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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.

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 [63]:
```
from __future__ import print_function

import random
import numpy as np
from cecs551.data_utils import load_CIFAR10
import matplotlib.pyplot as plt


%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'

# for auto-reloading extenrnal modules
# 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
```

Load data

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

In [64]:
```
from cecs551.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 = 'cecs551/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 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_val, y_val, X_test, y_test = get_CIFAR10_data()
```

```
Clear previously loaded 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 [65]:
```
from cecs551.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_color_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 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 [67]:
```
# Use the validation set to tune the learning rate and regularization
strength

from cecs551.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 s
trength. #
# 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 ca
reful     #
# you should be able to get accuracy of near 0.44 on the validation se
t.        #
#######################################################################
##########
np.random.seed(0)
for i in learning_rates:
    for j in regularization_strengths:
        svm=LinearSVM()
        svm.train(X_train_feats, y_train, learning_rate=i, reg=j,num_i
ters=2000, batch_size= 200,verbose=False)
        y_train_pred=svm.predict(X_train_feats)
        train_accuracy = np.mean(y_train_pred == y_train)
        y_val_pred=svm.predict(X_val_feats)
        val_accuracy = np.mean(y_val_pred == y_val)
        results[(i,j)] = (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_val)
```

```
lr 1.000000e-09 reg 5.000000e+04 train accuracy: 0.094449 val accura
cy: 0.106000
lr 1.000000e-09 reg 5.000000e+05 train accuracy: 0.098224 val accura
cy: 0.095000
lr 1.000000e-09 reg 5.000000e+06 train accuracy: 0.357653 val accura
cy: 0.332000
lr 1.000000e-08 reg 5.000000e+04 train accuracy: 0.092571 val accura
cy: 0.104000
lr 1.000000e-08 reg 5.000000e+05 train accuracy: 0.409041 val accura
cy: 0.406000
lr 1.000000e-08 reg 5.000000e+06 train accuracy: 0.410714 val accura
cy: 0.405000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.413204 val accura
cy: 0.412000
lr 1.000000e-07 reg 5.000000e+05 train accuracy: 0.405673 val accura
cy: 0.401000
lr 1.000000e-07 reg 5.000000e+06 train accuracy: 0.376796 val accura
cy: 0.374000
best validation accuracy achieved during cross-validation: 0.412000
```

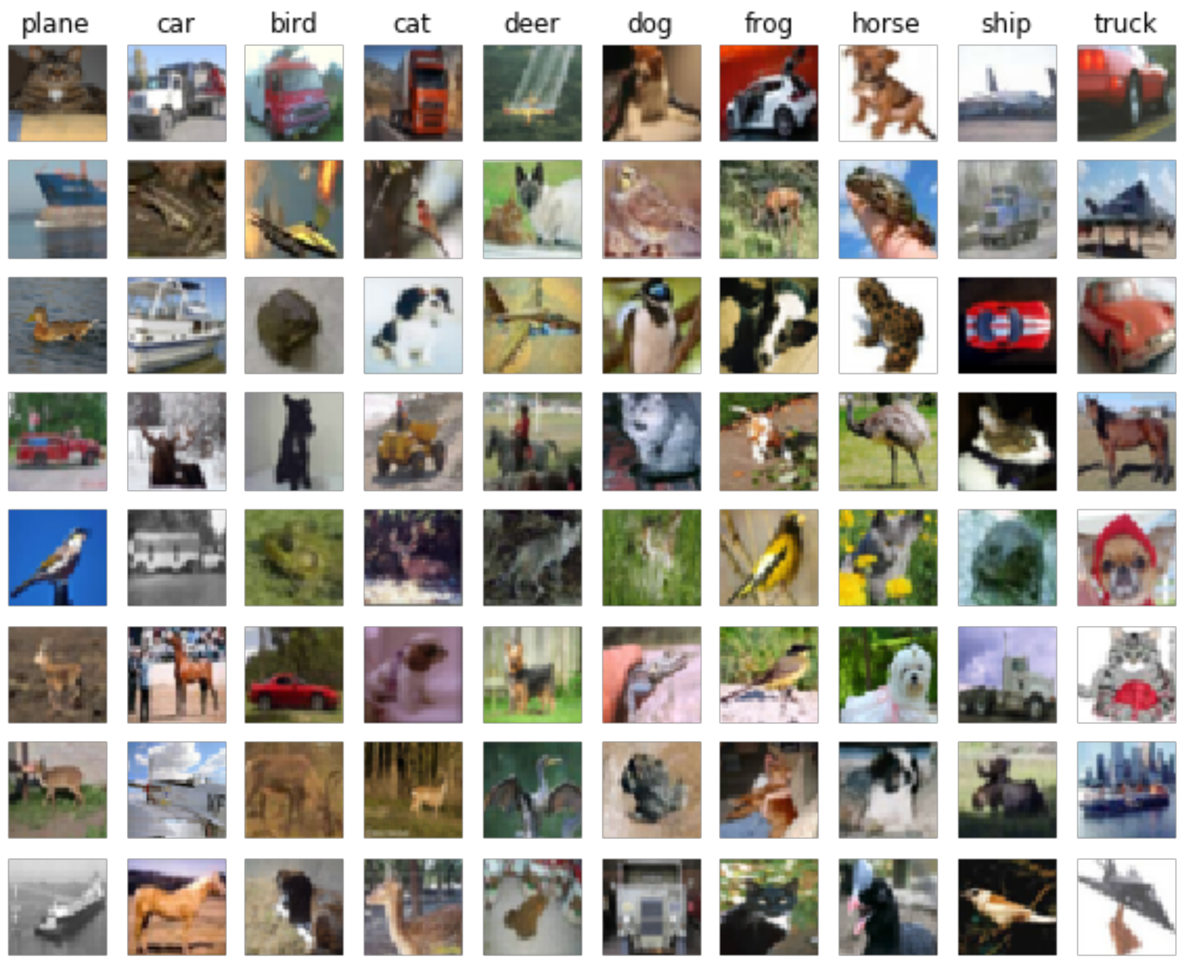
In [68]:

```
# 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)
```

```
0.416
```

In [69]:
```
# An important way to gain intuition about how an algorithm works is t
o
# visualize the mistakes that it makes. In this visualization, we show
examples
# of images that are misclassified by our current system. The first co
lumn
# 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', 'hors
e', 'ship', '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?

It does make sense because the ones that were misclassified have similar backgrounds of shapes of the objects.

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 [70]:
```
# 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 [73]:
```
from cecs551.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

# results = {}
# best_val = -1
# best_net = None

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

```
results = {}
best_val = -1
best_net = None
learning_rates = [1e-1, 5e-1]
regularization_strengths = [1e-3, 5e-3, 1e-2]
for i in learning_rates:
    for j in regularization_strengths:
        net = TwoLayerNet(input_dim, hidden_dim, num_classes)
        stats = net.train(X_train_feats, y_train, X_val_feats, y_val,
        num_iters=3000, batch_size=200,
        learning_rate=i, learning_rate_decay=0.95,
        reg= j, verbose=False)

        y_train_pred=net.predict(X_train_feats)
        train_accuracy = np.mean(y_train_pred == y_train)
        y_val_pred=net.predict(X_val_feats)
        val_accuracy = np.mean(y_val_pred == y_val)
        results[(i,j)] = (train_accuracy, val_accuracy)

        if best_val < val_accuracy:
            best_val = val_accuracy
            best_net = net

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)


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

```
lr 1.000000e-01 reg 1.000000e-03 train accuracy: 0.578571 val accura
cy: 0.548000
lr 1.000000e-01 reg 5.000000e-03 train accuracy: 0.546878 val accura
cy: 0.523000
lr 1.000000e-01 reg 1.000000e-02 train accuracy: 0.525694 val accura
cy: 0.507000
lr 5.000000e-01 reg 1.000000e-03 train accuracy: 0.717163 val accura
cy: 0.582000
lr 5.000000e-01 reg 5.000000e-03 train accuracy: 0.582408 val accura
cy: 0.553000
lr 5.000000e-01 reg 1.000000e-02 train accuracy: 0.527653 val accura
cy: 0.522000
best validation accuracy achieved during cross-validation: 0.582000
```

In [72]:

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

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

```
0.584
```

In [ ]: