图像特征练习

补充并完成本练习。

我们已经看到，通过在输入图像的像素上训练线性分类器，从而在图像分类任务上达到一个合理的性能。在本练习中，我们将展示我们可以通过对线性分类器（不是在原始像素上，而是在根据原始像素计算出的特征上）进行训练来改善分类性能。

你将在此notebook中完成本练习的所有工作。

In [1]:
```
import random
import numpy as np
from daseCV.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
```

数据加载

与之前的练习类似，我们将从磁盘加载CIFAR-10数据。

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

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

    # 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

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

特征提取

对于每一张图片我们将会计算它的方向梯度直方图（英語：Histogram of oriented gradient，简称HOG）以及在HSV颜色空间使用色相通道的颜色直方图。

简单来讲，HOG能提取图片的纹理信息而忽略颜色信息，颜色直方图则提取出颜色信息而忽略纹理信息。 因此，我们希望将两者结合使用而不是单独使用任一个。去实现这个设想是一个十分有趣的事情。

`hog_feature` 和 `color_histogram_hsv` 两个函数都可以对单个图像进行运算并返回改图像的一个特征向量。 extract_features函数输入一个图像集合和一个特征函数列表然后对每张图片运行每个特征函数， 然后将结果存储在一个矩阵中，矩阵的每一列是单个图像的所有特征向量的串联。

In [3]:

```
from daseCV.features import *

num_color_bins = 20 # Number of bins in the color histogram <- modified
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
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
Done extracting features for 15000 / 49000 images
Done extracting features for 16000 / 49000 images
Done extracting features for 17000 / 49000 images
Done extracting features for 18000 / 49000 images
Done extracting features for 19000 / 49000 images
```

```
Done extracting features for 20000 / 49000 images
Done extracting features for 21000 / 49000 images
Done extracting features for 22000 / 49000 images
Done extracting features for 23000 / 49000 images
Done extracting features for 24000 / 49000 images
Done extracting features for 25000 / 49000 images
Done extracting features for 26000 / 49000 images
Done extracting features for 27000 / 49000 images
Done extracting features for 28000 / 49000 images
Done extracting features for 29000 / 49000 images
Done extracting features for 30000 / 49000 images
Done extracting features for 31000 / 49000 images
Done extracting features for 32000 / 49000 images
Done extracting features for 33000 / 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
Done extracting features for 49000 / 49000 images
```

使用特征训练SVM

使用之前作业完成的多分类SVM代码来训练上面提取的特征。这应该比原始数据直接在SVM上训练会去的更好的效果。

In [4]:

```
# 使用验证集调整学习率和正则化强度

from daseCV.classifiers.linear_classifier import LinearSVM
from itertools import product

learning_rates = [1e-8, 5e-8]
regularization_strengths = [1e6]

results = {}
best_val = -1
best_svm = None

################################################################################
# 你需要做的:
# 使用验证集设置学习率和正则化强度。
# 这应该与你对SVM所做的验证相同;
# 将训练最好的的分类器保存在best_svm中。
# 你可能还想在颜色直方图中使用不同数量的bins。
# 如果你细心一点应该能够在验证集上获得接近0.44的准确性。
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

while True:
    # 我并不想通过手动反复运行来测试我的运气, 因此直接用循环来完成这件事会更好
    for lr, reg in list(product(learning_rates, regularization_strengths)):
        svm = LinearSVM()
        svm.train(X_train_feats, y_train, learning_rate=lr, reg=reg, num_iters=2000)
```

```
        trn_acc = (svm.predict(X_train_feats) == y_train).sum() / y_train.size
        val_acc = (svm.predict(X_val_feats) == y_val).sum() / y_val.size
        results[(lr, reg)] = (trn_acc, val_acc)
        if val_acc > best_val:
            best_svm = svm
            best_val = val_acc
            print(f'new best {best_val}')
    if best_val >= 0.44:
        print('ok')
        break

# *****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)
```

```
new best 0.421
new best 0.423
new best 0.428
new best 0.443
ok
lr 1.000000e-08 reg 1.000000e+06 train accuracy: 0.423306 val accuracy: 0.443000
lr 5.000000e-08 reg 1.000000e+06 train accuracy: 0.409776 val accuracy: 0.412000
best validation accuracy achieved during cross-validation: 0.443000
```

In [5]:

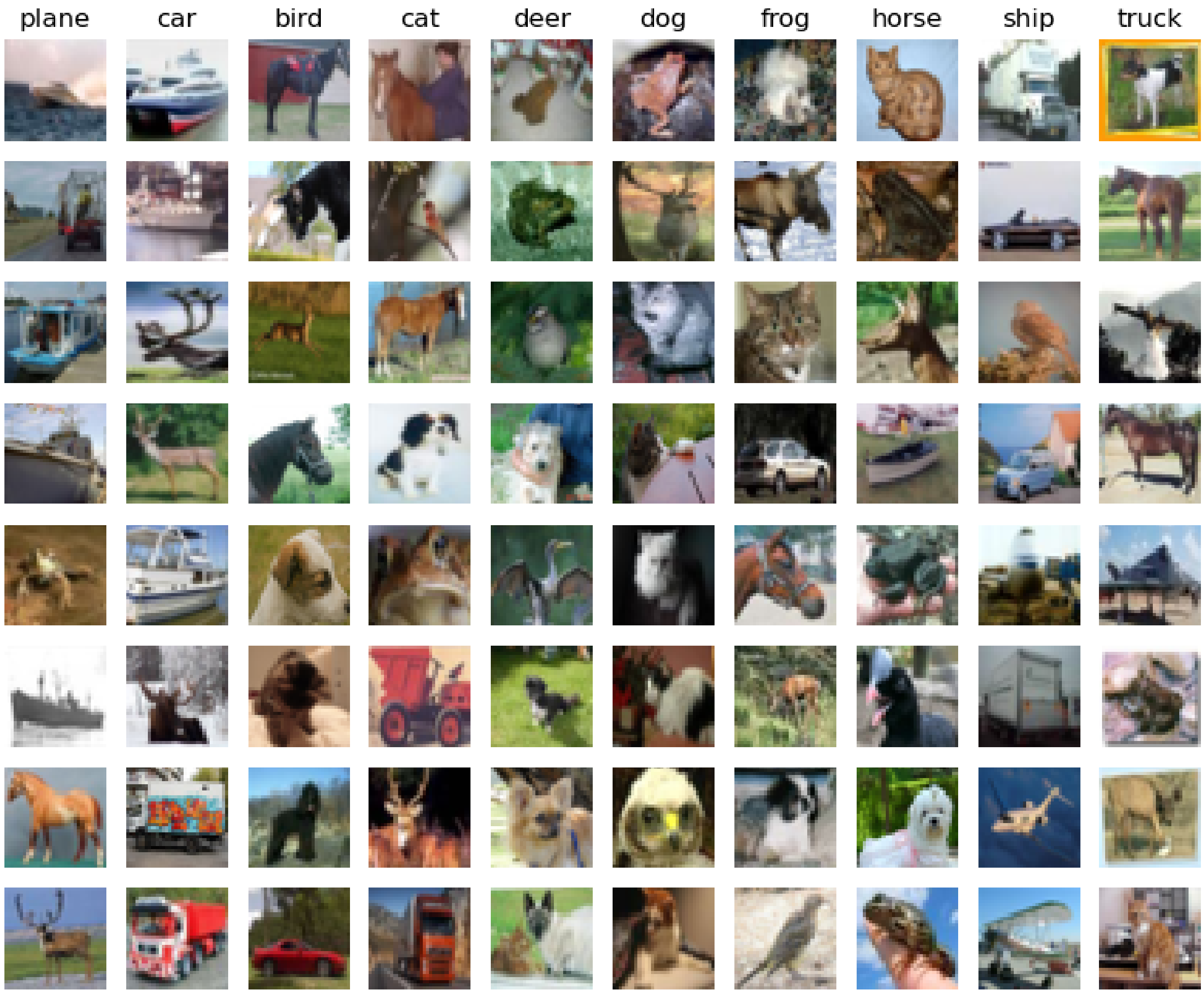
```
# Evaluate your trained SVM on the test set
y_test_pred = best_svm.predict(X_test_feats)
test_accuracy = np.mean(y_test == y_test_pred)
print(test_accuracy)
```

```
0.424
```

In [6]:

```
# 直观了解算法工作原理的一种重要方法是可视化它所犯的错误。
# 在此可视化中，我们显示了当前系统未正确分类的图像示例。
# 第一列显示的图像是我们的系统标记为" plane”，但其真实标记不是" plane”。

examples_per_class = 8
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', '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()
```



问题 1:

描述你看到的错误分类结果。你认为他们有道理吗？

答:

错误分类是有规律的, 将一张图片的颜色和纹理信息分开考虑时, 这些样本的颜色和纹理信息各自和该类别相似, 这导致它在该类别上的得分很高. 出现这个问题的原因是SVM无法考虑颜色和纹理信息的共同作用, 而只是简单将它们线性加和.

图像特征神经网络

在之前的练习中，我们看到在原始像素上训练两层神经网络比线性分类器具有更好的分类精度。在这里，我们已经看到使用图像特征的线性分类器优于使用原始像素的线性分类器。 为了完整起见，我们还应该尝试在图像特征上训练神经网络。这种方法应优于以前所有的方法：你应该能够轻松地在测试集上达到55%以上的分类精度；我们最好的模型可达到约60%的精度。

In [7]:
```
# 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, 165)
(49000, 164)
```

In [10]:

```
from daseCV.classifiers.neural_net import TwoLayerNet

input_dim = X_train_feats.shape[1]
hidden_dim = 500
num_classes = 10
best_acc = 0.0

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

################################################################################
# TODO: 使用图像特征训练两层神经网络。
# 您可能希望像上一节中那样对各种参数进行交叉验证。
# 将最佳的模型存储在best_net变量中。
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
# 只尝试一次就达到了要求, 可以归因为运气好
net.train(X_train_feats, y_train, X_val_feats, y_val, learning_rate=1e-1, num_iters=1000
print((net.predict(X_val_feats) == y_val).sum()/y_val.size)
best_net=net
# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
```

```
0.609
```

In [11]:

```
# 在测试集上运行得到的最好的神经网络分类器，应该能够获得55%以上的准确性。

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

```
0.594
```