Image features 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 (https://compsci697l.github.io/assignments.html) on the course website.

We have seen that we can achieve reasonable performance on an image classification task by training a linear classifier on the pixels of the input image. In this exercise we will show that we can improve our classification performance by training linear classifiers not on raw pixels but on features that are computed from the raw pixels.

All of your work for this exercise will be done in this notebook.

In [1]:

```
import random
import numpy as np
from asgn1.data_utils import load_CIFAR10
import matplotlib.pyplot as plt
%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'

# for auto-reloading extenrnal modules
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

Load data

Similar to previous exercises, we will load CIFAR-10 data from disk.

In [2]:

```
from asgn1.features import color_histogram_hsv, hog_feature

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
  # Load the raw CIFAR-10 data
  cifar10_dir = 'datasets/cifar-10-batches-py'
  X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

  # Subsample the data
  mask = range(num_training, num_training + num_validation)
  X_val = X_train[mask]
  y_val = y_train[mask]
  mask = range(num_training)
  X_train = X_train[mask]
  y_train = y_train[mask]
  mask = range(num_test)
  X_test = X_test[mask]
  y_test = y_test[mask]

  return X_train, y_train, X_val, y_val, X_test, y_test

X_train, y_train, X_val, y_val, X_test, y_test = get_CIFAR10_data()
```

Extract Features

For each image we will compute a Histogram of Oriented Gradients (HOG) as well as a color histogram using the hue channel in HSV color space. We form our final feature vector for each image by concatenating the HOG and color histogram feature vectors.

Roughly speaking, HOG should capture the texture of the image while ignoring color information, and the color histogram represents the color of the input image while ignoring texture. As a result, we expect that using both together ought to work better than using either alone. Verifying this assumption would be a good thing to try for the bonus section.

The `hog_feature` and `color_histogram_hsv` functions both operate on a single image and return a feature vector for that image. The extract_features function takes a set of images and a list of feature functions and evaluates each feature function on each image, storing the results in a matrix where each row is the concatenation of all feature vectors for a single image.

In [36]:

```
from asgn1.features import *

num_color_bins = 20 # Number of bins in the color histogram
feature_fns = [hog_feature, lambda img: color_histogram_hsv(img, nbin=num_color_bin
X_train_feats = extract_features(X_train, feature_fns, verbose=True)
X_val_feats = extract_features(X_val, feature_fns)
X_test_feats = extract_features(X_test, feature_fns)

# Preprocessing: Subtract the mean feature
mean_feat = np.mean(X_train_feats, axis=0, keepdims=True)
X_train_feats -= mean_feat
X_val_feats -= mean_feat
X_test_feats -= mean_feat

# Preprocessing: Divide by standard deviation. This ensures that each feature
# has roughly the same scale.
std_feat = np.std(X_train_feats, axis=0, keepdims=True)
X_train_feats /= std_feat
X_val_feats /= std_feat
X_test_feats /= std_feat

# Preprocessing: Add a bias dimension
X_train_feats = np.hstack([X_train_feats, np.ones((X_train_feats.shape[0], 1))])
X_val_feats = np.hstack([X_val_feats, np.ones((X_val_feats.shape[0], 1))])
X_test_feats = np.hstack([X_test_feats, np.ones((X_test_feats.shape[0], 1))])
```

```
Done extracting features for 1000 / 49000 images
Done extracting features for 2000 / 49000 images
Done extracting features for 3000 / 49000 images
Done extracting features for 4000 / 49000 images
Done extracting features for 5000 / 49000 images
Done extracting features for 6000 / 49000 images
Done extracting features for 7000 / 49000 images
Done extracting features for 8000 / 49000 images
Done extracting features for 9000 / 49000 images
Done extracting features for 10000 / 49000 images
Done extracting features for 11000 / 49000 images
Done extracting features for 12000 / 49000 images
Done extracting features for 13000 / 49000 images
Done extracting features for 14000 / 49000 images
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Done extracting features for 33000 / 49000 images
Done extracting features for 34000 / 49000 images
```

```
Done extracting features for 34000 / 49000 images
Done extracting features for 35000 / 49000 images
Done extracting features for 36000 / 49000 images
Done extracting features for 37000 / 49000 images
Done extracting features for 38000 / 49000 images
Done extracting features for 39000 / 49000 images
Done extracting features for 40000 / 49000 images
Done extracting features for 41000 / 49000 images
Done extracting features for 42000 / 49000 images
Done extracting features for 43000 / 49000 images
Done extracting features for 44000 / 49000 images
Done extracting features for 45000 / 49000 images
Done extracting features for 46000 / 49000 images
Done extracting features for 47000 / 49000 images
Done extracting features for 48000 / 49000 images
```

Train SVM on features

Using the multiclass SVM code developed earlier in the assignment, train SVMs on top of the features extracted above; this should achieve better results than training SVMs directly on top of raw pixels.

In [44]:

```
# Use the validation set to tune the learning rate and regularization strength

from asgn1.classifiers.linear_classifier import LinearSVM

learning_rates = [1e-9, 1e-8, 1e-7]
regularization_strengths = [1e6, 1e7]

results = {}
best_val = -1
best_svm = None
for i in learning_rates:
    for j in regularization_strengths:
        svm=LinearSVM()
        loss_hist = svm.train(X_train_feats, y_train, learning_rate=i, reg=j,
                      num_iters=5000, verbose=True)
        y_train_pred = svm.predict(X_train_feats)
        y_val_pred = svm.predict(X_val_feats)
        results[i,j]=[np.mean(y_train == y_train_pred),np.mean(y_val == y_val_pred)
        print np.mean(y_val == y_val_pred)
        if (np.mean(y_val == y_val_pred))>best_val:
            best_val=np.mean(y_val == y_val_pred)
            best_svm=svm
print results

################################################################################
# TODO:                                                                        #
# Use the validation set to set the learning rate and regularization strength. #
# This should be identical to the validation that you did for the SVM; save    #
# the best trained classifer in best_svm. You might also want to play          #
# with different numbers of bins in the color histogram. If you are careful    #
# you should be able to get accuracy of near 0.44 on the validation set.       #
################################################################################

################################################################################
#                              END OF YOUR CODE                                #
################################################################################

# 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
```

```
iteration 0 / 5000: loss 814.040786
iteration 100 / 5000: loss 668.052533
iteration 200 / 5000: loss 548.535087
iteration 300 / 5000: loss 450.686267
iteration 400 / 5000: loss 370.584043
iteration 500 / 5000: loss 305.017112
iteration 600 / 5000: loss 251.327452
iteration 700 / 5000: loss 207.389355
iteration 800 / 5000: loss 171.402248
iteration 900 / 5000: loss 141.955037
iteration 1000 / 5000: loss 117.837085
iteration 1100 / 5000: loss 98.100998
iteration 1200 / 5000: loss 81.943173
iteration 1300 / 5000: loss 68.717304
```

```
iteration 1400 / 5000: loss 57.884364
iteration 1500 / 5000: loss 49.022306
iteration 1600 / 5000: loss 41.758700
iteration 1700 / 5000: loss 35.821340
iteration 1800 / 5000: loss 30.957831
```

In [29]:

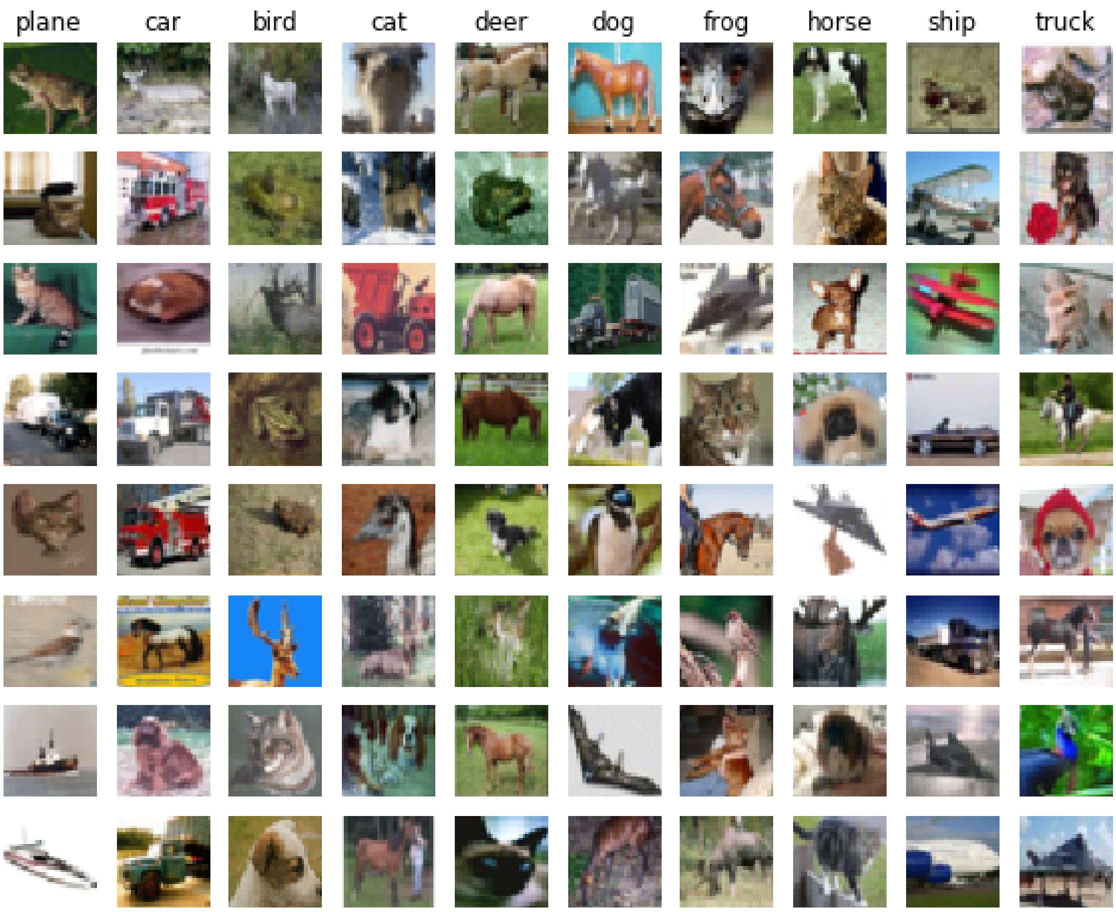
```
# Evaluate your trained SVM on the test set
y_test_pred = best_svm.predict(X_test_feats)
test_accuracy = np.mean(y_test == y_test_pred)
print test_accuracy
```

```
0.429
```

In [9]:

```
# An important way to gain intuition about how an algorithm works is to
# visualize the mistakes that it makes. In this visualization, we show examples
# of images that are misclassified by our current system. The first column
# shows images that our system labeled as "plane" but whose true label is
# something other than "plane".

examples_per_class = 8
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', '
for cls, cls_name in enumerate(classes):
    idxs = np.where((y_test != cls) & (y_test_pred == cls))[0]
    idxs = np.random.choice(idxs, examples_per_class, replace=False)
    for i, idx in enumerate(idxs):
        plt.subplot(examples_per_class, len(classes), i * len(classes) + cls + 1)
        plt.imshow(X_test[idx].astype('uint8'))
        plt.axis('off')
        if i == 0:
            plt.title(cls_name)
plt.show()
```



Inline question 1:

Describe the misclassification results that you see. Do they make sense?

Neural Network on image features

Earlier in this assigment we saw that training a two-layer neural network on raw pixels achieved better classification performance than linear classifiers on raw pixels. In this notebook we have seen that linear classifiers on image features outperform linear classifiers on raw pixels.

For completeness, we should also try training a neural network on image features. This approach should outperform all previous approaches: you should easily be able to achieve over 55% classification accuracy on the test set; our best model achieves about 60% classification accuracy.

In [10]:

```
print X_train_feats.shape
```

```
(49000, 155)
```

In [16]:

```
from asgn1.classifiers.neural_net import TwoLayerNet

input_dim = X_train_feats.shape[1]
hidden_dim = 500
num_classes = 10
learning_rates=np.logspace(-10, 0, 5)
regularization_strengths = np.logspace(-3, 5, 5)

net = TwoLayerNet(input_dim, hidden_dim, num_classes)
best_net = None
input_size = 32 * 32 * 3
for i in learning_rates:
    for j in regularization_strengths:
        stats = net.train(X_train_feats, y_train, X_val_feats, y_val,
                            num_iters=1600,batch_size=200,
                            learning_rate=i, learning_rate_decay=0.95,
                                reg=j, verbose=True)
        y_train_pred = net.predict(X_train_feats)
        y_val_pred = net.predict(X_val_feats)
        results[i,j]=[np.mean(y_train == y_train_pred),np.mean(y_val == y_val_pred)
        print np.mean(y_val == y_val_pred)
        if (np.mean(y_val == y_val_pred))>best_val:
            best_val=np.mean(y_val == y_val_pred)
            best_net=net
print results

################################################################################
# TODO: Train a two-layer neural network on image features. You may want to    #
# cross-validate various parameters as in previous sections. Store your best   #
# model in the best_net variable.                                              #
################################################################################

################################################################################
#                              END OF YOUR CODE                                #
################################################################################
```

```
iteration 0 / 1600: loss 2.302585
iteration 100 / 1600: loss 2.302586
iteration 200 / 1600: loss 2.302586
iteration 300 / 1600: loss 2.302586
iteration 400 / 1600: loss 2.302586
iteration 500 / 1600: loss 2.302586
iteration 600 / 1600: loss 2.302585
iteration 700 / 1600: loss 2.302585
iteration 800 / 1600: loss 2.302585
iteration 900 / 1600: loss 2.302585
iteration 1000 / 1600: loss 2.302585
iteration 1100 / 1600: loss 2.302585
iteration 1200 / 1600: loss 2.302585
iteration 1300 / 1600: loss 2.302586
iteration 1400 / 1600: loss 2.302586
iteration 1500 / 1600: loss 2.302586
0.103
iteration 0 / 1600: loss 2.302626
iteration 100 / 1600: loss 2.302626
iteration 200 / 1600: loss 2.302627
```