说。

# 问题和思考

# 问题是一开始做 knn 的时候查了一些 numpy 的用法，然后就是 jupyter 不支持补全，所以导致我有个地方写错了一直没有纠正，然后查了 1 个小时才发现是写错了一个字母....
# 还有就是 precision 和 recall 要考虑分母为 0 的情况。

# 思考就是，完整的过了一遍机器学习的流程，挺好的感觉，就是可以用 py 可能比 notebook 方便 QAQ...
```

[ ]:

```
```