```
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
--2021-10-15 05:58:04--  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  44.4MB/s    in 3.8s

2021-10-15 05:58:08 (42.5 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
```

多分类支撑向量机练习

完成此练习并且上交本ipynb（包含输出及代码）.

在这个练习中，你将会:

- 为SVM构建一个完全向量化的**损失函数**

- 实现**解析梯度**的向量化表达式
- 使用数值梯度检查你的代码是否正确
- 使用验证集**调整学习率和正则化项**
- 用**SGD（随机梯度下降）优化**损失函数
- **可视化** 最后学习到的权重

```
# 导入包
import random
import numpy as np
from daseCV.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

# 下面一行是notebook的magic命令，作用是让matplotlib在notebook内绘图（而不是新建一个窗口）
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # 设置绘图的默认大小
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# 该magic命令可以重载外部的python模块
# 相关资料可以去看 http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-i
%load_ext autoreload
%autoreload 2
```

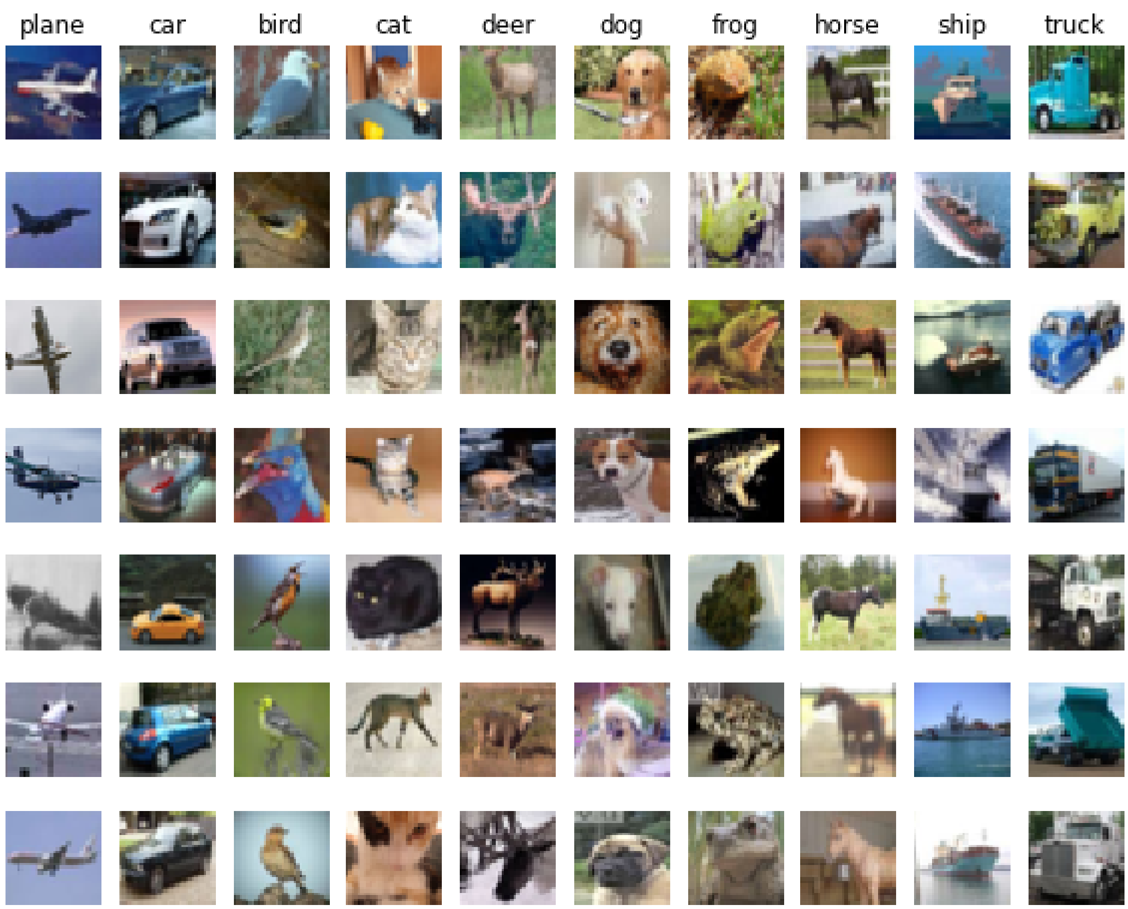
准备和预处理CIFAR-10的数据

```
# 导入原始CIFAR-10数据
cifar10_dir = 'daseCV/datasets/cifar-10-batches-py'

# 清空变量，防止多次定义变量（可能造成内存问题）
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)

# 完整性检查，打印出训练和测试数据的大小
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)
```

```
Training data shape:  (50000, 32, 32, 3)
Training labels shape:  (50000,)
```

```
Test data shape:  (10000, 32, 32, 3)
Test labels shape:  (10000,)
```

```
# 可视化部分数据
# 这里我们每个类别展示了7张图片
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)
    idxs = np.random.choice(idxs, samples_per_class, replace=False)
    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()
```




```
# 划分训练集，验证集和测试集，除此之外，
# 我们从训练集中抽取了一小部分作为代码开发的数据，
# 使用小批量的开发数据集能够快速开发代码
num_training = 49000
num_validation = 1000
num_test = 1000
num_dev = 500
```

```
# 从原始训练集中抽取出num_validation个样本作为验证集
mask = range(num_training, num_training + num_validation)
X_val = X_train[mask]
y_val = y_train[mask]

# 从原始训练集中抽取出num_training个样本作为训练集
mask = range(num_training)
X_train = X_train[mask]
y_train = y_train[mask]

# 从训练集中抽取num_dev个样本作为开发数据集
mask = np.random.choice(num_training, num_dev, replace=False)
X_dev = X_train[mask]
y_dev = y_train[mask]

# 从原始测试集中抽取num_test个样本作为测试集
mask = range(num_test)
X_test = X_test[mask]
y_test = y_test[mask]

print('Train data shape: ', X_train.shape)
print('Train labels shape: ', y_train.shape)
print('Validation data shape: ', X_val.shape)
print('Validation labels shape: ', y_val.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

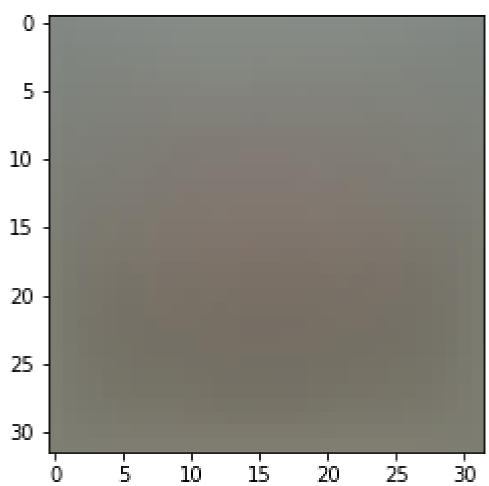
```
Train data shape:  (49000, 32, 32, 3)
Train labels shape:  (49000,)
Validation data shape:  (1000, 32, 32, 3)
Validation labels shape:  (1000,)
Test data shape:  (1000, 32, 32, 3)
Test labels shape:  (1000,)
```

```
# 预处理：把图片数据rehspae成行向量
X_train = np.reshape(X_train, (X_train.shape[0], -1))
X_val = np.reshape(X_val, (X_val.shape[0], -1))
X_test = np.reshape(X_test, (X_test.shape[0], -1))
X_dev = np.reshape(X_dev, (X_dev.shape[0], -1))

# 完整性检查，打印出数据的shape
print('Training data shape: ', X_train.shape)
print('Validation data shape: ', X_val.shape)
print('Test data shape: ', X_test.shape)
print('dev data shape: ', X_dev.shape)
```

```
Training data shape:  (49000, 3072)
Validation data shape:  (1000, 3072)
Test data shape:  (1000, 3072)
dev data shape:  (500, 3072)
```

```
# 预处理：减去image的平均值（均值规整化）
# 第一步：计算训练集中的图像均值
mean_image = np.mean(X_train, axis=0)
print(mean_image[:10]) # print a few of the elements
plt.figure(figsize=(4,4))
plt.imshow(mean_image.reshape((32,32,3)).astype('uint8')) # visualize the mean image
plt.show()

# 第二步：所有数据集减去均值
X_train -= mean_image
X_val -= mean_image
X_test -= mean_image
X_dev -= mean_image

# 第三步：拼接一个bias维，其中所有值都是1（bias trick），
# SVM可以联合优化数据和bias，即只需要优化一个权值矩阵W
X_train = np.hstack([X_train, np.ones((X_train.shape[0], 1))])
X_val = np.hstack([X_val, np.ones((X_val.shape[0], 1))])
X_test = np.hstack([X_test, np.ones((X_test.shape[0], 1))])
X_dev = np.hstack([X_dev, np.ones((X_dev.shape[0], 1))])

print(X_train.shape, X_val.shape, X_test.shape, X_dev.shape)
```

```
[130.64189796 135.98173469 132.47391837 130.05569388 135.34804082
 131.75402041 130.96055102 136.14328571 132.47636735 131.48467347]
```




```
(49000, 3073) (1000, 3073) (1000, 3073) (500, 3073)
```

SVM分类器

你需要在**daseCV/classifiers/linear_svm.py**里面完成编码

我们已经预先定义了一个函数 `compute_loss_naive`，该函数使用循环来计算多分类SVM损失函数

```
# 调用朴素版的损失计算函数
from daseCV.classifiers.linear_svm import svm_loss_naive
import time
```

```
# 生成一个随机的SVM权值矩阵（矩阵值很小）
W = np.random.randn(3073, 10) * 0.0001

loss, grad = svm_loss_naive(W, X_dev, y_dev, 0.000005)
print('loss: %f' % (loss, ))
```

```
loss: 8.892196
```

从上面的函数返回的`grad`现在是零。请推导支持向量机损失函数的梯度，并在svm_loss_naive中编码实现。

为了检查是否正确地实现了梯度，你可以用数值方法估计损失函数的梯度，并将数值估计与你计算出来的梯度进行比较。我们已经为你提供了检查的代码:

```
# 一旦你实现了梯度计算的功能，重新执行下面的代码检查梯度

# 计算损失和W的梯度
loss, grad = svm_loss_naive(W, X_dev, y_dev, 0.0)

# 数值估计梯度的方法沿着随机几个维度进行计算，并且和解析梯度进行比较，
# 这两个方法算出来的梯度应该在任何维度上完全一致(相对误差足够小)
from daseCV.gradient_check import grad_check_sparse
f = lambda w: svm_loss_naive(w, X_dev, y_dev, 0.0)[0]
grad_numerical = grad_check_sparse(f, W, grad)

# 把正则化项打开后继续再检查一遍梯度
# 你没有忘记正则化项吧？（忘了的罚抄100遍(๑•́ ₃•̀๑) ）
loss, grad = svm_loss_naive(W, X_dev, y_dev, 5e1)
f = lambda w: svm_loss_naive(w, X_dev, y_dev, 5e1)[0]
grad_numerical = grad_check_sparse(f, W, grad)
```

```
numerical: -9.456696 analytic: -9.538625, relative error: 4.313094e-03
numerical: 2.475763 analytic: 2.475763, relative error: 4.079706e-11
numerical: -9.873913 analytic: -9.973848, relative error: 5.035056e-03
numerical: 2.309884 analytic: 2.309884, relative error: 5.239593e-11
numerical: 9.325439 analytic: 9.283433, relative error: 2.257309e-03
numerical: -12.310084 analytic: -12.395819, relative error: 3.470216e-03
numerical: 7.845809 analytic: 7.845809, relative error: 6.947658e-11
numerical: -13.998347 analytic: -13.998347, relative error: 2.007755e-11
numerical: 0.107793 analytic: 0.107793, relative error: 3.216543e-09
numerical: 14.740548 analytic: 14.740548, relative error: 1.669424e-11
numerical: -21.221971 analytic: -21.227494, relative error: 1.301035e-04
numerical: -17.986466 analytic: -17.861571, relative error: 3.483993e-03
numerical: -9.862320 analytic: -9.924920, relative error: 3.163676e-03
numerical: 30.834819 analytic: 30.833514, relative error: 2.116132e-05
numerical: -4.736562 analytic: -4.673694, relative error: 6.680818e-03
numerical: -60.493429 analytic: -60.490843, relative error: 2.137081e-05
numerical: 13.630830 analytic: 13.632037, relative error: 4.428323e-05
numerical: 11.760652 analytic: 11.692249, relative error: 2.916598e-03
numerical: -17.506100 analytic: -17.499931, relative error: 1.762479e-04
numerical: 32.897598 analytic: 32.900068, relative error: 3.753722e-05
```

问题 1

有可能会出现某一个维度上的gradcheck没有完全匹配。这个问题是怎么引起的？有必要担心这个问题么？请举一个简单例子，能够导致梯度检查失败。如何改进这个问题？*提示：SVM的损失函数不是严格可微的*

你的回答： 在SVM损失函数为0的时候不可微，因此会导致梯度检查失败。

```
# 接下来实现svm_loss_vectorized函数，目前只计算损失
# 稍后再计算梯度
tic = time.time()
loss_naive, grad_naive = svm_loss_naive(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Naive loss: %e computed in %fs' % (loss_naive, toc - tic))

from daseCV.classifiers.linear_svm import svm_loss_vectorized
tic = time.time()
loss_vectorized, _ = svm_loss_vectorized(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Vectorized loss: %e computed in %fs' % (loss_vectorized, toc - tic))

# 两种方法算出来的损失应该是相同的，但是向量化实现的方法应该更快
print('difference: %f' % (loss_naive - loss_vectorized))
```

```
Naive loss: 8.892196e+00 computed in 0.143316s
Vectorized loss: 8.892196e+00 computed in 0.013666s
difference: -0.000000
```

```
# 完成svm_loss_vectorized函数，并用向量化方法计算梯度

# 朴素方法和向量化实现的梯度应该相同，但是向量化方法也应该更快
tic = time.time()
_, grad_naive = svm_loss_naive(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Naive loss and gradient: computed in %fs' % (toc - tic))

tic = time.time()
_, grad_vectorized = svm_loss_vectorized(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Vectorized loss and gradient: computed in %fs' % (toc - tic))

# 损失是一个标量，因此很容易比较两种方法算出的值，
# 而梯度是一个矩阵，所以我们用Frobenius范数来比较梯度的值
difference = np.linalg.norm(grad_naive - grad_vectorized, ord='fro')
print('difference: %f' % difference)
```

```
Naive loss and gradient: computed in 0.181463s
Vectorized loss and gradient: computed in 0.012588s
difference: 0.000000
```

随机梯度下降（Stochastic Gradient Descent）

我们现在有了向量化的损失函数表达式和梯度表达式，同时我们计算的梯度和数值梯度是匹配的。 接下来我们要做SGD。

```
# 在linear_classifier.py文件中，编码实现LinearClassifier.train()中的SGD功能，
# 运行下面的代码
from daseCV.classifiers import LinearSVM
svm = LinearSVM()
tic = time.time()
loss_hist = svm.train(X_train, y_train, learning_rate=1e-7, reg=2.5e4,
                      num_iters=1500, verbose=True)
toc = time.time()
print('That took %fs' % (toc - tic))
```

```
iteration 0 / 1500: loss 796.151534
iteration 100 / 1500: loss 476.701954
iteration 200 / 1500: loss 289.381329
iteration 300 / 1500: loss 175.849093
iteration 400 / 1500: loss 108.290194
iteration 500 / 1500: loss 68.311668
iteration 600 / 1500: loss 42.833250
iteration 700 / 1500: loss 27.931763
iteration 800 / 1500: loss 18.707524
iteration 900 / 1500: loss 13.250270
iteration 1000 / 1500: loss 10.139097
iteration 1100 / 1500: loss 8.286372
iteration 1200 / 1500: loss 6.798005
iteration 1300 / 1500: loss 5.975257
iteration 1400 / 1500: loss 6.386796
That took 11.974452s
```

```
# 一个有用的debugging技巧是把损失函数画出来
plt.plot(loss_hist)
plt.xlabel('Iteration number')
plt.ylabel('Loss value')
plt.show()
```


```
# 完成LinearSVM.predict函数,并且在训练集和验证集上评估其准确性
y_train_pred = svm.predict(X_train)
print('training accuracy: %f' % (np.mean(y_train == y_train_pred), ))
y_val_pred = svm.predict(X_val)
print('validation accuracy: %f' % (np.mean(y_val == y_val_pred), ))
```

```
training accuracy: 0.000000
validation accuracy: 0.000000
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: DeprecationWarni
  This is separate from the ipykernel package so we can avoid doing imports until
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: DeprecationWarni
  """
```

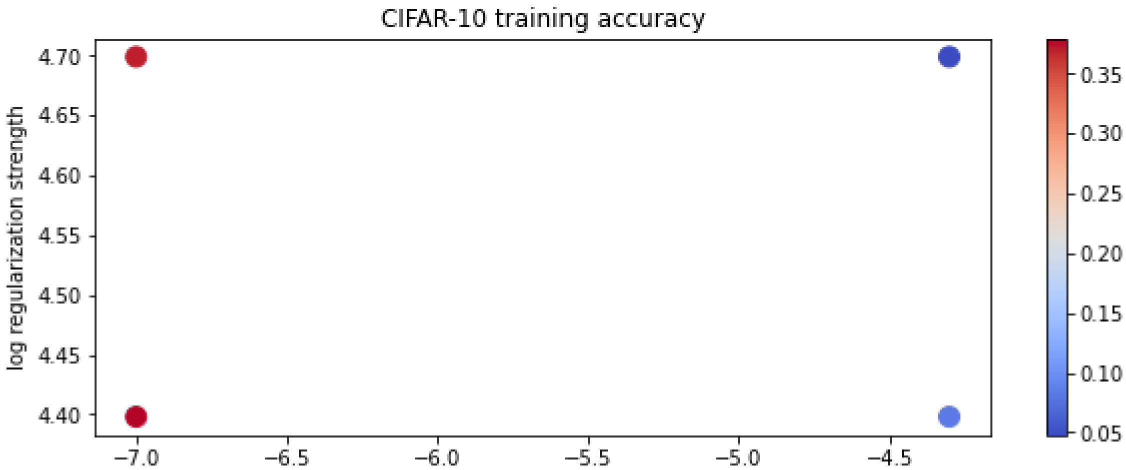
```
# 使用验证集来调整超参数(正则化强度和学习率)。
# 你可以尝试不同的学习速率和正则化项的值;
# 如果你细心的话,您应该可以在验证集上获得大约0.39的准确率。

# 注意:在搜索超参数时, 您可能会看到runtime/overflow的警告。
# 这是由极端超参值造成的,不是代码的bug。

learning_rates = [1e-7, 5e-5]
regularization_strengths = [2.5e4, 5e4]

# results是一个字典,把元组(learning_rate, regularization_strength)映射到元组(training_accu
# accuracy是样本中正确分类的比例
results = {}
best_val = -1   # 我们迄今为止见过最好的验证集准确率
best_svm = None # 拥有最高验证集准确率的LinearSVM对象

################################################################################
# TODO:
# 编写代码, 通过比较验证集的准确度来选择最佳超参数。
# 对于每个超参数组合, 在训练集上训练一个线性SVM, 在训练集和验证集上计算它的精度,
# 并将精度结果存储在results字典中。此外, 在best_val中存储最高验证集准确度,
# 在best_svm中存储拥有此精度的SVM对象。
#
```

```
# 提示：
# 在开发代码时，应该使用一个比较小的num_iter值，这样SVM就不会花费太多时间训练；
# 一旦您确信您的代码开发完成，您就应该使用一个较大的num_iter值重新训练并验证。
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# pass
for lr in learning_rates:
    for reg in regularization_strengths:
        # train svm
        print("-------------------------------")
        print("lr: %.6f, reg: %5.1f"%(lr, reg))
        svm = LinearSVM()
        svm.train(X_train, y_train, learning_rate=lr, reg=reg, num_iters=1500, verbose

        # compute accuracy
        train_accuracy = np.mean(y_train == svm.predict(X_train))
        val_accuracy = np.mean(y_val == svm.predict(X_val))
        print('train accuracy: %.4f'%(train_accuracy))
        print('validation accuracy: %.4f'%(val_accuracy))

        # store accuracy in dictionary
        results[(lr, reg)] = (train_accuracy, val_accuracy)

        # check if validation accuracy is best
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_svm = svm
# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# 打印results
for lr, reg in sorted(results):
    train_accuracy, val_accuracy = results[(lr, reg)]
    print('lr %e reg %e train accuracy: %f val accuracy: %f' % (
                lr, reg, train_accuracy, val_accuracy))

print('best validation accuracy achieved during cross-validation: %f' % best_val)
```

```
-------------------------------
lr: 0.000000, reg: 25000.0
train accuracy: 0.3791
validation accuracy: 0.3840
-------------------------------
lr: 0.000000, reg: 50000.0
train accuracy: 0.3710
validation accuracy: 0.3850
-------------------------------
lr: 0.000050, reg: 25000.0
train accuracy: 0.0829
validation accuracy: 0.0740
-------------------------------
lr: 0.000050, reg: 50000.0
/content/daseCV/classifiers/linear_svm.py:93: RuntimeWarning: overflow encounter
```

```
  loss += reg * np.sum( W * W)
/usr/local/lib/python3.7/dist-packages/numpy/core/fromnumeric.py:87: RuntimeWarn
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
/content/daseCV/classifiers/linear_svm.py:93: RuntimeWarning: overflow encounter
  loss += reg * np.sum( W * W)
train accuracy: 0.0480
validation accuracy: 0.0540
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.379082 val accuracy: 0.384000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.370980 val accuracy: 0.385000
lr 5.000000e-05 reg 2.500000e+04 train accuracy: 0.082939 val accuracy: 0.074000
lr 5.000000e-05 reg 5.000000e+04 train accuracy: 0.047959 val accuracy: 0.054000
best validation accuracy achieved during cross-validation: 0.385000
```

```
# 可是化交叉验证结果
import math
x_scatter = [math.log10(x[0]) for x in results]
y_scatter = [math.log10(x[1]) for x in results]

# 画出训练集准确率
marker_size = 100
colors = [results[x][0] for x in results]
plt.subplot(2, 1, 1)
plt.scatter(x_scatter, y_scatter, marker_size, c=colors, cmap=plt.cm.coolwarm)
plt.colorbar()
plt.xlabel('log learning rate')
plt.ylabel('log regularization strength')
plt.title('CIFAR-10 training accuracy')

# 画出验证集准确率
colors = [results[x][1] for x in results] # default size of markers is 20
plt.subplot(2, 1, 2)
plt.scatter(x_scatter, y_scatter, marker_size, c=colors, cmap=plt.cm.coolwarm)
plt.colorbar()
plt.xlabel('log learning rate')
plt.ylabel('log regularization strength')
plt.title('CIFAR-10 validation accuracy')
plt.show()
```




```
# 在测试集上测试最好的SVM分类器
y_test_pred = best_svm.predict(X_test)
test_accuracy = np.mean(y_test == y_test_pred)
print('linear SVM on raw pixels final test set accuracy: %f' % test_accuracy)
```

```
linear SVM on raw pixels final test set accuracy: 0.366000
```

```
# 画出每一类的权重
# 基于您选择的学习速度和正则化强度，画出来的可能不好看
w = best_svm.W[:-1,:] # 去掉bias
w = w.reshape(32, 32, 3, 10)
w_min, w_max = np.min(w), np.max(w)
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'tru
for i in range(10):
    plt.subplot(2, 5, i + 1)

    # 将权重调整为0到255之间
    wimg = 255.0 * (w[:, :, :, i].squeeze() - w_min) / (w_max - w_min)
    plt.imshow(wimg.astype('uint8'))
    plt.axis('off')
    plt.title(classes[i])
```

问题2

描述你的可视化权值是什么样子的，并提供一个简短的解释为什么它们看起来是这样的。

你的回答： 看起来像每个类别的均值

重要

这里是作业的结尾处，请执行以下步骤:

防止作业被吞

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

FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
FILES_TO_SAVE = ['daseCV/classifiers/linear_svm.py', 'daseCV/classifiers/linear_classi

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()))
```

✓ 0 秒 完成时间：下午3:22