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 (http://vision.stanford.edu/teaching/cs231n/assignments.html)](http://vision.stanford.edu/teaching/cs231n/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 cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

from __future__ import print_function

%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-ipyt
hon
%load_ext autoreload
%autoreload 2
```

Load data

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

In [2]:
```
from cs231n.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 = 'cs231n/datasets/cifar-10-batches-py'

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

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

# Cleaning up variables to prevent loading data multiple times (which may caus
e 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_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 your interests.

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 column is the concatenation of all feature vectors for a single image.

In [3]:
```
from cs231n.features import *

num_color_bins = 10 # Number of bins in the color histogram
feature_fns = [hog_feature, lambda img: color_histogram_hsv(img, nbin=num_colo
r_bins)]
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
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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
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Done extracting features for 46000 / 49000 images
Done extracting features for 47000 / 49000 images
Done extracting features for 48000 / 49000 images
```

In [5]:

```python
print('feature shape', X_train_feats.shape)
```

```
feature shape (49000, 155)
```

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 [10]:
```
# Use the validation set to tune the learning rate and regularization strength

from cs231n.classifiers.linear_classifier import LinearSVM

learning_rates = [1e-9, 1e-8, 1e-7]
regularization_strengths = [5e4, 5e5, 5e6]

results = {}
best_val = -1
best_svm = None

################################################################################
##
# 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.
 #
################################################################################
##
#ref: svm.ipynb
for l_rate in learning_rates:
    for reg in regularization_strengths:
        svm = LinearSVM()
        loss_hist = svm.train(X_train_feats, y_train,l_rate, reg,
                              num_iters=1000, verbose=False)
        y_train_pred = svm.predict(X_train_feats)
        train_accuracy=np.mean(y_train == X_train_feats)

        y_val_pred = svm.predict(X_val_feats)
        val_accuracy= np.mean(y_val == y_val_pred)

        results[(l_rate,reg)]=(train_accuracy,val_accuracy)
        if best_val< val_accuracy:
            best_val= val_accuracy
            best_svm= svm
################################################################################
##
#                              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_v
al)
```

```
C:\Users\BS-Huyen\Anaconda3\envs\cs231n_Chien\lib\site-packages\ipykernel_lau
ncher.py:27: DeprecationWarning: elementwise == comparison failed; this will
raise an error in the future.

lr 1.000000e-09 reg 5.000000e+04 train accuracy: 0.000000 val accuracy: 0.087
000
lr 1.000000e-09 reg 5.000000e+05 train accuracy: 0.000000 val accuracy: 0.086
000
lr 1.000000e-09 reg 5.000000e+06 train accuracy: 0.000000 val accuracy: 0.270
000
lr 1.000000e-08 reg 5.000000e+04 train accuracy: 0.000000 val accuracy: 0.107
000
lr 1.000000e-08 reg 5.000000e+05 train accuracy: 0.000000 val accuracy: 0.399
000
lr 1.000000e-08 reg 5.000000e+06 train accuracy: 0.000000 val accuracy: 0.401
000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.000000 val accuracy: 0.422
000
lr 1.000000e-07 reg 5.000000e+05 train accuracy: 0.000000 val accuracy: 0.397
000
lr 1.000000e-07 reg 5.000000e+06 train accuracy: 0.000000 val accuracy: 0.354
000
best validation accuracy achieved during cross-validation: 0.422000
```

In [11]:

```
# 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)
```

```
0.428
```

In [12]:
```
# An important way to gain intuition about how an algorithm works is to
# visualize the mistakes that it makes. In this visualization, we show example
s
# 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', 'shi
p', 'truck']
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 [13]:

```
# Preprocessing: Remove the bias dimension
# Make sure to run this cell only ONCE
print(X_train_feats.shape)
X_train_feats = X_train_feats[:, :-1]
X_val_feats = X_val_feats[:, :-1]
X_test_feats = X_test_feats[:, :-1]

print(X_train_feats.shape)
```

```
(49000, 155)
(49000, 154)
```

In [24]:
```
from cs231n.classifiers.neural_net import TwoLayerNet

input_dim = X_train_feats.shape[1]
hidden_dim = 500
num_classes = 10

net = TwoLayerNet(input_dim, hidden_dim, num_classes)
best_net = None

##############################################################################
##
# 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.
 #
##############################################################################
##
learning_rate=[10,1,1e-1]
regularization=[0,0.1,0.01]


for lr in learning_rate:
    for reg in regularization:

        net = TwoLayerNet(input_dim, hidden_dim, num_classes)

        # Train the network
        stats = net.train(X_train_feats, y_train, X_val_feats, y_val,
                    num_iters=1000, batch_size=200,
                    learning_rate=lr, learning_rate_decay=0.95,
                    reg=reg, verbose=False)

        # Predict on the train set
        train_acc = (net.predict(X_train_feats) == y_train).mean()

        # Predict on the validation set
        val_acc = (net.predict(X_val_feats) == y_val).mean()
        if val_acc> best_val:
            best_val=val_acc
            best_net=net
            best_stats=stats
#          print('lr%e reg%f  train_acc%f val_acc:%f ' %(lr,reg,train_acc, val_
acc))
print ('best accuracy:',best_val)
# show_charts(best_stats)
##############################################################################
##
#                               END OF YOUR CODE
 #
##############################################################################
##
```

```
E:\Chien\PROGRAMING SKILLS\lap trinh Python\spring1718_assignment1\assignment
1\cs231n\classifiers\neural_net.py:107: RuntimeWarning: divide by zero encoun
tered in log
  log_correct_softmax_prob=-np.log(log_correct_softmax_prob)#Nx1
E:\Chien\PROGRAMING SKILLS\lap trinh Python\spring1718_assignment1\assignment
1\cs231n\classifiers\neural_net.py:99: RuntimeWarning: overflow encountered i
n subtract
  scores-=scores_max #NxC= NxC -Nx1
E:\Chien\PROGRAMING SKILLS\lap trinh Python\spring1718_assignment1\assignment
1\cs231n\classifiers\neural_net.py:113: RuntimeWarning: overflow encountered
in multiply
  loss+= reg*np.sum(W1*W1) +reg*np.sum(W2*W2)
E:\Chien\PROGRAMING SKILLS\lap trinh Python\spring1718_assignment1\assignment
1\cs231n\classifiers\neural_net.py:113: RuntimeWarning: invalid value encount
ered in double_scalars
  loss+= reg*np.sum(W1*W1) +reg*np.sum(W2*W2)
E:\Chien\PROGRAMING SKILLS\lap trinh Python\spring1718_assignment1\assignment
1\cs231n\classifiers\neural_net.py:99: RuntimeWarning: invalid value encounte
red in subtract
  scores-=scores_max #NxC= NxC -Nx1
C:\Users\BS-Huyen\Anaconda3\envs\cs231n_Chien\lib\site-packages\numpy\core\fr
omnumeric.py:83: RuntimeWarning: overflow encountered in reduce
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
E:\Chien\PROGRAMING SKILLS\lap trinh Python\spring1718_assignment1\assignment
1\cs231n\classifiers\neural_net.py:78: RuntimeWarning: invalid value encounte
red in maximum
  hidden_layer1= np.maximum(np.dot(X,W1)+b1,0)# added Relu after first layer
#NxH1= [NxD]x[DxH1] +H1
C:\Users\BS-Huyen\Anaconda3\envs\cs231n_Chien\lib\site-packages\numpy\core\fr
omnumeric.py:83: RuntimeWarning: invalid value encountered in reduce
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
E:\Chien\PROGRAMING SKILLS\lap trinh Python\spring1718_assignment1\assignment
1\cs231n\classifiers\neural_net.py:144: RuntimeWarning: invalid value encount
ered in less_equal
  dhidden[hidden_layer1<=0]=0 # back gradient through Relu function

best accuracy: 0.557
```

In [25]:

```
# Run your best neural net classifier on the test set. You should be able
# to get more than 55% accuracy.

test_acc = (best_net.predict(X_test_feats) == y_test).mean()
print(test_acc)
```

```
0.536
```