Multiclass Support Vector Machine exercise

Complete and hand in this completed worksheet (including its outputs and any supporting code outside of the worksheet) with your assignment submission. For more details see the [assignments page (http://vision.stanford.edu/teaching/cs231n/assignments.html)](http://vision.stanford.edu/teaching/cs231n/assignments.html) on the course website.

In this exercise you will:

- implement a fully-vectorized **loss function** for the SVM
- implement the fully-vectorized expression for its **analytic gradient**
- **check your implementation** using numerical gradient
- use a validation set to **tune the learning rate and regularization** strength
- **optimize** the loss function with **SGD**
- **visualize** the final learned weights

In [134]:

```
# Run some setup code for this notebook.
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

# This is a bit of magic to make matplotlib figures appear inline in t
he
# notebook rather than in a new window.
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plo
ts
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# Some more magic so that the notebook will reload external python mod
ules;
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules
-in-ipython
%load_ext autoreload
%autoreload 2
```

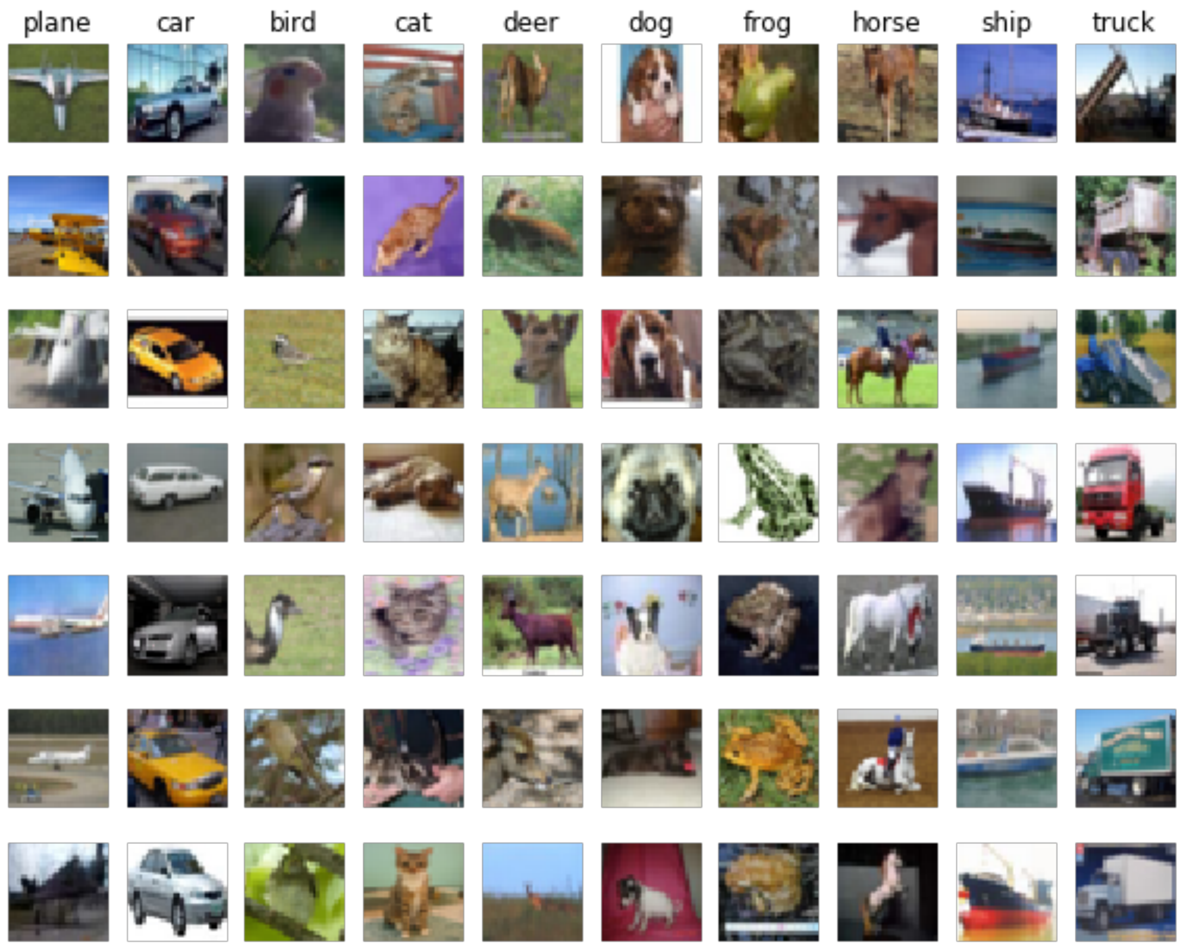
```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

CIFAR-10 Data Loading and Preprocessing

In [135]:
```
# Load the raw CIFAR-10 data.
cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

# Cleaning up variables to prevent loading data multiple times (which
may cause memory issue)
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)

# As a sanity check, we print out the size of the training and test da
ta.
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,)
```

In [136]:
```
# Visualize some examples from the dataset.
# We show a few examples of training images from each class.
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'hors
e', 'ship', 'truck']
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()
```


plane
car
bird
cat
deer
dog
frog
horse
ship
truck

In [137]:

```
# Split the data into train, val, and test sets. In addition we will
# create a small development set as a subset of the training data;
# we can use this for development so our code runs faster.
num_training = 49000
num_validation = 1000
num_test = 1000
num_dev = 500

# Our validation set will be num_validation points from the original
# training set.
mask = range(num_training, num_training + num_validation)
X_val = X_train[mask]
y_val = y_train[mask]

# Our training set will be the first num_train points from the origina
l
# training set.
mask = range(num_training)
X_train = X_train[mask]
y_train = y_train[mask]

# We will also make a development set, which is a small subset of
# the training set.
mask = np.random.choice(num_training, num_dev, replace=False)
X_dev = X_train[mask]
y_dev = y_train[mask]

# We use the first num_test points of the original test set as our
# test set.
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)
```

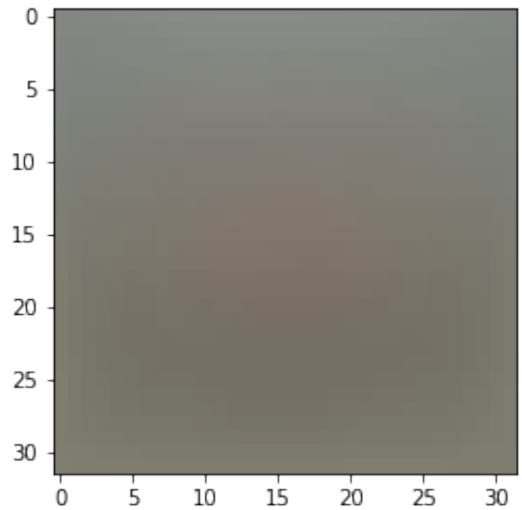
```
Train data shape:  (49000, 32, 32, 3)
Train labels shape:  (49000,)
Validation data shape:  (1000, 32, 32, 3)
Validation labels shape:  (1000,)
Test data shape:  (1000, 32, 32, 3)
Test labels shape:  (1000,)
```

In [138]:
```
# Preprocessing: reshape the image data into rows
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))

# As a sanity check, print out the shapes of the data
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 [139]:
```
# Preprocessing: subtract the mean image
# first: compute the image mean based on the training data
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()

# second: subtract the mean image from train and test data
X_train -= mean_image
X_val -= mean_image
X_test -= mean_image
X_dev -= mean_image

# third: append the bias dimension of ones (i.e. bias trick) so that o
ur SVM
# only has to worry about optimizing a single weight matrix 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 Classifier

Your code for this section will all be written inside `cs231n/classifiers/linear_svm.py` .

As you can see, we have prefilled the function `svm_loss_naive` which uses for loops to evaluate the multiclass SVM loss function.

In [140]:
```
# Evaluate the naive implementation of the loss we provided for you:
from cs231n.classifiers.linear_svm import svm_loss_naive
import time

# generate a random SVM weight matrix of small numbers
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: 9.556129
```

The `grad` returned from the function above is right now all zero. Derive and implement the gradient for the SVM cost function and implement it inline inside the function `svm_loss_naive` . You will find it helpful to interleave your new code inside the existing function.

To check that you have correctly implemented the gradient correctly, you can numerically estimate the gradient of the loss function and compare the numeric estimate to the gradient that you computed. We have provided code that does this for you:

In [141]:

```
# Once you've implemented the gradient, recompute it with the code bel
ow
# and gradient check it with the function we provided for you

# Compute the loss and its gradient at W.
loss, grad = svm_loss_naive(W, X_dev, y_dev, 0.0)

# Numerically compute the gradient along several randomly chosen dimen
sions, and
# compare them with your analytically computed gradient. The numbers s
hould match
# almost exactly along all dimensions.
from cs231n.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)

# do the gradient check once again with regularization turned on
# you didn't forget the regularization gradient did you?
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: 1.398617 analytic: 0.000000, relative error: 1.000000e+00
numerical: 6.894196 analytic: 0.000000, relative error: 1.000000e+00
numerical: -36.241177 analytic: 0.000000, relative error: 1.000000e+
00
numerical: 12.263645 analytic: 0.000000, relative error: 1.000000e+0
0
numerical: -8.174303 analytic: 0.000000, relative error: 1.000000e+0
0
numerical: 27.384101 analytic: 0.000000, relative error: 1.000000e+0
0
numerical: -29.206113 analytic: 0.000000, relative error: 1.000000e+
00
numerical: -0.072241 analytic: 0.000000, relative error: 1.000000e+0
0
numerical: 8.244012 analytic: 0.000000, relative error: 1.000000e+00
numerical: 10.005147 analytic: 0.000000, relative error: 1.000000e+0
0
numerical: 0.506922 analytic: 0.005874, relative error: 9.770913e-01
numerical: -1.811488 analytic: 0.005121, relative error: 1.000000e+0
0
numerical: 42.397012 analytic: 0.001566, relative error: 9.999262e-0
1
numerical: 32.493101 analytic: -0.018471, relative error: 1.000000e+
00
numerical: -3.961386 analytic: 0.006077, relative error: 1.000000e+0
0
numerical: -2.258468 analytic: 0.002197, relative error: 1.000000e+0
0
numerical: 5.272086 analytic: -0.022157, relative error: 1.000000e+0
0
numerical: -0.514169 analytic: 0.005980, relative error: 1.000000e+0
0
numerical: -9.784324 analytic: 0.006605, relative error: 1.000000e+0
0
numerical: -11.236171 analytic: 0.002423, relative error: 1.000000e+
00
```

Inline Question 1

It is possible that once in a while a dimension in the gradcheck will not match exactly. What could such a discrepancy be caused by? Is it a reason for concern? What is a simple example in one dimension where a gradient check could fail? How would change the margin affect of the frequency of this happening? *Hint: the SVM loss function is not strictly speaking differentiable*

$\color{blue}{Your Answer:}$ Not entirely sure what the question is asking. If we are referring to when there are discrepencies with the loss function, then yes, it could be that the loss function does not fully differentiate which causes the gradcheck to not match exactly.

In [142]:

```
# Next implement the function svm_loss_vectorized; for now only comput
e the loss;
# we will implement the gradient in a moment.
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 cs231n.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))

# The losses should match but your vectorized implementation should be
much faster.
print('difference: %f' % (loss_naive - loss_vectorized))
```

```
Naive loss: 9.556129e+00 computed in 0.014977s
Vectorized loss: 9.556129e+00 computed in 0.002795s
difference: 0.000000
```

In [148]:

```
# Complete the implementation of svm_loss_vectorized, and compute the
gradient
# of the loss function in a vectorized way.

# The naive implementation and the vectorized implementation should ma
tch, but
# the vectorized version should still be much faster.
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))

# The loss is a single number, so it is easy to compare the values com
puted
# by the two implementations. The gradient on the other hand is a matr
ix, so
# we use the Frobenius norm to compare them.
difference = np.linalg.norm(grad_naive - grad_vectorized, ord='fro')
print('difference: %f' % difference)
```

```
Naive loss and gradient: computed in 0.013766s
Vectorized loss and gradient: computed in 0.000287s
difference: 0.000000
```

Stochastic Gradient Descent

We now have vectorized and efficient expressions for the loss, the gradient and our gradient matches the numerical gradient. We are therefore ready to do SGD to minimize the loss. Your code for this part will be written inside `cs231n/classifiers/linear_classifier.py` .

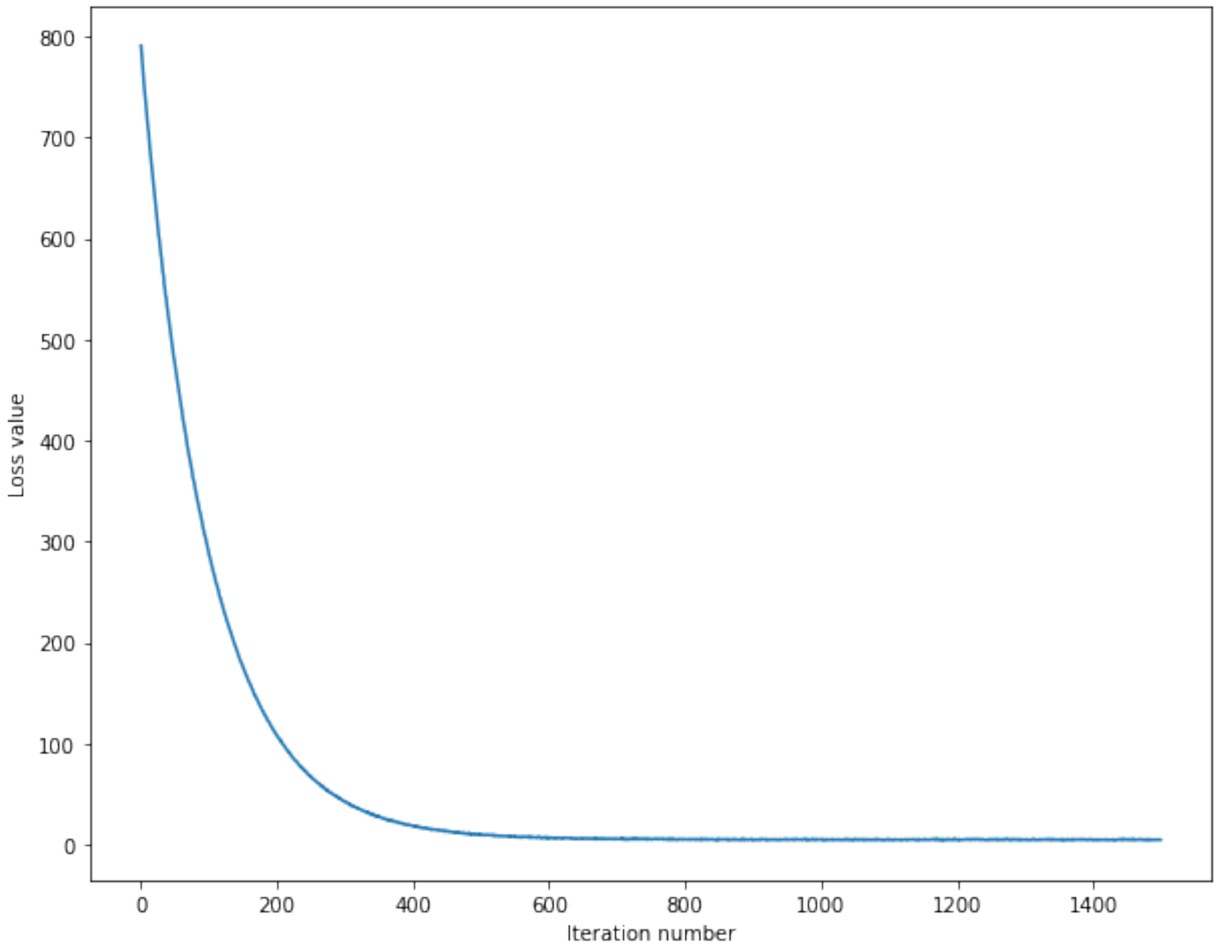
In [144]:

```
# In the file linear_classifier.py, implement SGD in the function
# LinearClassifier.train() and then run it with the code below.
from cs231n.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 790.718095
iteration 100 / 1500: loss 286.693907
iteration 200 / 1500: loss 107.788907
iteration 300 / 1500: loss 43.050307
iteration 400 / 1500: loss 18.666922
iteration 500 / 1500: loss 9.911225
iteration 600 / 1500: loss 6.825496
iteration 700 / 1500: loss 6.095525
iteration 800 / 1500: loss 5.745249
iteration 900 / 1500: loss 4.891450
iteration 1000 / 1500: loss 5.554712
iteration 1100 / 1500: loss 5.305421
iteration 1200 / 1500: loss 5.030613
iteration 1300 / 1500: loss 5.282118
iteration 1400 / 1500: loss 5.450685
That took 3.111909s
```

In [145]:

```
# A useful debugging strategy is to plot the loss as a function of
# iteration number:
plt.plot(loss_hist)
plt.xlabel('Iteration number')
plt.ylabel('Loss value')
plt.show()
```



In [146]:

```
# Write the LinearSVM.predict function and evaluate the performance on
both the
# training and validation set
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: 0.371510
validation accuracy: 0.377000
```

In [130]:

```
# Use the validation set to tune hyperparameters (regularization stren
gth and
# learning rate). You should experiment with different ranges for the
learning
# rates and regularization strengths; if you are careful you should be
able to
# get a classification accuracy of about 0.39 on the validation set.
```

```
# Note: you may see runtime/overflow warnings during hyper-parameter s
earch.
# This may be caused by extreme values, and is not a bug.

# results is dictionary mapping tuples of the form
# (learning_rate, regularization_strength) to tuples of the form
# (training_accuracy, validation_accuracy). The accuracy is simply the
fraction
# of data points that are correctly classified.
results = {}
best_val = -1   # The highest validation accuracy that we have seen so
far.
best_svm = None # The LinearSVM object that achieved the highest valid
ation rate.

######################################################################
##########
# TODO:
#
# Write code that chooses the best hyperparameters by tuning on the va
lidation #
# set. For each combination of hyperparameters, train a linear SVM on
the      #
# training set, compute its accuracy on the training and validation se
ts, and  #
# store these numbers in the results dictionary. In addition, store th
e best   #
# validation accuracy in best_val and the LinearSVM object that achiev
es this  #
# accuracy in best_svm.
#
#
#
# Hint: You should use a small value for num_iters as you develop your
#
# validation code so that the SVMs don't take much time to train; once
you are #
# confident that your validation code works, you should rerun the vali
dation   #
# code with a larger value for num_iters.
#
######################################################################
##########

# Provided as a reference. You may or may not want to change these hyp
erparameters
learning_rates = [1e-7, 5e-5]
regularization_strengths = [2.5e4, 5e4]

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

```
for lr in learning_rates:
    for reg in regularization_strengths:
        #linear SVM - updated above already
        loss_hist = svm.train(X_train, y_train, learning_rate=lr, reg=
reg, num_iters=10000,
                    verbose=True)
        #pull from above - y_train_pred = svm.predict(X_train)
        train_accuracy = np.mean(svm.predict(X_train) == y_train)
        #pull from above - y_val_pred = svm.predict(X_val)
        val_accuracy = np.mean(svm.predict(X_val) == y_val)

        if val_accuracy > best_val:
            best_val = val_accuracy
            best_svm = svm




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

# Print out 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)
```

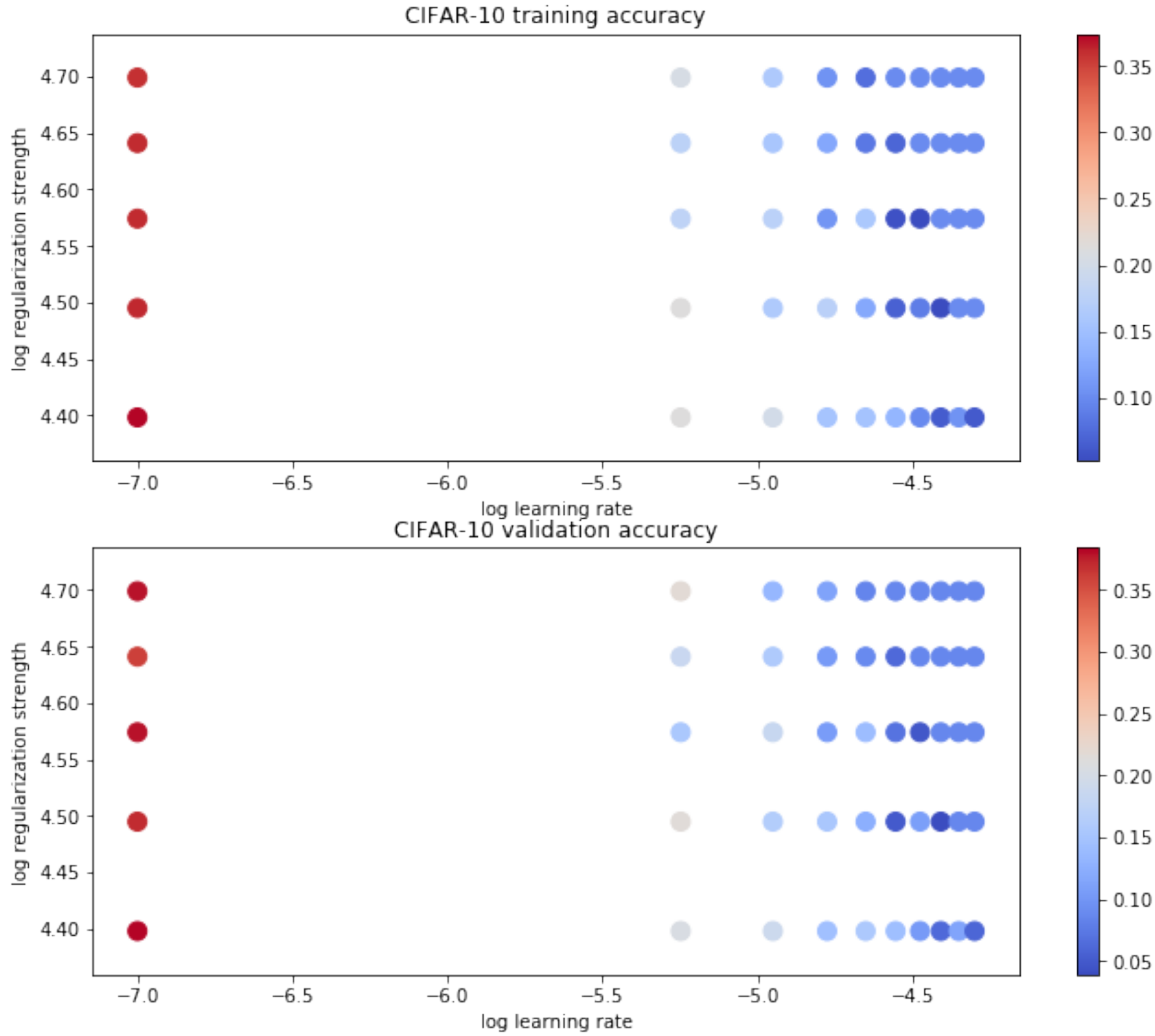
```
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.374000 val accura
cy: 0.384000
lr 1.000000e-07 reg 3.125000e+04 train accuracy: 0.363857 val accura
cy: 0.371000
lr 1.000000e-07 reg 3.750000e+04 train accuracy: 0.362408 val accura
cy: 0.379000
lr 1.000000e-07 reg 4.375000e+04 train accuracy: 0.362000 val accura
cy: 0.361000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.358959 val accura
cy: 0.379000
lr 5.644444e-06 reg 2.500000e+04 train accuracy: 0.213612 val accura
cy: 0.205000
lr 5.644444e-06 reg 3.125000e+04 train accuracy: 0.214143 val accura
cy: 0.216000
lr 5.644444e-06 reg 3.750000e+04 train accuracy: 0.179245 val accura
cy: 0.156000
lr 5.644444e-06 reg 4.375000e+04 train accuracy: 0.177041 val accura
cy: 0.186000
lr 5.644444e-06 reg 5.000000e+04 train accuracy: 0.204653 val accura
cy: 0.219000
lr 1.118889e-05 reg 2.500000e+04 train accuracy: 0.200265 val accura
cy: 0.190000
lr 1.118889e-05 reg 3.125000e+04 train accuracy: 0.165102 val accura
cy: 0.163000
lr 1.118889e-05 reg 3.750000e+04 train accuracy: 0.176143 val accura
cy: 0.185000
```

```
lr 1.118889e-05 reg 4.375000e+04 train accuracy: 0.158082 val accura
cy: 0.159000
lr 1.118889e-05 reg 5.000000e+04 train accuracy: 0.163878 val accura
cy: 0.134000
lr 1.673333e-05 reg 2.500000e+04 train accuracy: 0.155796 val accura
cy: 0.145000
lr 1.673333e-05 reg 3.125000e+04 train accuracy: 0.174714 val accura
cy: 0.154000
lr 1.673333e-05 reg 3.750000e+04 train accuracy: 0.108673 val accura
cy: 0.106000
lr 1.673333e-05 reg 4.375000e+04 train accuracy: 0.124633 val accura
cy: 0.104000
lr 1.673333e-05 reg 5.000000e+04 train accuracy: 0.106776 val accura
cy: 0.112000
lr 2.227778e-05 reg 2.500000e+04 train accuracy: 0.155184 val accura
cy: 0.157000
lr 2.227778e-05 reg 3.125000e+04 train accuracy: 0.126204 val accura
cy: 0.124000
lr 2.227778e-05 reg 3.750000e+04 train accuracy: 0.161061 val accura
cy: 0.141000
lr 2.227778e-05 reg 4.375000e+04 train accuracy: 0.085898 val accura
cy: 0.089000
lr 2.227778e-05 reg 5.000000e+04 train accuracy: 0.077653 val accura
cy: 0.085000
lr 2.782222e-05 reg 2.500000e+04 train accuracy: 0.140184 val accura
cy: 0.144000
lr 2.782222e-05 reg 3.125000e+04 train accuracy: 0.067490 val accura
cy: 0.051000
lr 2.782222e-05 reg 3.750000e+04 train accuracy: 0.056857 val accura
cy: 0.070000
lr 2.782222e-05 reg 4.375000e+04 train accuracy: 0.071082 val accura
cy: 0.062000
lr 2.782222e-05 reg 5.000000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 3.336667e-05 reg 2.500000e+04 train accuracy: 0.098959 val accura
cy: 0.105000
lr 3.336667e-05 reg 3.125000e+04 train accuracy: 0.088898 val accura
cy: 0.108000
lr 3.336667e-05 reg 3.750000e+04 train accuracy: 0.052367 val accura
cy: 0.048000
lr 3.336667e-05 reg 4.375000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 3.336667e-05 reg 5.000000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 3.891111e-05 reg 2.500000e+04 train accuracy: 0.064714 val accura
cy: 0.063000
lr 3.891111e-05 reg 3.125000e+04 train accuracy: 0.052224 val accura
cy: 0.039000
lr 3.891111e-05 reg 3.750000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 3.891111e-05 reg 4.375000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 3.891111e-05 reg 5.000000e+04 train accuracy: 0.100265 val accura
```

```
cy: 0.087000
lr 4.445556e-05 reg 2.500000e+04 train accuracy: 0.107408 val accura
cy: 0.114000
lr 4.445556e-05 reg 3.125000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 4.445556e-05 reg 3.750000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 4.445556e-05 reg 4.375000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 4.445556e-05 reg 5.000000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 5.000000e-05 reg 2.500000e+04 train accuracy: 0.063388 val accura
cy: 0.060000
lr 5.000000e-05 reg 3.125000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 5.000000e-05 reg 3.750000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 5.000000e-05 reg 4.375000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
lr 5.000000e-05 reg 5.000000e+04 train accuracy: 0.100265 val accura
cy: 0.087000
best validation accuracy achieved during cross-validation: 0.384000
```

In [131]:

```
# Visualize the cross-validation results
import math
import pdb

# pdb.set_trace()

x_scatter = [math.log10(x[0]) for x in results]
y_scatter = [math.log10(x[1]) for x in results]

# plot training accuracy
marker_size = 100
colors = [results[x][0] for x in results]
plt.subplot(2, 1, 1)
plt.tight_layout(pad=3)
plt.scatter(x_scatter, y_scatter, marker_size, c=colors, cmap=plt.cm.c
oolwarm)
plt.colorbar()
plt.xlabel('log learning rate')
plt.ylabel('log regularization strength')
plt.title('CIFAR-10 training accuracy')

# plot validation accuracy
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.c
oolwarm)
plt.colorbar()
plt.xlabel('log learning rate')
plt.ylabel('log regularization strength')
plt.title('CIFAR-10 validation accuracy')
plt.show()
```



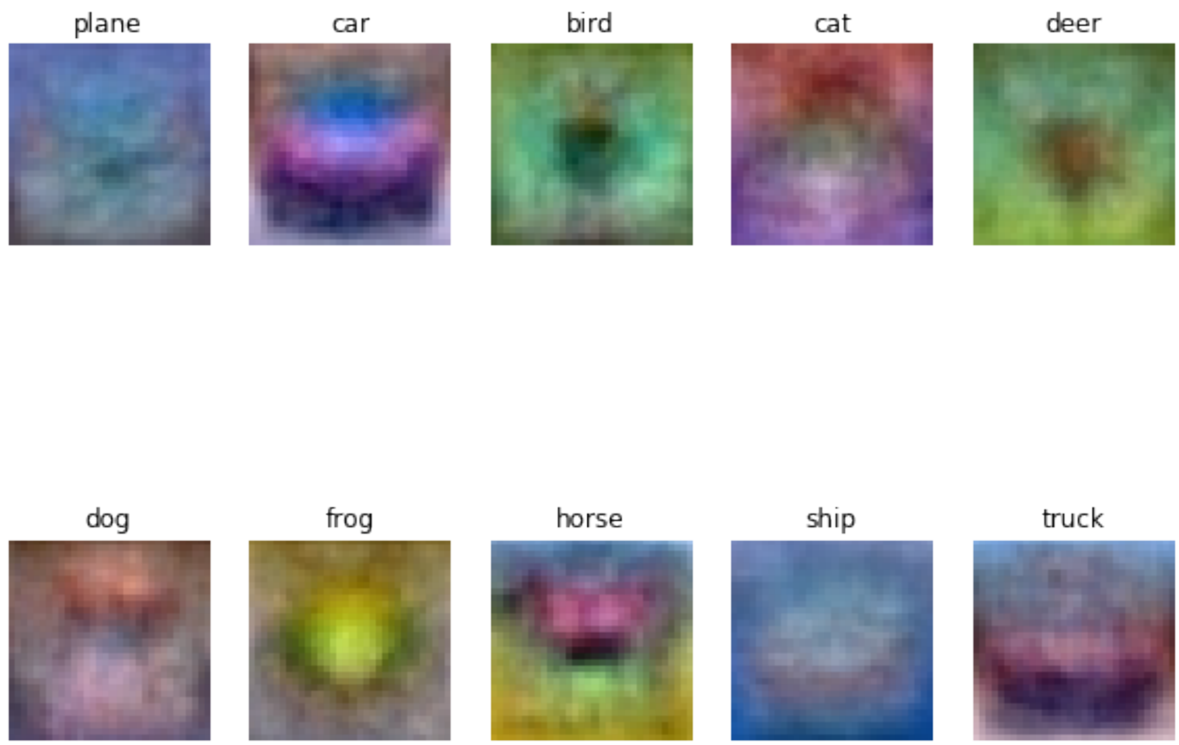
In [124]:

```
# Evaluate the best svm on test set
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_ac
curacy)
```

```
linear SVM on raw pixels final test set accuracy: 0.371000
```

In [125]:

```python
# Visualize the learned weights for each class.
# Depending on your choice of learning rate and regularization strength, these may
# or may not be nice to look at.
w = best_svm.W[:-1,:] # strip out the 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', 'truck']
for i in range(10):
    plt.subplot(2, 5, i + 1)

    # Rescale the weights to be between 0 and 255
    wimg = 255.0 * (w[:, :, :, i].squeeze() - w_min) / (w_max - w_min)
    plt.imshow(wimg.astype('uint8'))
    plt.axis('off')
    plt.title(classes[i])
```



Inline question 2

Describe what your visualized SVM weights look like, and offer a brief explanation for why they look they way that they do.

$\color{blue}{\textit{Your Answer :}}$ they look like initial outlines for what the different image classes are. It could look this way because the robustness of the network analyzing the dataset is not as strong/robust as if we were to use a more complex CNN.

In [ ]: