```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call dr
```

```
from google.colab import drive

drive.mount('/content/drive', force_remount=True)

# 输入daseCV所在的路径
# 'daseCV' 文件夹包括 '.py', 'classifiers' 和'datasets'文件夹
# 例如 'CV/assignments/assignment1/daseCV/'
FOLDERNAME =  '/content/drive/MyDrive/assignment1/daseCV'

assert FOLDERNAME is not None, "[!] Enter the foldername."

%cd drive/My\ Drive
%cp -r $FOLDERNAME ../../
%cd ../../
%cd daseCV/datasets/
!bash get_datasets.sh
%cd ../../
```

```
Mounted at /content/drive
/content/drive/My Drive
/content
/content/daseCV/datasets
--2021-10-10 13:11:25--  http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
Resolving www.cs.toronto.edu (www.cs.toronto.edu)... 128.100.3.30
Connecting to www.cs.toronto.edu (www.cs.toronto.edu)|128.100.3.30|:80... connec
HTTP request sent, awaiting response... 200 OK
Length: 170498071 (163M) [application/x-gzip]
Saving to: ‘cifar-10-python.tar.gz’

cifar-10-python.tar 100%[===================>] 162.60M  43.8MB/s    in 4.2s

2021-10-10 13:11:30 (39.0 MB/s) - ‘cifar-10-python.tar.gz’ saved [170498071/1704

cifar-10-batches-py/
cifar-10-batches-py/data_batch_4
cifar-10-batches-py/readme.html
cifar-10-batches-py/test_batch
cifar-10-batches-py/data_batch_3
cifar-10-batches-py/batches.meta
cifar-10-batches-py/data_batch_2
cifar-10-batches-py/data_batch_5
cifar-10-batches-py/data_batch_1
/content
```

K-近邻算法 (kNN) 练习

补充并完成本练习。

kNN分类器包含两个阶段:

- 训练阶段，分类器获取训练数据并简单地记住它。
- 测试阶段, kNN将测试图像与所有训练图像进行比较，并计算出前k个最相似的训练示例的标签来对每个测试图像进行分类。
- 对k值进行交叉验证

在本练习中，您将实现这些步骤，并了解基本的图像分类、交叉验证和熟练编写高效矢量化代码的能力。

```
# 运行notebook的一些初始化代码

import random
import numpy as np
from daseCV.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

# 使得matplotlib的图像在当前页显示而不是新的窗口。
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# 一些更神奇的，使notebook重新加载外部的python模块;
# 参见 http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

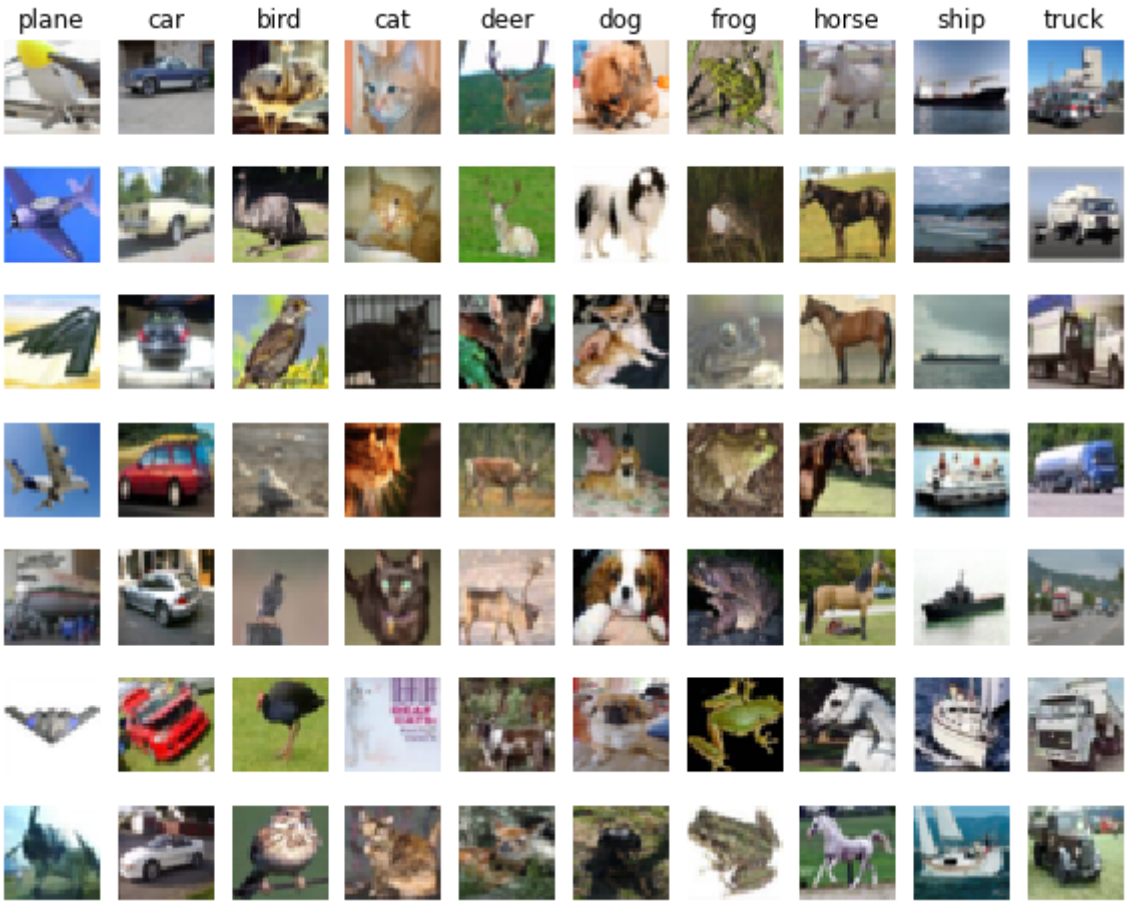
```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

```
# 加载未处理的 CIFAR-10 数据.
cifar10_dir = 'daseCV/datasets/cifar-10-batches-py'

# 清理变量以防止多次加载数据（这可能会导致内存问题）
try:
   del X_train, y_train
   del X_test, y_test
   print('Clear previously loaded data.')
except:
   pass

X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

# 作为健全性检查，我们打印出训练和测试数据的形状。
print('Training data shape: ', X_train.shape)
print('Training labels shape: ', y train.shape)
```

```
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

```
Clear previously loaded data.
Training data shape:  (50000, 32, 32, 3)
Training labels shape:  (50000,)
Test data shape:  (10000, 32, 32, 3)
Test labels shape:  (10000,)
```

```
# 可视化数据集中的一些示例。
# 我们展示了训练图像的所有类别的一些示例。
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'tru
num_classes = len(classes)
samples_per_class = 7
for y, cls in enumerate(classes):
    idxs = np.flatnonzero(y_train == y) # flatnonzero表示返回所给数列的非零项的索引值，这里表
    idxs = np.random.choice(idxs, samples_per_class, replace=False) # replace表示抽取的
    for i, idx in enumerate(idxs):
        plt_idx = i * num_classes + y + 1
        plt.subplot(samples_per_class, num_classes, plt_idx)
        plt.imshow(X_train[idx].astype('uint8'))
        plt.axis('off')
        if i == 0:
            plt.title(cls)
plt.show()
```



```
# 在练习中使用更小的子样本可以提高代码的效率
num_training = 5000
mask = list(range(num_training))
X_train = X_train[mask]
y_train = y_train[mask]

num_test = 500
mask = list(range(num_test))
X_test = X_test[mask]
y_test = y_test[mask]

# 将图像数据调整为行
X_train = np.reshape(X_train, (X_train.shape[0], -1))
X_test = np.reshape(X_test, (X_test.shape[0], -1))
print(X_train.shape, X_test.shape)
```

```
(5000, 3072) (500, 3072)
```

```
from daseCV.classifiers import KNearestNeighbor

# 创建一个kNN分类器实例。
# 请记住，kNN分类器的训练并不会做什么：
# 分类器仅记住数据并且不做进一步处理
classifier = KNearestNeighbor()
classifier.train(X_train, y_train)
```

现在，我们要使用kNN分类器对测试数据进行分类。回想一下，我们可以将该过程分为两个步骤：

1. 首先，我们必须计算所有测试样本与所有训练样本之间的距离。
2. 给定这些距离，对于每个测试示例，我们找到k个最接近的示例，并让它们对标签进行投票

让我们开始计算所有训练和测试示例之间的距离矩阵。 假设有 **Ntr** 的训练样本和 **Nte** 的测试样本, 该过程的结果存储在一个 **Nte x Ntr** 矩阵中，其中每个元素 (i,j) 表示的是第 i 个测试样本和第 j 个 训练样本的距离。

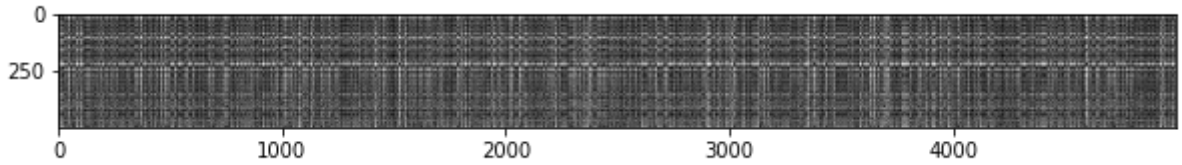
注意: 在完成此notebook中的三个距离的计算时请不要使用numpy提供的np.linalg.norm()函数。

首先打开 `daseCV/classifiers/k_nearest_neighbor.py` 并且补充完成函数 `compute_distances_two_loops` ，这个函数使用双重循环（效率十分低下）来计算距离矩阵。

```
# 打开 daseCV/classifiers/k_nearest_neighbor.py 并且补充完成
# compute_distances_two_loops.

# 测试你的代码：
dists = classifier.compute_distances_two_loops(X_test)
print(dists.shape)
```

```
(500, 5000)
```

```
# 我们可视化距离矩阵：每行代表一个测试样本与训练样本的距离
plt.imshow(dists, interpolation='none')
plt.show()
```



问题 1

请注意距离矩阵中的结构化图案，其中某些行或列的可见亮度更高。（请注意，使用默认的配色方案，黑色表示低距离，而白色表示高距离。）

- 数据中导致行亮度更高的原因是什么?
- 那列方向的是什么原因呢?

答：

- 某些测试样本与训练集差异较大；
- 某些训练样本与测试集差异较大。

```
# 现在实现函数predict_labels并运行以下代码：
# 我们使用k = 1（这是最近的邻居）。
y_test_pred = classifier.predict_labels(dists, k=1)

# 计算并打印出预测的精度
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
```

```
    Got 137 / 500 correct => accuracy: 0.274000
```

你预期的精度应该为 `27%` 左右。 现在让我们尝试更大的 `k`,比如 `k = 5`：

```
y_test_pred = classifier.predict_labels(dists, k=5)
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
```

```
    Got 139 / 500 correct => accuracy: 0.278000
```

你应该能看到一个比 `k = 1` 稍微好一点的结果。

问题 2

我们还可以使用其他距离指标，例如L1距离。

记图像 I_k 的每个位置 (i, j) 的像素值为 $p_{ij}^{(k)}$，

所有图像上的所有像素的均值 μ 为

$$\mu = \frac{1}{nhw} \sum_{k=1}^{n} \sum_{i=1}^{h} \sum_{j=1}^{w} p_{ij}^{(k)}$$

并且所有图像的每个像素的均值 μ_{ij} 为

$$\mu_{ij} = \frac{1}{n} \sum_{k=1}^{n} p_{ij}^{(k)}.$$

标准差 σ 以及每个像素的标准差 σ_{ij} 的定义与之类似。

以下哪个预处理步骤不会改变使用L1距离的最近邻分类器的效果？选择所有符合条件的答案。

1. 减去均值 μ ($\tilde{p}_{ij}^{(k)} = p_{ij}^{(k)} - \mu$.)
2. 减去每个像素均值 μ_{ij} ($\tilde{p}_{ij}^{(k)} = p_{ij}^{(k)} - \mu_{ij}$.)
3. 减去均值 μ 然后除以标准偏差 σ.
4. 减去每个像素均值 μ_{ij} 并除以每个素标准差 σ_{ij}.
5. 旋转数据的坐标轴。

*你的回答：*1、2、3

*你的解释：*由于 L1 距离是 $|x_1 - x_2| + |y_1 - y_2|$，因此同时减去一个相同的数，结果不会改变。此外，如果所有像素点都除以同一个数，则相对大小也不变，因此结果也不会改变

```
# 现在，通过部分矢量化并且使用单层循环的来加快距离矩阵的计算。
# 需要实现函数compute_distances_one_loop并运行以下代码：

dists_one = classifier.compute_distances_one_loop(X_test)

# 为了确保我们的矢量化实现正确，我们要保证它的结果与最原始的实现方式结果一致。
# 有很多方法可以确定两个矩阵是否相似。最简单的方法之一就是Frobenius范数。
# 如果您以前从未了解过Frobenius范数，它其实是两个矩阵的所有元素之差的平方和的平方根；
# 换句话说，就是将矩阵重整为向量并计算它们之间的欧几里得距离。

difference = np.linalg.norm(dists - dists_one, ord='fro')
print('One loop difference was: %f' % (difference, ))
if difference < 0.001:
    print('Good! The distance matrices are the same')
else:
    print('Uh-oh! The distance matrices are different')
```

```
One loop difference was: 0.000000
Good! The distance matrices are the same
```

```
# 现在完成compute_distances_no_loops实现完全矢量化的版本并运行代码
dists_two = classifier.compute_distances_no_loops(X_test)

# 检查距离矩阵是否与我们之前计算出的矩阵一致：
difference = np.linalg.norm(dists - dists_two, ord='fro')
print('No loop difference was: %f' % (difference, ))
if difference < 0.001:
    print('Good! The distance matrices are the same')
else:
    print('Uh-oh! The distance matrices are different')
```

```
No loop difference was: 0.000000
Good! The distance matrices are the same
```

```
# 让我们比较一下三种实现方式的速度
def time_function(f, *args):
    """
    Call a function f with args and return the time (in seconds) that it took to execu
    """
    import time
    tic = time.time()
    f(*args)
    toc = time.time()
    return toc - tic

two_loop_time = time_function(classifier.compute_distances_two_loops, X_test)
print('Two loop version took %f seconds' % two_loop_time)

one_loop_time = time_function(classifier.compute_distances_one_loop, X_test)
print('One loop version took %f seconds' % one_loop_time)

no_loop_time = time_function(classifier.compute_distances_no_loops, X_test)
print('No loop version took %f seconds' % no_loop_time)

# 你应该会看到使用完全矢量化的实现会有明显更佳的性能！

# 注意：在部分计算机上，当您从两层循环转到单层循环时，
# 您可能看不到速度的提升，甚至可能会看到速度变慢。
```

```
Two loop version took 39.260826 seconds
One loop version took 31.184861 seconds
No loop version took 0.504093 seconds
```

交叉验证

我们已经实现了kNN分类器，并且可以设置k = 5。现在，将通过交叉验证来确定此超参数的最佳值。

```
num_folds = 5
```

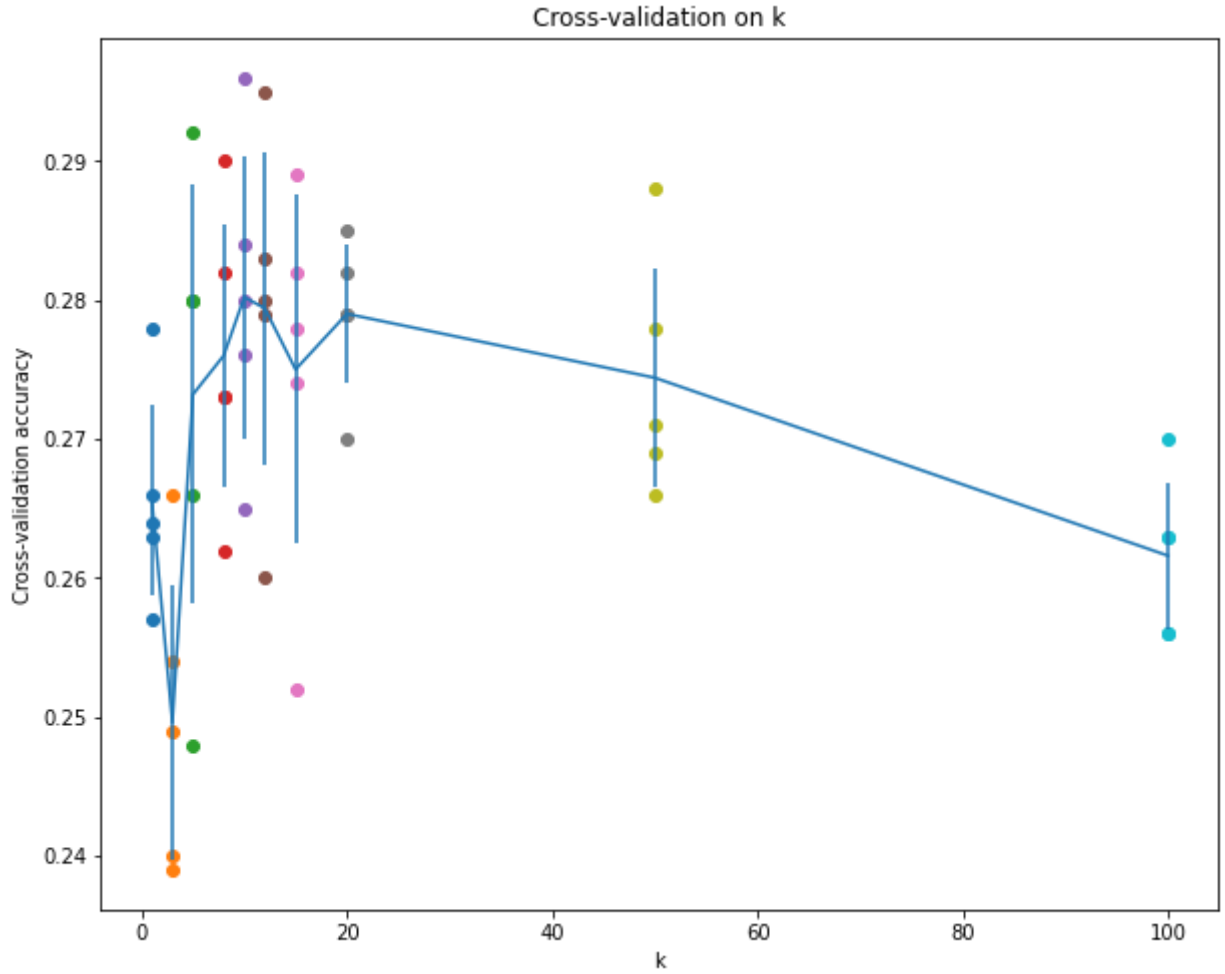
```
k_choices = [1, 3, 5, 8, 10, 12, 15, 20, 50, 100]

X_train_folds = []
y_train_folds = []
################################################################################
# 需要完成的事情：
# 将训练数据分成多个部分。拆分后，X_train_folds和y_train_folds均应为长度为num_folds的列表，
# 其中y_train_folds [i]是X_train_folds [i]中各点的标签向量。
# 提示：查阅numpy的array_split函数。
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# pass
X_train_folds=np.split(X_train,5,axis=0)
y_train_folds=np.split(y_train,5,axis=0)
# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# A dictionary holding the accuracies for different values of k that we find when runn
# 一个字典，存储我们进行交叉验证时不同k的值的精度。
# 运行交叉验证后，k_to_accuracies[k]应该是长度为num_folds的列表，存储了k值下的精度值。
k_to_accuracies = {}


################################################################################
# 需要完成的事情：
# 执行k的交叉验证，以找到k的最佳值。
# 对于每个可能的k值，运行k-最近邻算法 num_folds 次，
# 在每次循环下，你都会用所有拆分的数据（除了其中一个需要作为验证集）作为训练数据。
# 然后存储所有的精度结果到k_to_accuracies[k]中。
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# 交叉验证。有时候，训练集数量较小（因此验证集的数量更小），人们会使用一种被称为
# 交叉验证的方法，这种方法更加复杂些。还是用刚才的例子，如果是交叉验证集，我们就
# 不是取1000个图像，而是将训练集平均分成5份，其中4份用来训练，1份用来验证。然后
# 我们循环着取其中4份来训练，其中1份来验证，最后取所有5次验证结果的平均值作为算
# 法验证结果。

for k in k_choices:
    k_to_accuracies[k] = []
    for i in range(num_folds):
        # prepare training data for the current fold
        X_train_fold = np.concatenate([ fold for j, fold in enumerate(X_train_folds) i
        y_train_fold = np.concatenate([ fold for j, fold in enumerate(y_train_folds) i

        # use of k-nearest-neighbor algorithm
        classifier.train(X_train_fold, y_train_fold)
        y_pred_fold = classifier.predict(X_train_folds[i], k=k, num_loops=0)

        # Compute the fraction of correctly predicted examples
        num_correct = np.sum(y_pred_fold == y_train_folds[i])
        accuracy = float(num_correct) / X_train_folds[i].shape[0]
```

```
            k_to_accuracies[k].append(accuracy)

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    # 打印出计算的精度
    for k in sorted(k_to_accuracies):
        for accuracy in k_to_accuracies[k]:
            print('k = %d, accuracy = %f' % (k, accuracy))
```

```
k = 1, accuracy = 0.263000
k = 1, accuracy = 0.257000
k = 1, accuracy = 0.264000
k = 1, accuracy = 0.278000
k = 1, accuracy = 0.266000
k = 3, accuracy = 0.239000
k = 3, accuracy = 0.249000
k = 3, accuracy = 0.240000
k = 3, accuracy = 0.266000
k = 3, accuracy = 0.254000
k = 5, accuracy = 0.248000
k = 5, accuracy = 0.266000
k = 5, accuracy = 0.280000
k = 5, accuracy = 0.292000
k = 5, accuracy = 0.280000
k = 8, accuracy = 0.262000
k = 8, accuracy = 0.282000
k = 8, accuracy = 0.273000
k = 8, accuracy = 0.290000
k = 8, accuracy = 0.273000
k = 10, accuracy = 0.265000
k = 10, accuracy = 0.296000
k = 10, accuracy = 0.276000
k = 10, accuracy = 0.284000
k = 10, accuracy = 0.280000
k = 12, accuracy = 0.260000
k = 12, accuracy = 0.295000
k = 12, accuracy = 0.279000
k = 12, accuracy = 0.283000
k = 12, accuracy = 0.280000
k = 15, accuracy = 0.252000
k = 15, accuracy = 0.289000
k = 15, accuracy = 0.278000
k = 15, accuracy = 0.282000
k = 15, accuracy = 0.274000
k = 20, accuracy = 0.270000
k = 20, accuracy = 0.279000
k = 20, accuracy = 0.279000
k = 20, accuracy = 0.282000
k = 20, accuracy = 0.285000
k = 50, accuracy = 0.271000
k = 50, accuracy = 0.288000
k = 50, accuracy = 0.278000
k = 50, accuracy = 0.269000
k = 50, accuracy = 0.266000
k = 100, accuracy = 0.256000
k = 100, accuracy = 0.270000
```

```
k = 100, accuracy = 0.263000
k = 100, accuracy = 0.256000
k = 100, accuracy = 0.263000
```

```
# 绘制原始观察结果
for k in k_choices:
    accuracies = k_to_accuracies[k]
    plt.scatter([k] * len(accuracies), accuracies)

# 用与标准偏差相对应的误差线绘制趋势线
accuracies_mean = np.array([np.mean(v) for k,v in sorted(k_to_accuracies.items())])
accuracies_std = np.array([np.std(v) for k,v in sorted(k_to_accuracies.items())])
plt.errorbar(k_choices, accuracies_mean, yerr=accuracies_std)
plt.title('Cross-validation on k')
plt.xlabel('k')
plt.ylabel('Cross-validation accuracy')
plt.show()
```




```
# 根据上述交叉验证结果，为k选择最佳值，使用所有训练数据重新训练分类器，
# 并在测试中对其进行测试数据。您应该能够在测试数据上获得28%以上的准确性。

best_k = k_choices[accuracies_mean.argmax()]

classifier = KNearestNeighbor()
```

```
classifier = KNearestNeighbor()
classifier.train(X_train, y_train)
y_test_pred = classifier.predict(X_test, k=best_k)

# Compute and display the accuracy
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
```

```
Got 141 / 500 correct => accuracy: 0.282000
```

问题 3

下列关于k-NN的陈述中哪些是在分类器中正确的设置，并且对所有的k都有效？选择所有符合条件的选项。

1. k-NN分类器的决策边界是线性的。
2. 1-NN的训练误差将始终低于5-NN。
3. 1-NN的测试误差将始终低于5-NN。
4. 使用k-NN分类器对测试示例进行分类所需的时间随训练集的大小而增加。
5. 以上都不是。

*你的回答：*5

*你的解释：*K-NN 的决策边界不是线性的，所以1不对；其训练误差及测试误差大小，与 K 的关系不能完全确定，所以2，3不对；分类的时间只与 k 的大小有关，与训练集大小无关，所以4不对。

重要

防止作业被吞

这里是作业的结尾处，请执行以下步骤:

1. 点击 `File -> Save` 或者用 `control+s` 组合键，确保你最新的的notebook的作业已经保存到谷歌云。
2. 执行以下代码确保 `.py` 文件保存回你的谷歌云。

```
import os

# /content/daseCV/classifiers/k_nearest_neighbor.py
FOLDER_TO_SAVE = os.path.join('/content', FOLDERNAME)
FILES_TO_SAVE = ['daseCV/classifiers/k_nearest_neighbor.py']

for files in FILES_TO_SAVE:
    with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])), 'w') as f:
      f.write(''.join(open(files).readlines()))
```