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

In [1]:

```
# 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
%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
%load_ext autoreload
%autoreload 2
```

准备和预处理CIFAR-10的数据

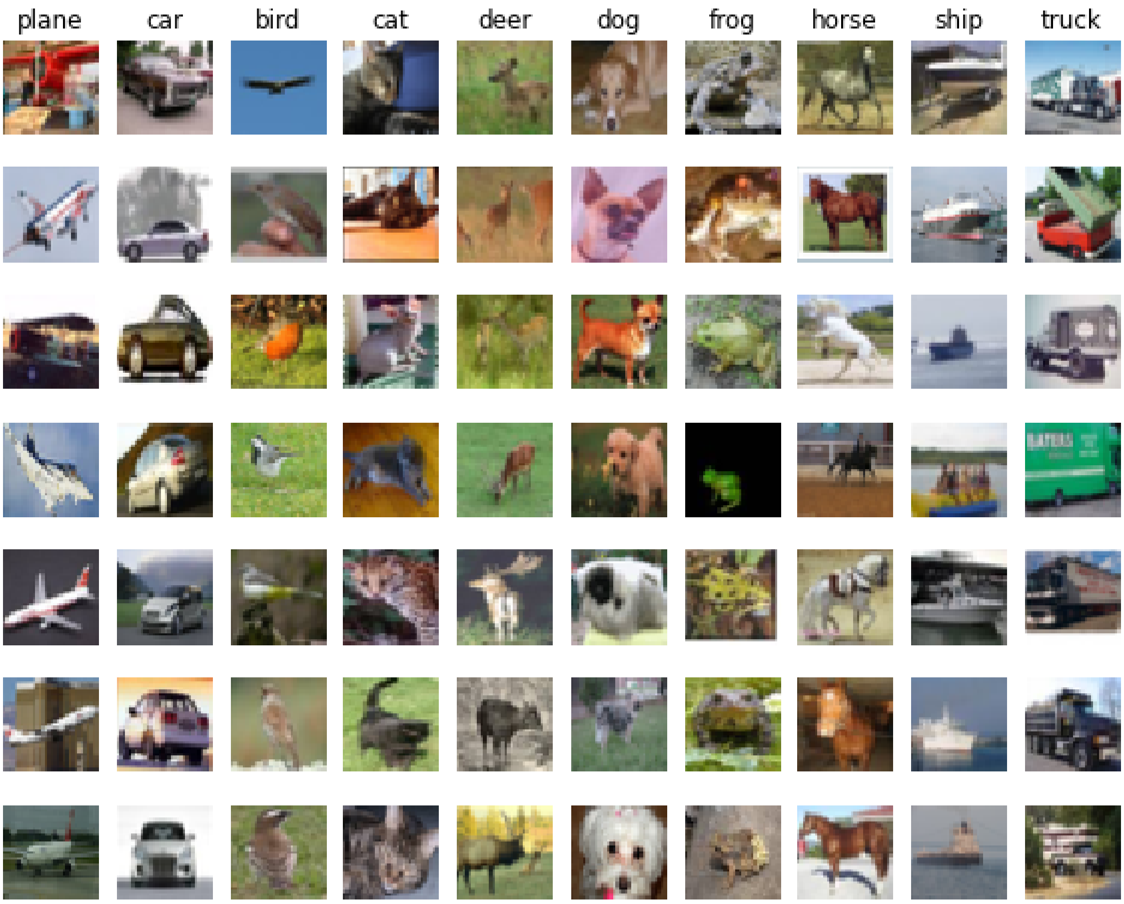
In [2]:

```
# 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,)
```

In [3]:

```
# 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()
```



In [4]:

```
# 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,)
```

In [5]:

```
# 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)
```

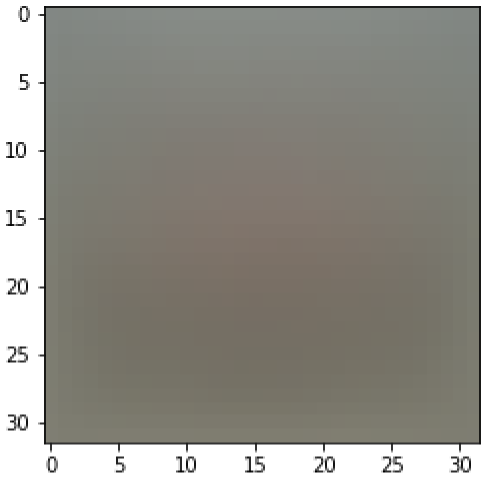
```
Training data shape:  (49000, 3072)
Validation data shape:  (1000, 3072)
Test data shape:  (1000, 3072)
dev data shape:  (500, 3072)
```

In [6]:

```
# 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

In [7]:

```
# 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: 8.505560
```

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:

In [8]:

```
# 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: 12.265425 analytic: 12.265425, relative error: 1.073525e-11
numerical: -25.077439 analytic: -25.077439, relative error: 1.023996e-11
numerical: 16.413698 analytic: 16.413698, relative error: 2.540213e-11
numerical: 10.764114 analytic: 10.764114, relative error: 1.058814e-11
numerical: 3.519302 analytic: 3.519302, relative error: 4.867798e-11
numerical: 24.318342 analytic: 24.318342, relative error: 3.619136e-12
numerical: -14.978000 analytic: -14.978000, relative error: 2.701585e-11
numerical: 0.890257 analytic: 0.890257, relative error: 2.406150e-10
numerical: 29.454000 analytic: 29.454000, relative error: 5.387872e-12
numerical: -5.055075 analytic: -5.055075, relative error: 6.321558e-11
numerical: 15.632491 analytic: 15.632491, relative error: 1.749029e-12
numerical: 8.376447 analytic: 8.376447, relative error: 2.492588e-11
numerical: 5.521101 analytic: 5.521101, relative error: 2.724934e-11
numerical: 17.958195 analytic: 17.958195, relative error: 9.465887e-12
numerical: -17.268320 analytic: -17.268320, relative error: 4.388244e-12
numerical: 3.601826 analytic: 3.601826, relative error: 1.765734e-11
numerical: -1.537920 analytic: -1.537920, relative error: 1.254608e-10
numerical: -18.474514 analytic: -18.474514, relative error: 2.490792e-11
numerical: 27.415215 analytic: 27.415215, relative error: 5.967255e-12
numerical: 3.325238 analytic: 3.325238, relative error: 2.295082e-11
```

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：

SVM损失函数并不一定是可微的，因此计算得出的解析梯度与数值梯度可能会有区别。如果max(0, a) 中 a<0，就会得到 0 ，这种情况下就不能完全匹配了。可以通过减小规模来尽量减少这样问题的发生。

SVM损失的maximum函数在零点处不可导导致了某一个维度上的gradcheck没有完全匹配。这种情况不必要担心。

能够导致梯度检查失的例子：

数值梯度dnumerical = [f(x + h) - f(x - h)] / (2 h)，当x=0时由于maximum函数使得f(- h)=0，此时dnumerical = f(h) / (2 h)

解析梯度danalytic = 0不等于数值梯度。

减小h可以改善这种情况。

In [9]:
```
# 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: 8.505560e+00 computed in 0.501905s
Vectorized loss: 8.505560e+00 computed in 0.004689s
difference: -0.000000
```

In [10]:

```
# 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 1.396679s
Vectorized loss and gradient: computed in 0.004589s
difference: 0.000000
```

随机梯度下降（Stochastic Gradient Descent）

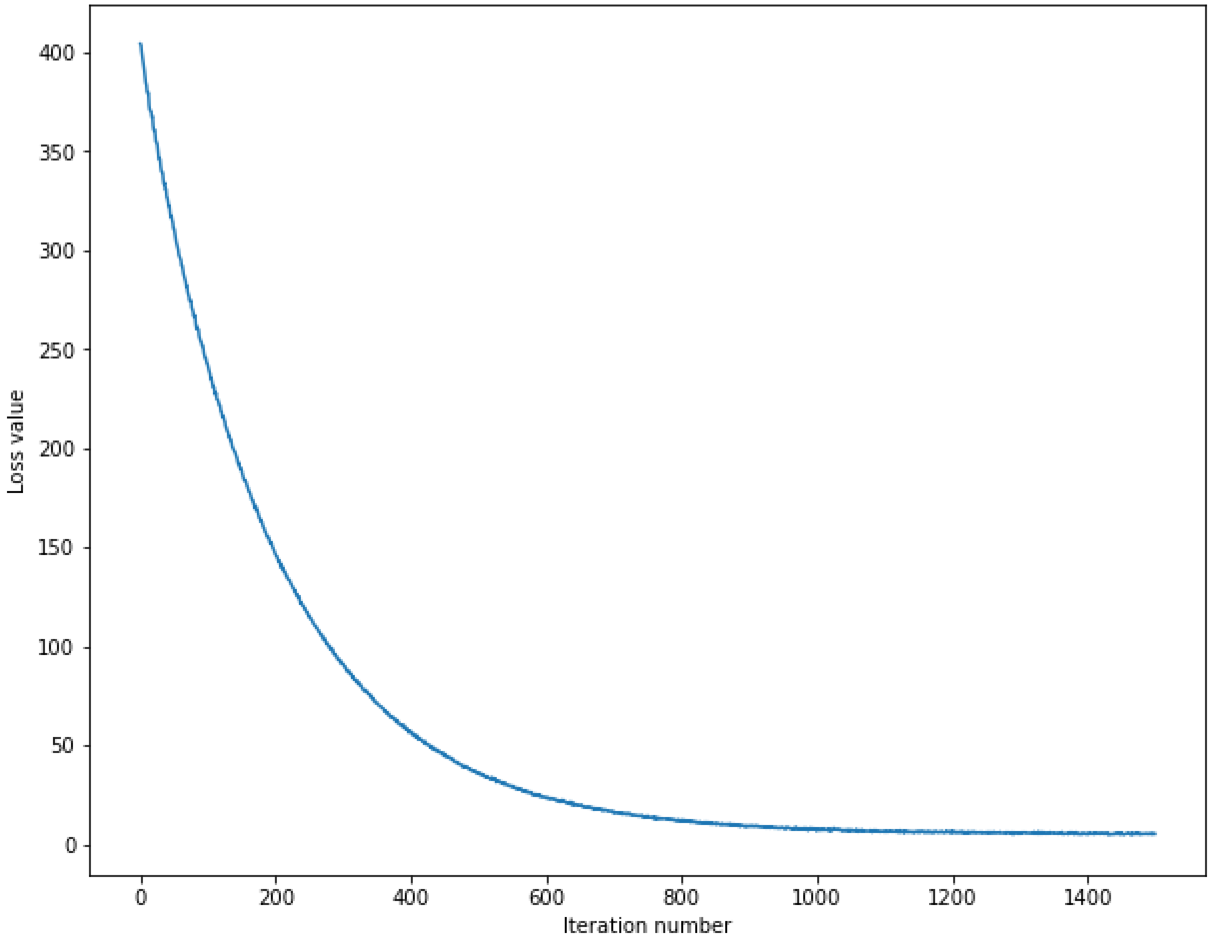
我们现在有了向量化的损失函数表达式和梯度表达式，同时我们计算的梯度和数值梯度是匹配的。 接下来我们要做SGD。

In [11]:

```
# 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 404.282552
iteration 100 / 1500: loss 241.258133
iteration 200 / 1500: loss 146.253508
iteration 300 / 1500: loss 90.914405
iteration 400 / 1500: loss 56.904966
iteration 500 / 1500: loss 35.974580
iteration 600 / 1500: loss 23.344221
iteration 700 / 1500: loss 15.653573
iteration 800 / 1500: loss 11.731714
iteration 900 / 1500: loss 8.933918
iteration 1000 / 1500: loss 7.143474
iteration 1100 / 1500: loss 6.577221
iteration 1200 / 1500: loss 5.717763
iteration 1300 / 1500: loss 5.223116
iteration 1400 / 1500: loss 4.947980
That took 47.599225s
```

In [12]:
```
# 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()
```



In [13]:
```
# 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: 0.378898
validation accuracy: 0.398000
```

In [14]:
```
# 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_
# 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)*****

for lr in learning_rates:
    for rs in regularization_strengths:
        svm = LinearSVM()
        loss_hist = svm.train(X_train, y_train, learning_rate=lr, reg=rs, num_iters=2
        y_train_pred = svm.predict(X_train)
        train_acc = np.mean(y_train == y_train_pred)
        y_val_pred = svm.predict(X_val)
        val_acc = np.mean(y_val == y_val_pred)

        results[(lr, rs)] = (train_acc, val_acc)

        if val_acc > best_val:
            best_val = val_acc
            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)
```

```
iteration 0 / 2000: loss 414.511306
iteration 100 / 2000: loss 243.034494
iteration 200 / 2000: loss 147.262926
iteration 300 / 2000: loss 89.669825
iteration 400 / 2000: loss 56.281823
iteration 500 / 2000: loss 36.718504
iteration 600 / 2000: loss 24.000226
iteration 700 / 2000: loss 16.655087
iteration 800 / 2000: loss 12.007787
iteration 900 / 2000: loss 9.469810
iteration 1000 / 2000: loss 7.394045
iteration 1100 / 2000: loss 6.413827
iteration 1200 / 2000: loss 5.973528
iteration 1300 / 2000: loss 5.516387
iteration 1400 / 2000: loss 5.055509
iteration 1500 / 2000: loss 5.771968
iteration 1600 / 2000: loss 5.582649
iteration 1700 / 2000: loss 5.130109
iteration 1800 / 2000: loss 4.789993
iteration 1900 / 2000: loss 4.547126
iteration 0 / 2000: loss 805.574586
iteration 100 / 2000: loss 292.742839
iteration 200 / 2000: loss 109.272698
iteration 300 / 2000: loss 43.231203
iteration 400 / 2000: loss 19.200756
iteration 500 / 2000: loss 10.468064
iteration 600 / 2000: loss 7.250755
iteration 700 / 2000: loss 6.014274
```

```
iteration 800 / 2000: loss 6.048282
iteration 900 / 2000: loss 5.268002
iteration 1000 / 2000: loss 5.459758
iteration 1100 / 2000: loss 5.071448
iteration 1200 / 2000: loss 5.405700
iteration 1300 / 2000: loss 5.553137
iteration 1400 / 2000: loss 5.442683
iteration 1500 / 2000: loss 5.399471
iteration 1600 / 2000: loss 5.852035
iteration 1700 / 2000: loss 5.954318
iteration 1800 / 2000: loss 5.687477
iteration 1900 / 2000: loss 5.129230
iteration 0 / 2000: loss 415.162528
iteration 100 / 2000: loss 1014.344783
iteration 200 / 2000: loss 1048.364032
iteration 300 / 2000: loss 1071.770320
iteration 400 / 2000: loss 1157.161657
iteration 500 / 2000: loss 1050.005995
iteration 600 / 2000: loss 926.186339
iteration 700 / 2000: loss 913.983089
iteration 800 / 2000: loss 1048.000609
iteration 900 / 2000: loss 931.537353
iteration 1000 / 2000: loss 936.359841
iteration 1100 / 2000: loss 1138.386381
iteration 1200 / 2000: loss 747.332796
iteration 1300 / 2000: loss 953.135496
iteration 1400 / 2000: loss 717.424910
iteration 1500 / 2000: loss 1142.510101
iteration 1600 / 2000: loss 756.092058
iteration 1700 / 2000: loss 1097.428725
iteration 1800 / 2000: loss 1143.095743
iteration 1900 / 2000: loss 973.013949
iteration 0 / 2000: loss 790.031738
iteration 100 / 2000: loss 42558263648644407127165341987634570854 4.000000
```

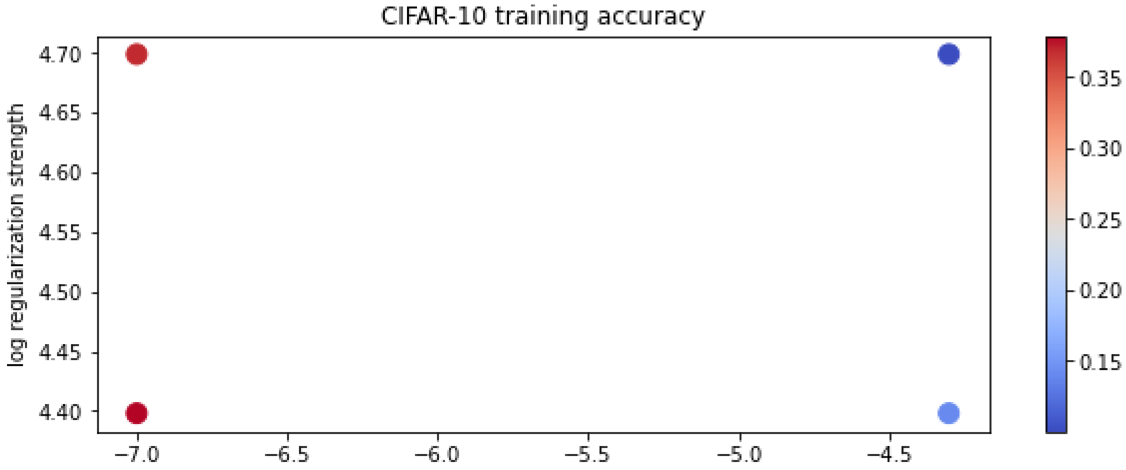
```
iteration 200 / 2000: loss 7034540135341947098256850427257444506793565374434966100154 2
669128729362432.000000
iteration 300 / 2000: loss 1162753145294566410531803030373038894702696641410475113957 0
243815742970303308600961668427014364130151290109952.000000
iteration 400 / 2000: loss 1921937825189034105867135130205583641618957390118064439657 7
8996548837473982634097357885129690714985847874012019770924655119412084071726144343244
8.000000
iteration 500 / 2000: loss 3176809298551991896841247405656004747568916080157657861015 0
5439233738796842406094633327557227124468944920439012981372593260688186143867875844555 8
852699654576479688820957413071912 96.000000
iteration 600 / 2000: loss 5251011342353791761951444570244371189534913068809067692078 5
7318290169652879779537922388023224160851249386982222532410278846869182470030957435100 7
8794308490101123672331109788513032221985764811608522493331867640528896.000000
iteration 700 / 2000: loss 8679501199551436066970823176440637780666213847137107224544 1
4148390564225873959620949006655648909556992167733903057609969239864584589207353425926 1
0861986938447082075183433000935663980327081953486056527001850624145398056872880921717 9
4568009839410151424.000000
iteration 800 / 2000: loss 1434652034844893517268960889184926810784040174396239925879 1
2029786430625114328977273897069884426858876868221759025071509666587986474830109653990 6
5813341580133695265713968041384839365467197302947943687301716038868171544888913645057 4
063757107787994595950685255945107829344894999951153561 6.000000
```

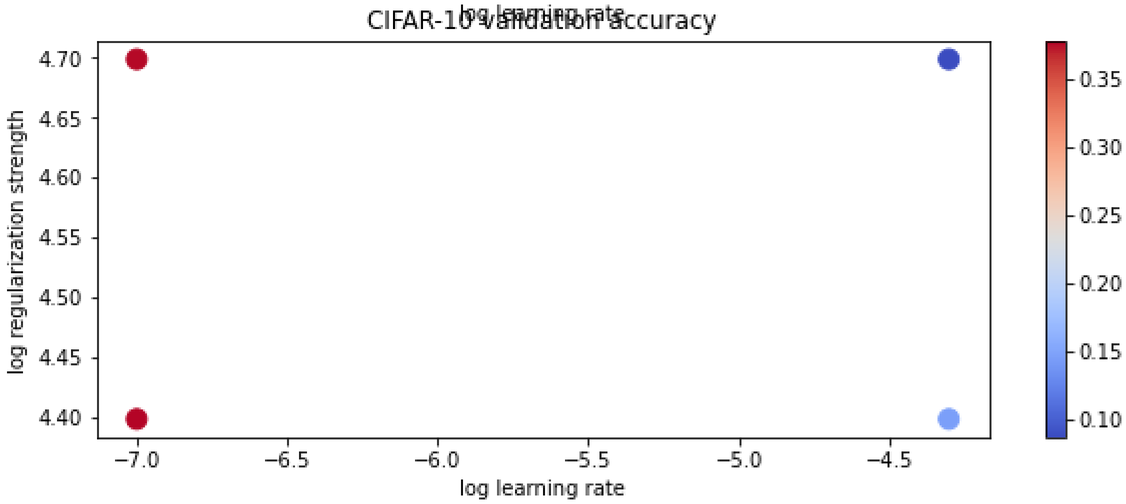
```
/home/public/10215501435-1442-161/daseCV/classifiers/linear_svm.py:87: RuntimeWarning:
overflow encountered in double_scalars
  loss = np.sum(margins) / num_train + 0.5 * reg * np.sum(W * W)
/opt/conda/lib/python3.9/site-packages/numpy/core/fromnumeric.py:87: RuntimeWarning: o
verflow encountered in reduce
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
/home/public/10215501435-1442-161/daseCV/classifiers/linear_svm.py:87: RuntimeWarning:
overflow encountered in multiply
  loss = np.sum(margins) / num_train + 0.5 * reg * np.sum(W * W)
iteration 900 / 2000: loss inf
iteration 1000 / 2000: loss inf
iteration 1100 / 2000: loss inf
iteration 1200 / 2000: loss inf
iteration 1300 / 2000: loss inf
```

```
iteration 1400 / 2000: loss inf
iteration 1500 / 2000: loss inf
iteration 1600 / 2000: loss inf
iteration 1700 / 2000: loss inf
/home/public/10215501435-1442-161/daseCV/classifiers/linear_svm.py:85: RuntimeWarning: overflow encountered in subtract
  margins = np.maximum(0, scores - correct_class_scores +1)
/home/public/10215501435-1442-161/daseCV/classifiers/linear_svm.py:85: RuntimeWarning: invalid value encountered in subtract
  margins = np.maximum(0, scores - correct_class_scores +1)
/home/public/10215501435-1442-161/daseCV/classifiers/linear_svm.py:105: RuntimeWarning: overflow encountered in multiply
  dW = dW/num_train + reg*W
/home/public/10215501435-1442-161/daseCV/classifiers/linear_classifier.py:72: RuntimeWarning: invalid value encountered in add
  self.W += - learning_rate * grad
iteration 1800 / 2000: loss nan
iteration 1900 / 2000: loss nan
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.378653 val accuracy: 0.378000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.368469 val accuracy: 0.376000
lr 5.000000e-05 reg 2.500000e+04 train accuracy: 0.141082 val accuracy: 0.145000
lr 5.000000e-05 reg 5.000000e+04 train accuracy: 0.100265 val accuracy: 0.087000
best validation accuracy achieved during cross-validation: 0.378000
```

In [15]:

```
# 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()
```





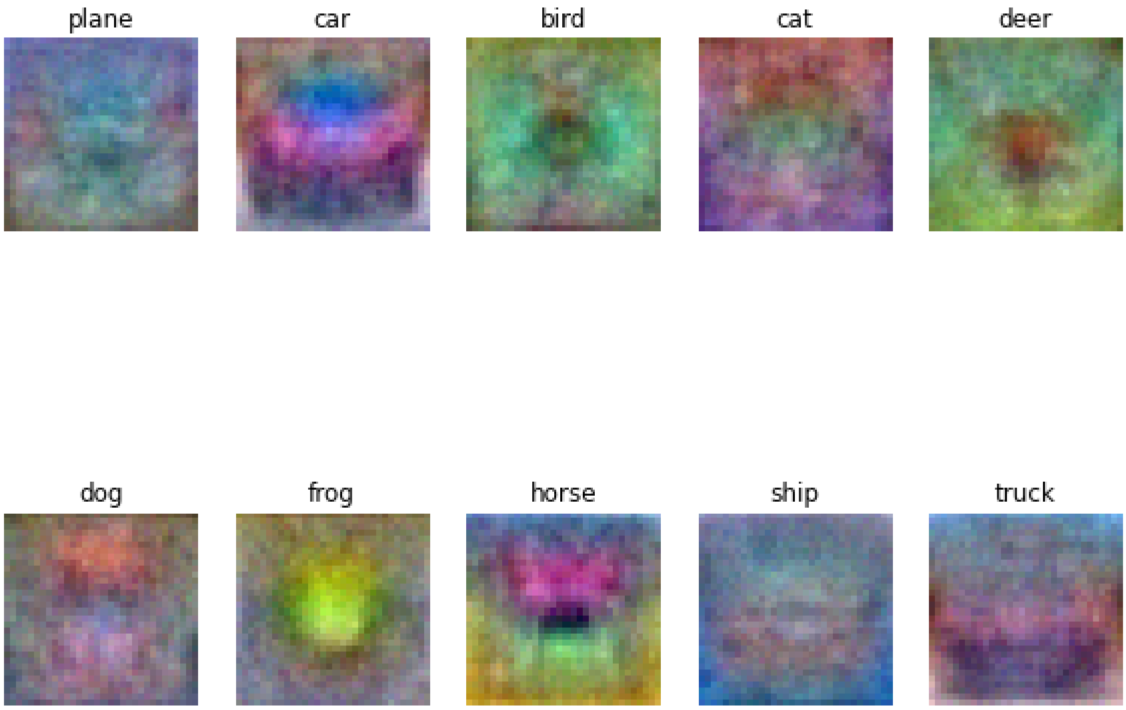
In [16]:

```
# 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: 0.386000
```

In [17]:

```
# 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：

看起来像数据集中一个类别的图片平均下来的样子，单看权值可能不像tag所描述的样子，这可能是因为数据集中的一个物体的特征出现在了图片的不同方位，因此出现了各种图片的特征看起来重合起来的情况。svm的权重是对应类别的训练集的平均，因为权重跟训练集的图像越相似，做内积的时候得分越高，通过训练svm会使得权重跟该类别的平均值接近。

Data for leaderboard

这里额外提供了一组未给标签的测试集X，用于leaderborad上的竞赛。

提示：该题的目的是鼓励同学们探索能够提升模型性能的方法。

In [19]:

```
# leaderboard的测试数据
X = np.load("./input/X_3073.npy")
################################################################################
# 需要完成的事情:
# 找到更合适的svm
# 提示：如果你不想花时间，你也可以直接使用上面已经训练好的best_svm。
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
svm_leaderboard = best_svm
preds = svm_leaderboard.predict(X)
```

提醒：运行完下面代码之后，点击下面的submit，然后去leaderboard上查看你的成绩。本模型对应的成绩在phase2的leaderboard中。

In [20]:

```
import os
#输出格式
def output_file(preds, phase_id=2):
```

```
    path=os.getcwd()
    if not os.path.exists(path + '/output/phase_{}'.format(phase_id)):
        os.mkdir(path + '/output/phase_{}'.format(phase_id))
    path=path + '/output/phase_{}/prediction.npy'.format(phase_id)
    np.save(path,preds)
def zip_fun(phase_id=2):
    path=os.getcwd()
    output_path = path + '/output'
    files = os.listdir(output_path)
    for _file in files:
        if _file.find('zip') != -1:
            os.remove(output_path + '/' + _file)
    newpath=path+'/output/phase_{}'.format(phase_id)
    os.chdir(newpath)
    cmd = 'zip ../prediction_phase_{}.zip prediction.npy'.format(phase_id)
    os.system(cmd)
    os.chdir(path)
output_file(preds)
zip_fun()
```

In [ ]: