features

September 28, 2018

1 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 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 [6]: import random
        import numpy as np
        from cs682.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-ipython
        %load_ext autoreload
        %autoreload 2
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

1.1 Load data

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

```
In [7]: from cs682.features import color_histogram_hsv, hog_feature
```

```python
def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs682/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
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.
```

1.2 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.

```python
In [8]: from cs682.features import *
```

```python
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
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
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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
```

1.3 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 [9]: # Use the validation set to tune the learning rate and regularization strength

        from cs682.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

        svm1 = LinearSVM()
        for i in learning_rates:
            for j in regularization_strengths:
                loss_history = svm1.train(X_train_feats, y_train, learning_rate=i, reg=j, num_i
                y_train_predict = svm1.predict(X_train_feats)
```

```
                train_accuracy = np.mean(y_train_predict == y_train)
                y_validation_predict = svm1.predict(X_val_feats)
                val_accuracy = np.mean(y_validation_predict == y_val)
                results[(i, j)] = (train_accuracy, val_accuracy)

                if val_accuracy > best_val:
                    best_val = val_accuracy
                    best_svm = svm1
        ################################################################################
        # 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)
```

```
lr 1.000000e-09 reg 5.000000e+04 train accuracy: 0.090122 val accuracy: 0.083000
lr 1.000000e-09 reg 5.000000e+05 train accuracy: 0.090429 val accuracy: 0.083000
lr 1.000000e-09 reg 5.000000e+06 train accuracy: 0.188204 val accuracy: 0.193000
lr 1.000000e-08 reg 5.000000e+04 train accuracy: 0.415367 val accuracy: 0.417000
lr 1.000000e-08 reg 5.000000e+05 train accuracy: 0.415776 val accuracy: 0.413000
lr 1.000000e-08 reg 5.000000e+06 train accuracy: 0.404551 val accuracy: 0.395000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.415694 val accuracy: 0.420000
lr 1.000000e-07 reg 5.000000e+05 train accuracy: 0.408673 val accuracy: 0.390000
lr 1.000000e-07 reg 5.000000e+06 train accuracy: 0.370102 val accuracy: 0.357000
best validation accuracy achieved during cross-validation: 0.420000
```

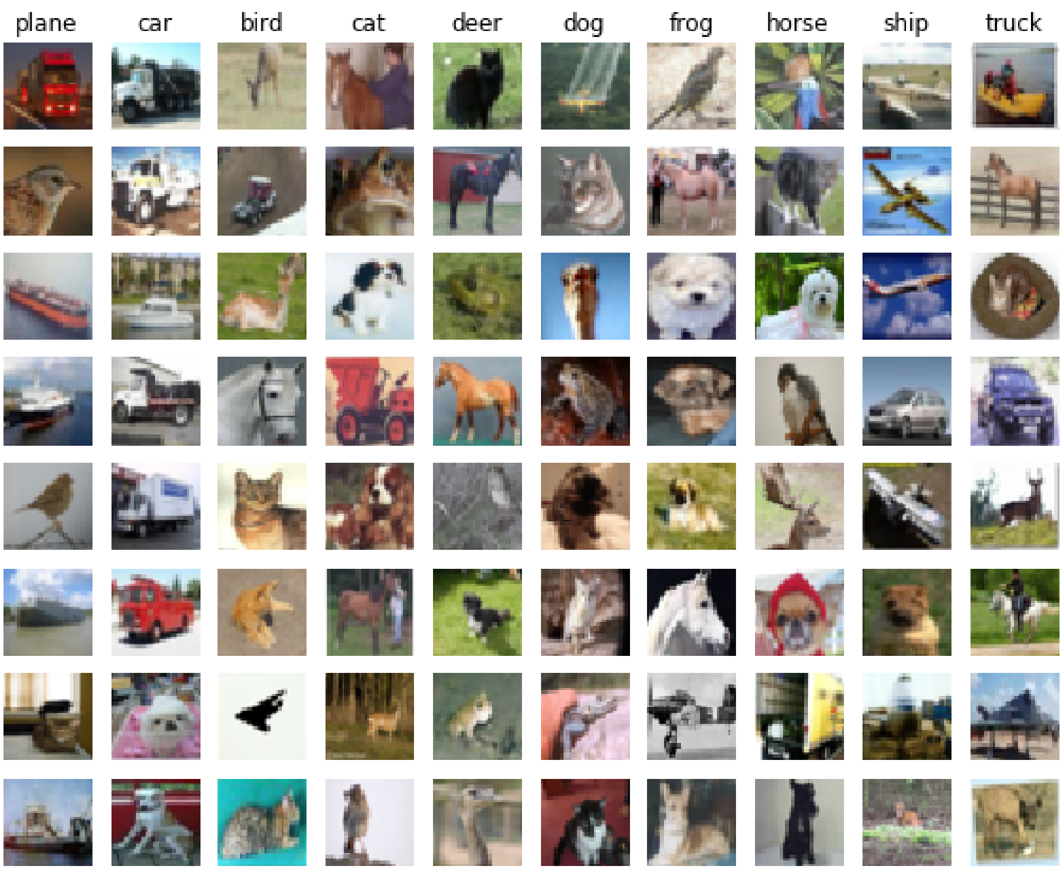
In [10]:
```
# Evaluate your trained SVM on the test set
y_test_pred = best_svm.predict(X_test_feats)
test_accuracy = np.mean(y_test == y_test_pred)
print(test_accuracy)
```

```
0.36
```

In [11]:
```
# 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', 'tru
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()
```



1.3.1 Inline question 1:

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

Yeah, they make sense at some level. Objects close to to each other share similar features and can be misclassified. Like cat is tagged as a dog, and a truck as a car.

1.4 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 [12]: # 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 [13]: from cs682.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

         learning_rates = [1]
         regularization = [4e-4]
         hidden_layer = [700]
         best_accuracy = -1
         #training_epochs = []
         #parameters = {}
         for i in learning_rates:
             for j in regularization:
                 for k in hidden_layer:

                     stats = net.train(X_train_feats, y_train, X_val_feats, y_val, num_iters=1
                                       learning_rate_decay=0.95, reg=j, verbose=False)
```

```
                #print(stats)
                temp = stats['val_acc_history'][-1]
                print('learning rates: %e, regularization: %e, hidden: %e, accuracy is: %
                        % (i, j, k, temp))
                if temp > best_accuracy:
                    best_accuracy = temp
                    best_net = net
    ################################################################################
    # 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.                                              #
    ################################################################################
    # Your code
    ################################################################################
    #                              END OF YOUR CODE                                #
    ################################################################################
```

```
learning rates: 1.000000e+00, regularization: 4.000000e-04, hidden: 7.000000e+02, accuracy is:
```

In [14]:
```
# 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)
```

```
0.559
```