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/cs175/assignments.html)](http://vision.stanford.edu/teaching/cs175/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 [89]:
```
mport random
mport numpy as np
rom cs175.data_utils import load_CIFAR10
mport matplotlib.pyplot as plt

rom __future__ import print_function

matplotlib inline
lt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
lt.rcParams['image.interpolation'] = 'nearest'
lt.rcParams['image.cmap'] = 'gray'

 for auto-reloading extenrnal modules
 see http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipyt
on
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 [90]:
```
rom cs175.features import color_histogram_hsv, hog_feature

ef get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
   # Load the raw CIFAR-10 data
   cifar10_dir = 'cs175/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

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

In [91]:
```
rom cs175.features import *

um_color_bins = 10 # Number of bins in the color histogram
eature_fns = [hog_feature, lambda img: color_histogram_hsv(img, nbin=num_colo
_bins)]
_train_feats = extract_features(X_train, feature_fns, verbose=True)
_val_feats = extract_features(X_val, feature_fns)
_test_feats = extract_features(X_test, feature_fns)

 Preprocessing: Subtract the mean feature
ean_feat = np.mean(X_train_feats, axis=0, keepdims=True)
_train_feats -= mean_feat
_val_feats -= mean_feat
_test_feats -= mean_feat

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

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

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 [92]:
```
 Use the validation set to tune the learning rate and regularization strength

rom cs175.classifiers.linear_classifier import LinearSVM

earning_rates = [5e-6, 1e-7, 5e-7, 1e-8]
egularization_strengths = [4.5e4, 5e4, 5.5e4, 6e4]

esults = {}
est_val = -1
est_svm = None

ass
################################################################################
#
 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.

################################################################################
#
or learn in learning_rates:
   for reg in regularization_strengths:
       svm = LinearSVM()
       svm.train(X_train_feats, y_train, learning_rate=learn, reg=reg, num_it
rs=2000)
       p_train = svm.predict(X_train_feats)
       p_val   = svm.predict(X_val_feats)

       train_acc = np.mean(p_train == y_train)
       val_acc   = np.mean(p_val == y_val)

       if val_acc > best_val:
           best_val = val_acc
           best_svm = svm

       results[(learn, reg)] = train_acc, val_acc
################################################################################
#
                              END OF YOUR CODE

################################################################################
#

 Print out results.
or 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))
```

```
rint('best validation accuracy achieved during cross-validation: %f' % best_v
l)
```

```
r 1.000000e-08 reg 4.500000e+04 train accuracy: 0.107694 val accuracy: 0.100
00
r 1.000000e-08 reg 5.000000e+04 train accuracy: 0.120816 val accuracy: 0.107
00
r 1.000000e-08 reg 5.500000e+04 train accuracy: 0.111776 val accuracy: 0.114
00
r 1.000000e-08 reg 6.000000e+04 train accuracy: 0.098898 val accuracy: 0.108
00
r 1.000000e-07 reg 4.500000e+04 train accuracy: 0.175102 val accuracy: 0.184
00
r 1.000000e-07 reg 5.000000e+04 train accuracy: 0.182429 val accuracy: 0.185
00
r 1.000000e-07 reg 5.500000e+04 train accuracy: 0.183388 val accuracy: 0.194
00
r 1.000000e-07 reg 6.000000e+04 train accuracy: 0.213163 val accuracy: 0.235
00
r 5.000000e-07 reg 4.500000e+04 train accuracy: 0.177653 val accuracy: 0.195
00
r 5.000000e-07 reg 5.000000e+04 train accuracy: 0.197041 val accuracy: 0.215
00
r 5.000000e-07 reg 5.500000e+04 train accuracy: 0.195347 val accuracy: 0.192
00
r 5.000000e-07 reg 6.000000e+04 train accuracy: 0.192653 val accuracy: 0.209
00
r 5.000000e-06 reg 4.500000e+04 train accuracy: 0.277163 val accuracy: 0.317
00
r 5.000000e-06 reg 5.000000e+04 train accuracy: 0.288020 val accuracy: 0.309
00
r 5.000000e-06 reg 5.500000e+04 train accuracy: 0.268531 val accuracy: 0.284
00
r 5.000000e-06 reg 6.000000e+04 train accuracy: 0.279490 val accuracy: 0.287
00
est validation accuracy achieved during cross-validation: 0.317000
```

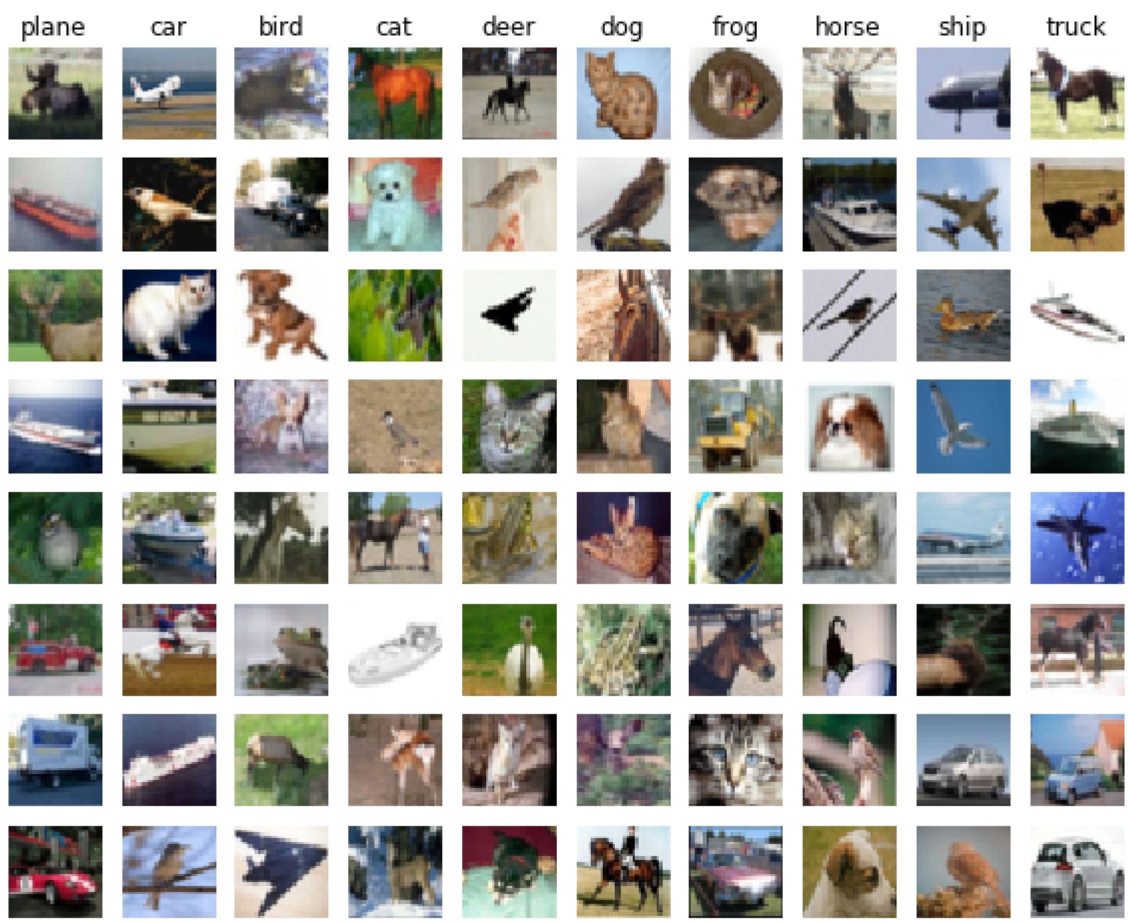
In [93]:

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

```
0.285
```

In [94]:

```
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

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".

xamples_per_class = 8
lasses = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'shi
', 'truck']
or 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 +
)
       plt.imshow(X_test[idx].astype('uint8'))
       plt.axis('off')
       if i == 0:
           plt.title(cls_name)
lt.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.

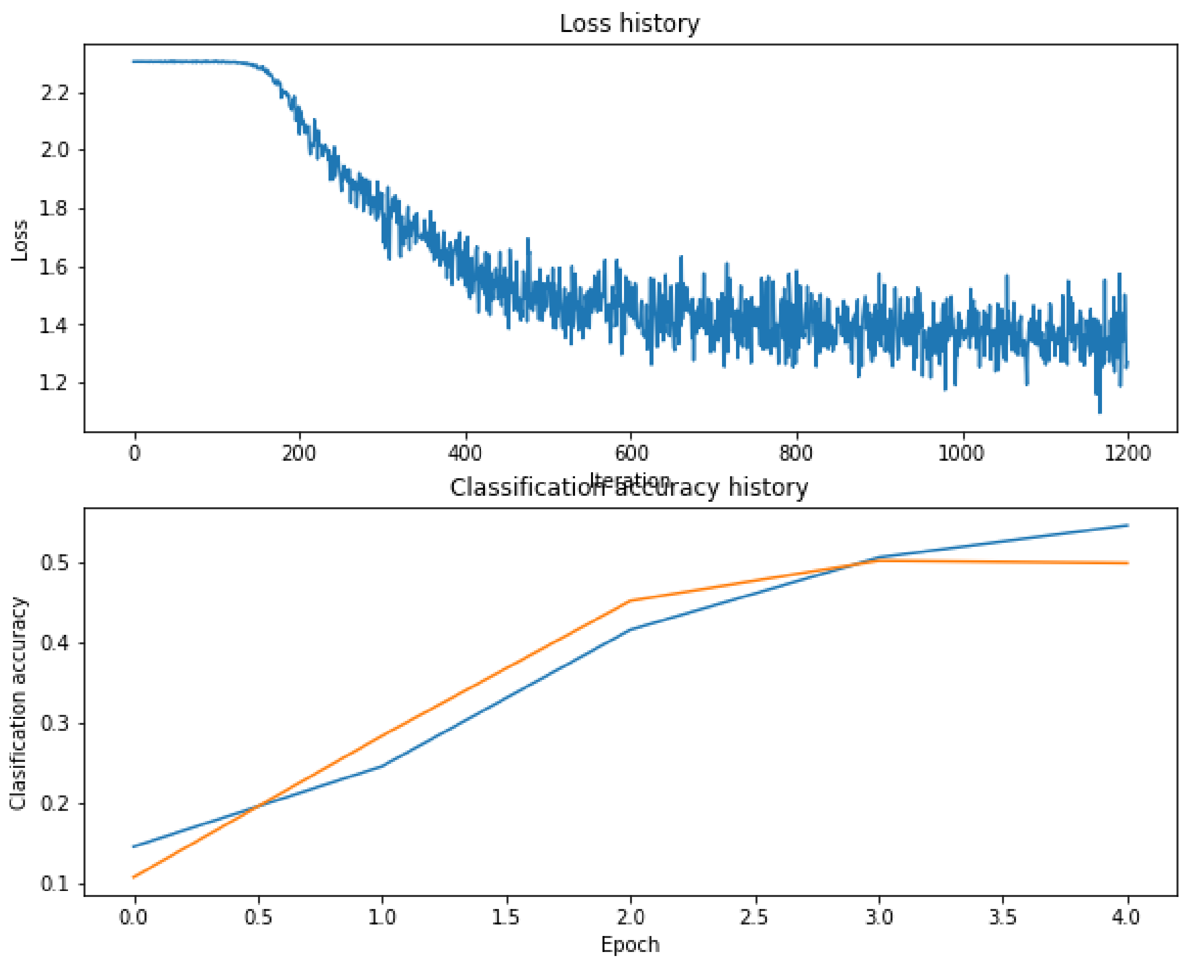
In [95]:
```
rint(X_train_feats.shape)
```

```
(49000L, 155L)
```

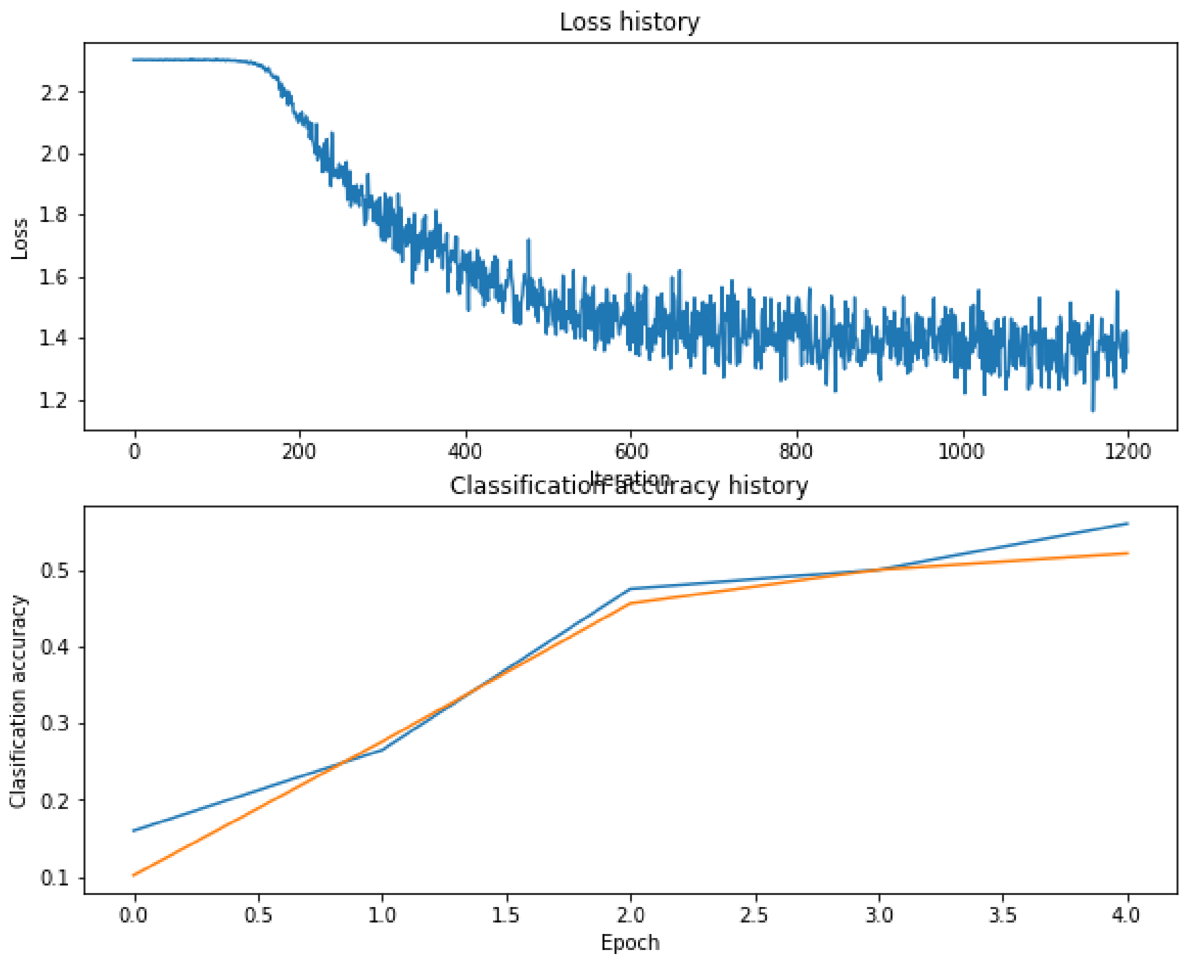
In [96]:
```
rom cs175.classifiers.neural_net import TwoLayerNet

nput_dim = X_train_feats.shape[1]
idden_dim = 500
um_classes = 10

et = TwoLayerNet(input_dim, hidden_dim, num_classes)
est_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.

################################################################################
#
atch_size = [200]
earning_rates = [1e-1, 2e-1, 3e-1]
egularization_strengths = [5e-4, 1e-3,]
idden_size = [500]
est_acc = -1
or hid in hidden_size:
   print("hidden: ", hid)
   for bs in batch_size:
       print("batch: ", bs)
       for learn in learning_rates:
           print("learning: ", learn)
           for reg in regularization_strengths:
               print("reg: ", reg)
               net = TwoLayerNet(input_dim, hid, num_classes)
               stats = net.train(X_train_feats,y_train,X_val_feats,y_val,num_
ters=1200,batch_size=bs,
                                 learning_rate=learn,reg=reg,verbose=True)
               val_acc = (net.predict(X_val_feats) == y_val).mean()
               if val_acc > best_acc:
                   best_net = net
                   best_acc = val_acc
                   best_stats = stats

               # Plot the loss function and train / validation accuracies
               plt.subplot(2, 1, 1)
               plt.plot(stats['loss_history'])
               plt.title('Loss history')
               plt.xlabel('Iteration')
               plt.ylabel('Loss')

               plt.subplot(2, 1, 2)
               plt.plot(stats['train_acc_history'], label='train')
               plt.plot(stats['val_acc_history'], label='val')
               plt.title('Classification accuracy history')
               plt.xlabel('Epoch')
               plt.ylabel('Clasification accuracy')
               plt.show()
```

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

################################################################################
#
```

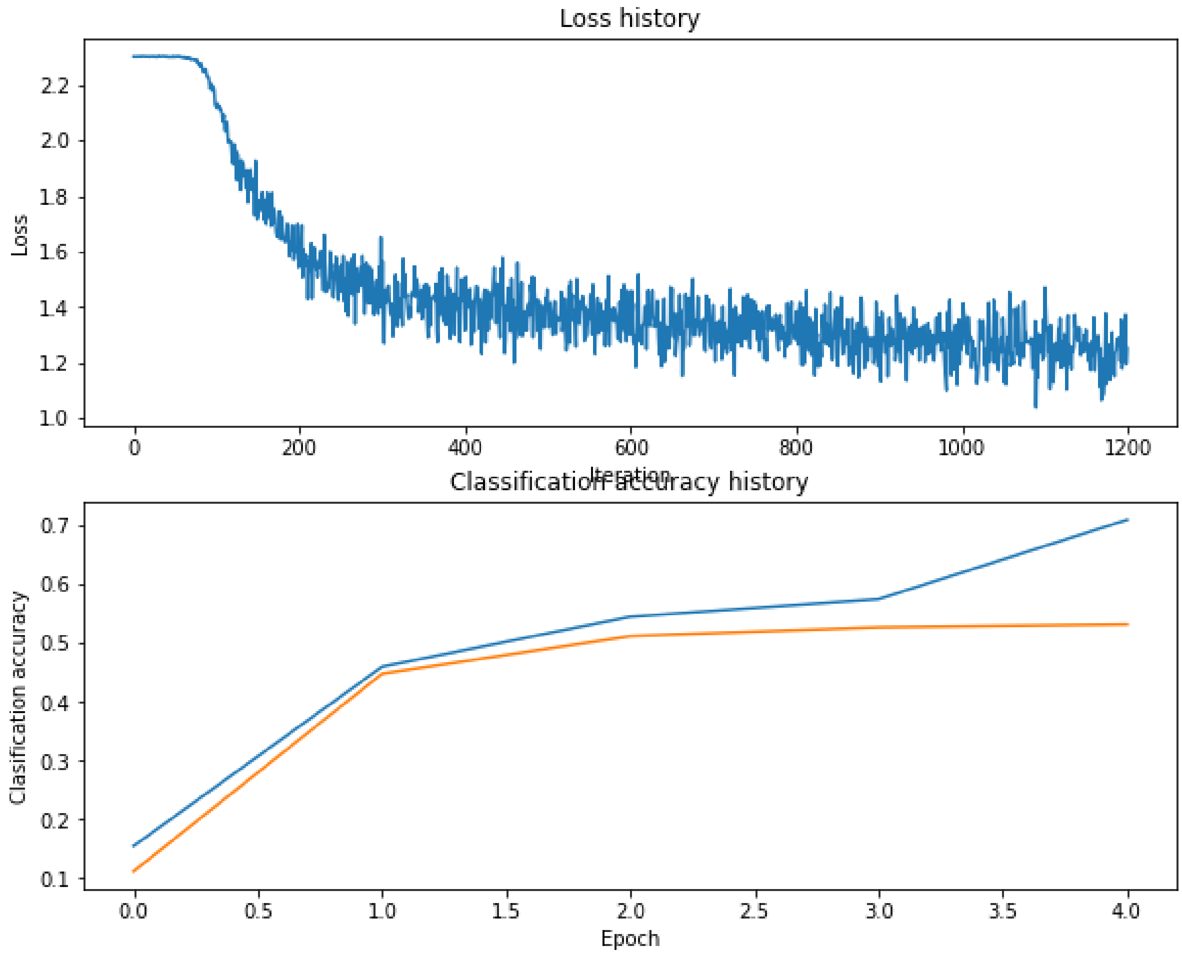
```
hidden:  500
batch:  200
learning:  0.1
reg:  0.0005
iteration 0 / 1200: loss 2.302586
iteration 100 / 1200: loss 2.303600
iteration 200 / 1200: loss 2.053419
iteration 300 / 1200: loss 1.848397
iteration 400 / 1200: loss 1.681598
iteration 500 / 1200: loss 1.565326
iteration 600 / 1200: loss 1.426184
iteration 700 / 1200: loss 1.367890
iteration 800 / 1200: loss 1.583489
iteration 900 / 1200: loss 1.573623
iteration 1000 / 1200: loss 1.372810
iteration 1100 / 1200: loss 1.338747
```



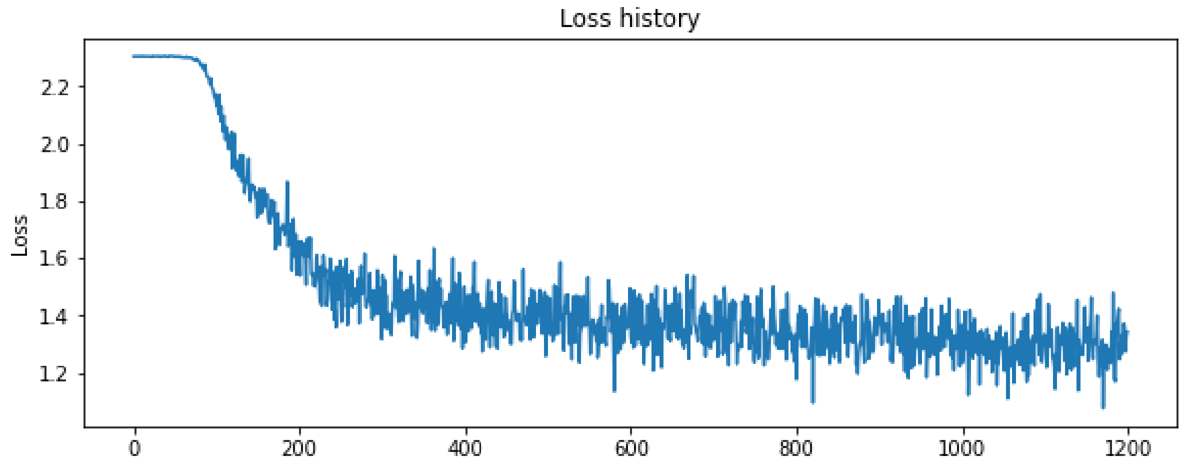
```
reg:  0.001
iteration 0 / 1200: loss 2.302586
iteration 100 / 1200: loss 2.301353
iteration 200 / 1200: loss 2.118878
iteration 300 / 1200: loss 1.715180
iteration 400 / 1200: loss 1.651171
iteration 500 / 1200: loss 1.477381
iteration 600 / 1200: loss 1.507628
iteration 700 / 1200: loss 1.424014
iteration 800 / 1200: loss 1.507432
iteration 900 / 1200: loss 1.325960
iteration 1000 / 1200: loss 1.380670
iteration 1100 / 1200: loss 1.429797
```

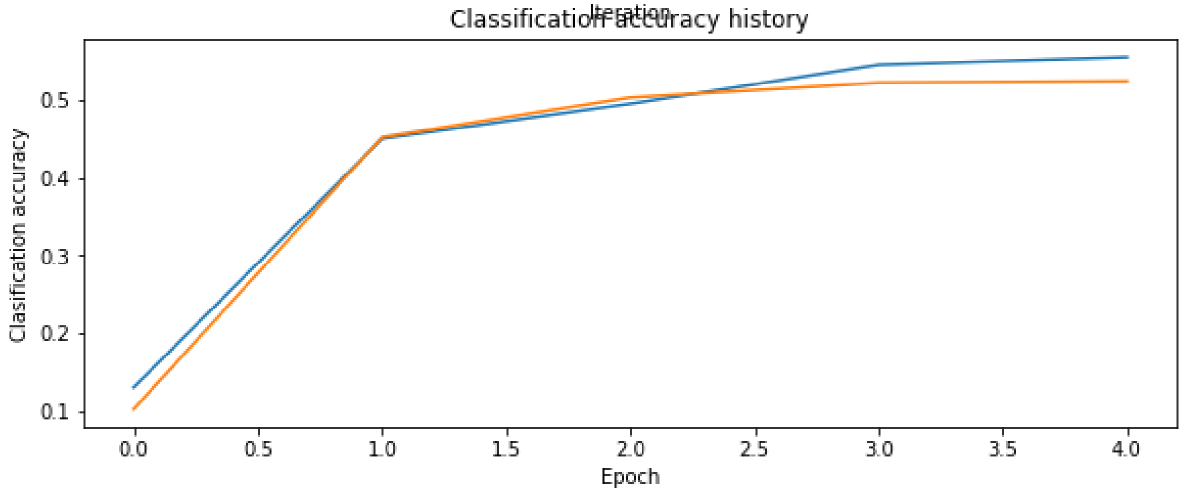



```
learning:  0.2
reg:  0.0005
iteration 0 / 1200: loss 2.302585
iteration 100 / 1200: loss 2.117439
iteration 200 / 1200: loss 1.610700
iteration 300 / 1200: loss 1.565562
iteration 400 / 1200: loss 1.314654
iteration 500 / 1200: loss 1.400723
iteration 600 / 1200: loss 1.335673
iteration 700 / 1200: loss 1.405001
iteration 800 / 1200: loss 1.384284
iteration 900 / 1200: loss 1.361855
iteration 1000 / 1200: loss 1.337030
iteration 1100 / 1200: loss 1.470556
```

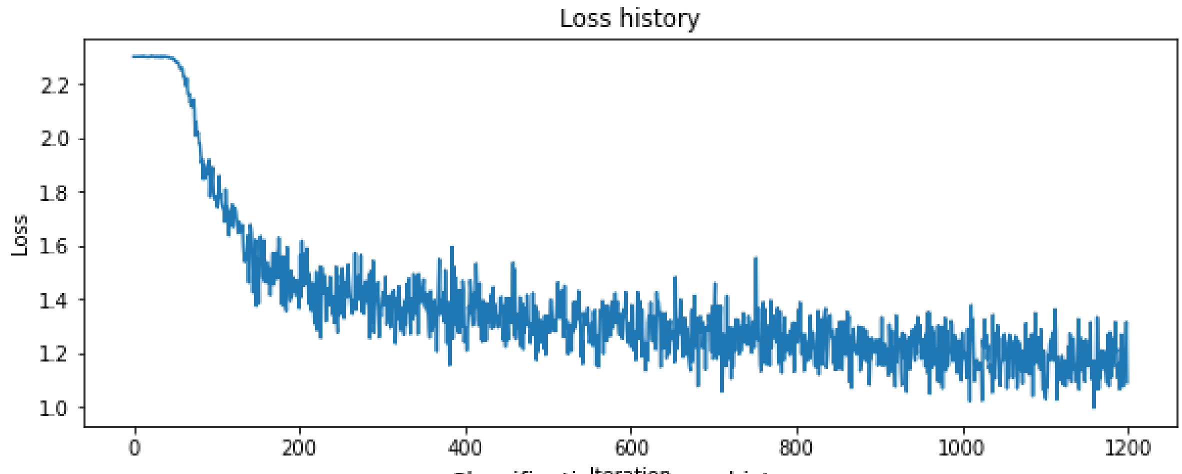


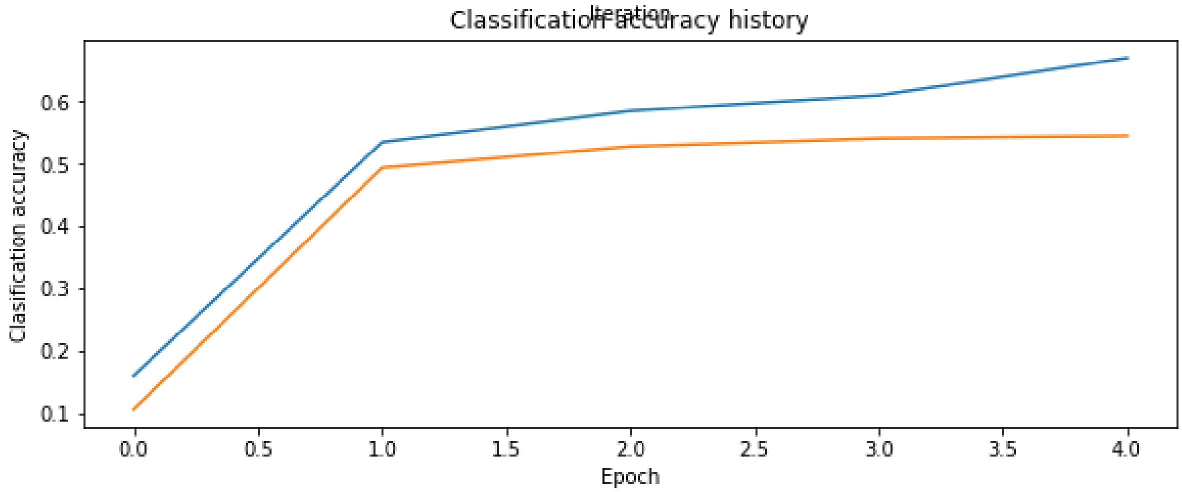

```
reg:  0.001
iteration 0 / 1200: loss 2.302586
iteration 100 / 1200: loss 2.130747
iteration 200 / 1200: loss 1.595028
iteration 300 / 1200: loss 1.542322
iteration 400 / 1200: loss 1.305486
iteration 500 / 1200: loss 1.341420
iteration 600 / 1200: loss 1.329719
iteration 700 / 1200: loss 1.315019
iteration 800 / 1200: loss 1.177863
iteration 900 / 1200: loss 1.387880
iteration 1000 / 1200: loss 1.234898
iteration 1100 / 1200: loss 1.331981
```



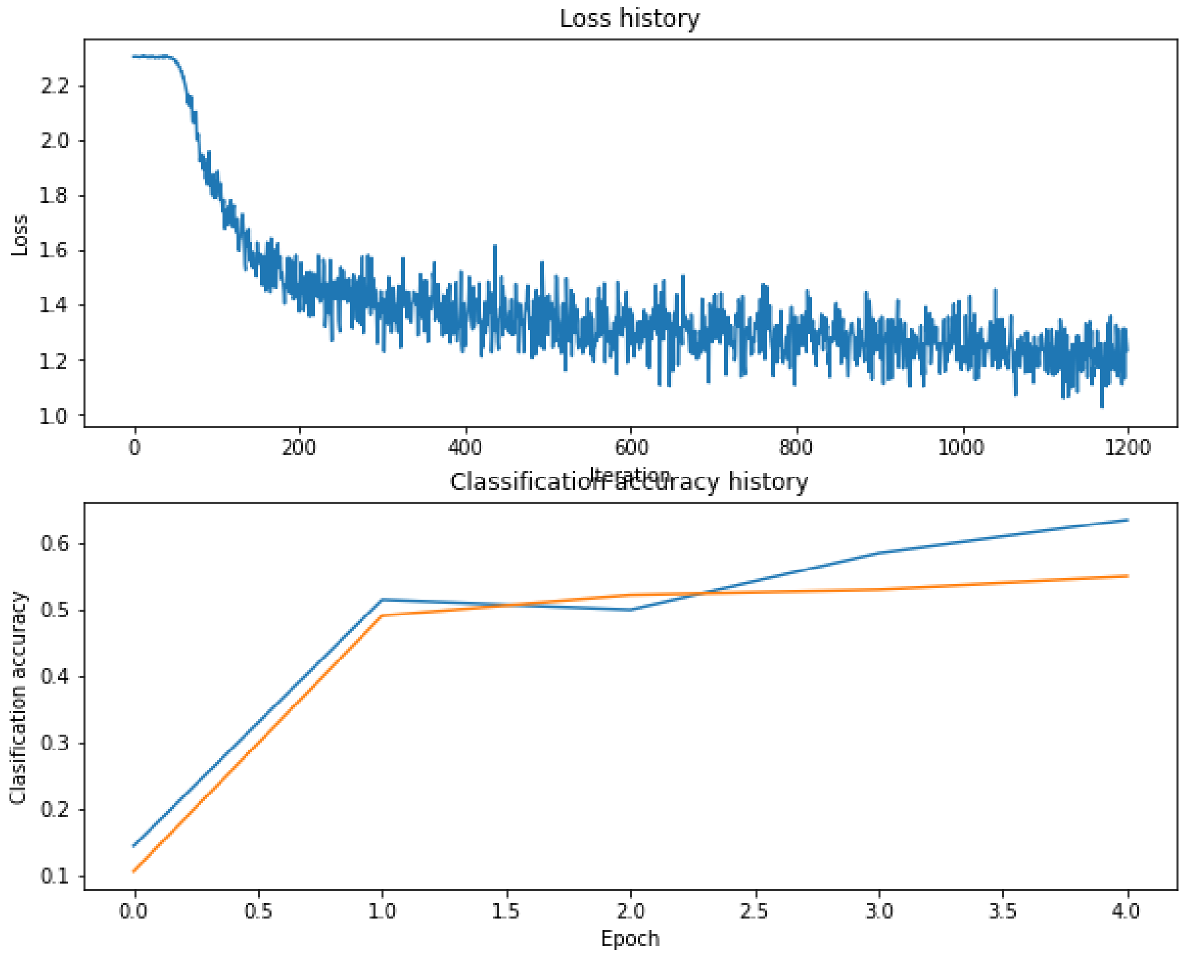



```
learning:  0.3
reg:  0.0005
iteration 0 / 1200: loss 2.302586
iteration 100 / 1200: loss 1.760567
iteration 200 / 1200: loss 1.367418
iteration 300 / 1200: loss 1.408214
iteration 400 / 1200: loss 1.295996
iteration 500 / 1200: loss 1.285062
iteration 600 / 1200: loss 1.225087
iteration 700 / 1200: loss 1.189065
iteration 800 / 1200: loss 1.313224
iteration 900 / 1200: loss 1.252515
iteration 1000 / 1200: loss 1.276671
iteration 1100 / 1200: loss 1.051662
```






```
reg:  0.001
iteration 0 / 1200: loss 2.302586
iteration 100 / 1200: loss 1.829317
iteration 200 / 1200: loss 1.374978
iteration 300 / 1200: loss 1.372994
iteration 400 / 1200: loss 1.247994
iteration 500 / 1200: loss 1.291218
iteration 600 / 1200: loss 1.379834
iteration 700 / 1200: loss 1.432419
iteration 800 / 1200: loss 1.250521
iteration 900 / 1200: loss 1.343784
iteration 1000 / 1200: loss 1.247016
iteration 1100 / 1200: loss 1.236755
```



In [99]:

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

est_acc = (net.predict(X_test_feats) == y_test).mean()
rint(test_acc)
```

```
0.559
```

Bonus: Design your own features!

You have seen that simple image features can improve classification performance. So far we have tried HOG and color histograms, but other types of features may be able to achieve even better classification performance.

For bonus points, design and implement a new type of feature and use it for image classification on CIFAR-10. Explain how your feature works and why you expect it to be useful for image classification. Implement it in this notebook, cross-validate any hyperparameters, and compare its performance to the HOG + Color histogram baseline.

Bonus: Do something extra!

Use the material and code we have presented in this assignment to do something interesting. Was there another question we should have asked? Did any cool ideas pop into your head as you were working on the assignment? This is your chance to show off!