q1

January 11, 2016

1 Dropout and Data Augmentation

In this exercise we will implement two ways to reduce overfitting.

Like the previous assignment, we will train ConvNets to recognize the categories in CIFAR-10. However unlike the previous assignment where we used 49,000 images for training, in this exercise we will use just 500 images for training.

If we try to train a high-capacity model like a ConvNet on this small amount of data, we expect to overfit, and end up with a solution that does not generalize. We will see that we can drastically reduce overfitting by using dropout and data augmentation.

In [1]:
```
# A bit of setup

import numpy as np
import matplotlib.pyplot as plt
from time import time
from cs231n.layers import *
from cs231n.fast_layers import *

%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

def rel_error(x, y):
    """ returns relative error """
    return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))
```

2 Load data

For this exercise our training set will contain 500 images and our validation and test sets will contain 1000 images as usual.

In [2]:
```
from cs231n.data_utils import load_CIFAR10

def get_CIFAR10_data(num_training=500, num_validation=1000, num_test=1000, normalize=True):
    """
    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for the two-layer neural net classifier. These are the same steps as
```

```
        we used for the SVM, but condensed to a single function.
        """
        # 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 = range(num_training, num_training + num_validation)
        X_val = X_train[mask]
        y_val = y_train[mask]
        mask = range(num_training)
        X_train = X_train[mask]
        y_train = y_train[mask]
        mask = range(num_test)
        X_test = X_test[mask]
        y_test = y_test[mask]

        # Normalize the data: subtract the mean image
        if normalize:
            mean_image = np.mean(X_train, axis=0)
            X_train -= mean_image
            X_val -= mean_image
            X_test -= mean_image

        # Transpose so that channels come first
        X_train = X_train.transpose(0, 3, 1, 2).copy()
        X_val = X_val.transpose(0, 3, 1, 2).copy()
        X_test = X_test.transpose(0, 3, 1, 2).copy()

        return X_train, y_train, X_val, y_val, X_test, y_test


    # Invoke the above function to get our data.
    X_train, y_train, X_val, y_val, X_test, y_test = get_CIFAR10_data(num_training=500)
    print 'Train data shape: ', X_train.shape
    print 'Train labels shape: ', y_train.shape
    print 'Validation data shape: ', X_val.shape
    print 'Validation labels shape: ', y_val.shape
    print 'Test data shape: ', X_test.shape
    print 'Test labels shape: ', y_test.shape
```

```
Train data shape:  (500, 3, 32, 32)
Train labels shape:  (500,)
Validation data shape:  (1000, 3, 32, 32)
Validation labels shape:  (1000,)
Test data shape:  (1000, 3, 32, 32)
Test labels shape:  (1000,)
```

3 Overfit

Now that we've loaded our data, we will attempt to train a three layer convnet on this data. The three layer convnet has the architecture

`conv - relu - pool - affine - relu - affine - softmax`

We will use 32 5x5 filters, and our hidden affine layer will have 128 neurons.

This is a very expressive model given that we have only 500 training samples, so we should expect to massively overfit this dataset, and achieve a training accuracy of nearly 0.9 with a much lower validation accuracy.

```
In [3]: from cs231n.classifiers.convnet import *
        from cs231n.classifier_trainer import ClassifierTrainer

        model = init_three_layer_convnet(filter_size=5, num_filters=(32, 128))
        trainer = ClassifierTrainer()
        best_model, loss_history, train_acc_history, val_acc_history = trainer.train(
                  X_train, y_train, X_val, y_val, model, three_layer_convnet, dropout=None,
                  reg=0.05, learning_rate=0.00005, batch_size=50, num_epochs=15,
                  learning_rate_decay=1.0, update='rmsprop', verbose=True)
```

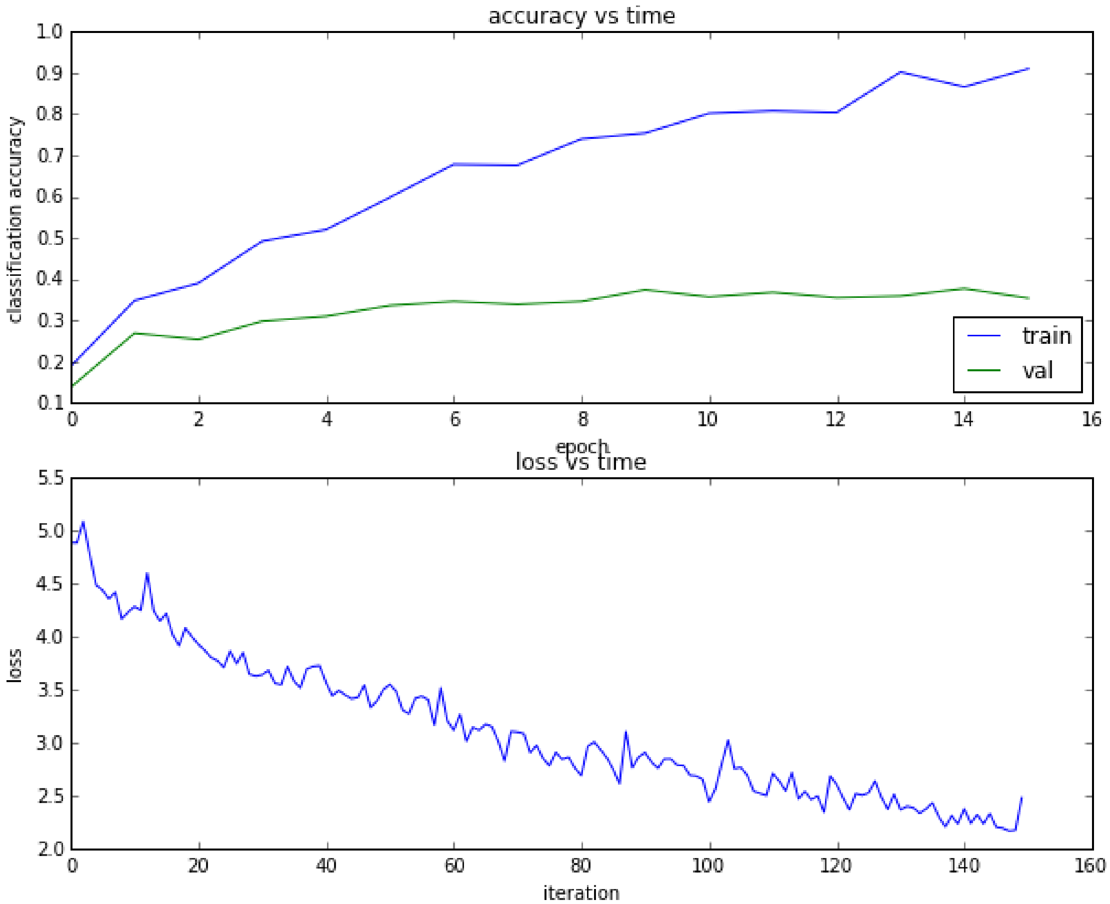
```
starting iteration  0
Finished epoch 0 / 15: cost 4.881619, train: 0.188000, val 0.137000, lr 5.000000e-05
Finished epoch 1 / 15: cost 4.226069, train: 0.348000, val 0.269000, lr 5.000000e-05
starting iteration  10
Finished epoch 2 / 15: cost 3.995205, train: 0.390000, val 0.254000, lr 5.000000e-05
starting iteration  20
Finished epoch 3 / 15: cost 3.622365, train: 0.492000, val 0.298000, lr 5.000000e-05
starting iteration  30
Finished epoch 4 / 15: cost 3.720741, train: 0.520000, val 0.310000, lr 5.000000e-05
starting iteration  40
Finished epoch 5 / 15: cost 3.496883, train: 0.598000, val 0.336000, lr 5.000000e-05
starting iteration  50
Finished epoch 6 / 15: cost 3.204336, train: 0.678000, val 0.346000, lr 5.000000e-05
starting iteration  60
Finished epoch 7 / 15: cost 3.101823, train: 0.676000, val 0.339000, lr 5.000000e-05
starting iteration  70
Finished epoch 8 / 15: cost 2.755542, train: 0.740000, val 0.346000, lr 5.000000e-05
starting iteration  80
Finished epoch 9 / 15: cost 2.861839, train: 0.754000, val 0.374000, lr 5.000000e-05
starting iteration  90
Finished epoch 10 / 15: cost 2.649203, train: 0.802000, val 0.357000, lr 5.000000e-05
starting iteration  100
Finished epoch 11 / 15: cost 2.496764, train: 0.808000, val 0.368000, lr 5.000000e-05
starting iteration  110
Finished epoch 12 / 15: cost 2.682331, train: 0.804000, val 0.355000, lr 5.000000e-05
starting iteration  120
Finished epoch 13 / 15: cost 2.508946, train: 0.902000, val 0.359000, lr 5.000000e-05
starting iteration  130
Finished epoch 14 / 15: cost 2.231781, train: 0.866000, val 0.377000, lr 5.000000e-05
starting iteration  140
Finished epoch 15 / 15: cost 2.476902, train: 0.910000, val 0.354000, lr 5.000000e-05
finished optimization. best validation accuracy: 0.377000
```

```
In [4]: # Visualize the loss and accuracy for our network trained on a small dataset

        plt.subplot(2, 1, 1)
        plt.plot(train_acc_history)
        plt.plot(val_acc_history)
        plt.title('accuracy vs time')
        plt.legend(['train', 'val'], loc=4)
        plt.xlabel('epoch')
```

```
plt.ylabel('classification accuracy')

plt.subplot(2, 1, 2)
plt.plot(loss_history)
plt.title('loss vs time')
plt.xlabel('iteration')
plt.ylabel('loss')
plt.show()
```



4 Dropout

The first way we will reduce overfitting is to use dropout.

Open the file cs231n/layers.py and implement the dropout_forward and dropout_backward functions. We can check the forward pass by looking at the statistics of the outputs in train and test modes, and we can check the backward pass using numerical gradient checking.

```
In [5]: # Check the dropout forward pass

        x = np.random.randn(100, 100)
        dropout_param_train = {'p': 0.25, 'mode': 'train'}
        dropout_param_test = {'p': 0.25, 'mode': 'test'}
```

```
out_train, _ = dropout_forward(x, dropout_param_train)
out_test, _ = dropout_forward(x, dropout_param_test)

# Test dropout training mode; about 25% of the elements should be nonzero
print np.mean(out_train != 0)

# Test dropout test mode; all of the elements should be nonzero
print np.mean(out_test != 0)
```

```
0.2462
1.0
```

```
In [6]: from cs231n.gradient_check import eval_numerical_gradient_array

        # Check the dropout backward pass

        x = np.random.randn(5, 4)
        dout = np.random.randn(*x.shape)
        dropout_param = {'p': 0.8, 'mode': 'train', 'seed': 123}

        dx_num = eval_numerical_gradient_array(lambda x: dropout_forward(x, dropout_param)[0], x, dout)

        _, cache = dropout_forward(x, dropout_param)
        dx = dropout_backward(dout, cache)

        # The error should be around 1e-12
        print 'Testing dropout_backward function:'
        print 'dx error: ', rel_error(dx_num, dx)
```

```
Testing dropout_backward function:
dx error:  7.71652972481e-12
```

5 Data Augmentation

The next way we will reduce overfitting is to implement data augmentation. Since we have very little training data, we will use what little training data we have to generate artificial data, and use this artificial data to train our network.

CIFAR-10 images are 32x32, and up until this point we have used the entire image as input to our convnets. Now we will do something different: our convnet will expect a smaller input (say 28x28). Instead of feeding our training images directly to the convnet, at training time we will randomly crop each training image to 28x28, randomly flip half of the training images horizontally, and randomly adjust the contrast and tint of each training image.

Open the file `cs231n/data_augmentation.py` and implement the `random_flips`, `random_crops`, `random_contrast`, and `random_tint` functions. In the same file we have implemented the `fixed_crops` function to get you started. When you are done you can run the cell below to visualize the effects of each type of data augmentation.

```
In [7]: from cs231n.data_augmentation import *

        X = get_CIFAR10_data(num_training=100, normalize=False)[0]
        num_imgs = 8
        print X.dtype
        X = X[np.random.randint(100, size=num_imgs)]
```

```python
X_flip = random_flips(X)
X_rand_crop = random_crops(X, (28, 28))

# To give more dramatic visualizations we use large scales for random contrast
# and tint adjustment.
X_contrast = random_contrast(X, scale=(0.5, 1.0))
X_tint = random_tint(X, scale=(-50, 50))

next_plt = 1
for i in xrange(num_imgs):
    titles = ['original', 'flip', 'rand crop', 'contrast', 'tint']
    for j, XX in enumerate([X, X_flip, X_rand_crop, X_contrast, X_tint]):
        plt.subplot(num_imgs, 5, next_plt)
        img = XX[i].transpose(1, 2, 0)
        if j == 4:
            # For visualization purposes we rescale the pixel values of the
            # tinted images
            low, high = np.min(img), np.max(img)
            img = 255 * (img - low) / (high - low)
        plt.imshow(img.astype('uint8'))
        if i == 0:
            plt.title(titles[j])
        plt.gca().axis('off')
        next_plt += 1
plt.show()
```

```
float64
```

6 Train again

We will now train a new network with the same training data and the same architecture, but using data augmentation and dropout.

If everything works, you should see a higher validation accuracy than above and a smaller gap between the training accuracy and the validation accuracy.

Networks with dropout usually take a bit longer to train, so we will use more training epochs this time.

In [8]:
```
input_shape = (3, 28, 28)

def augment_fn(X):
    out = random_flips(random_crops(X, input_shape[1:]))
    out = random_tint(random_contrast(out))
    return out

def predict_fn(X):
    return fixed_crops(X, input_shape[1:], 'center')
```

```python
model = init_three_layer_convnet(filter_size=5, input_shape=input_shape, num_filters=(32, 128))
trainer = ClassifierTrainer()

best_model, loss_history, train_acc_history, val_acc_history = trainer.train(
          X_train, y_train, X_val, y_val, model, three_layer_convnet,
          reg=0.05, learning_rate=0.00005, learning_rate_decay=1.0,
          batch_size=50, num_epochs=30, update='rmsprop', verbose=True, dropout=0.6,
          augment_fn=augment_fn, predict_fn=predict_fn)
```

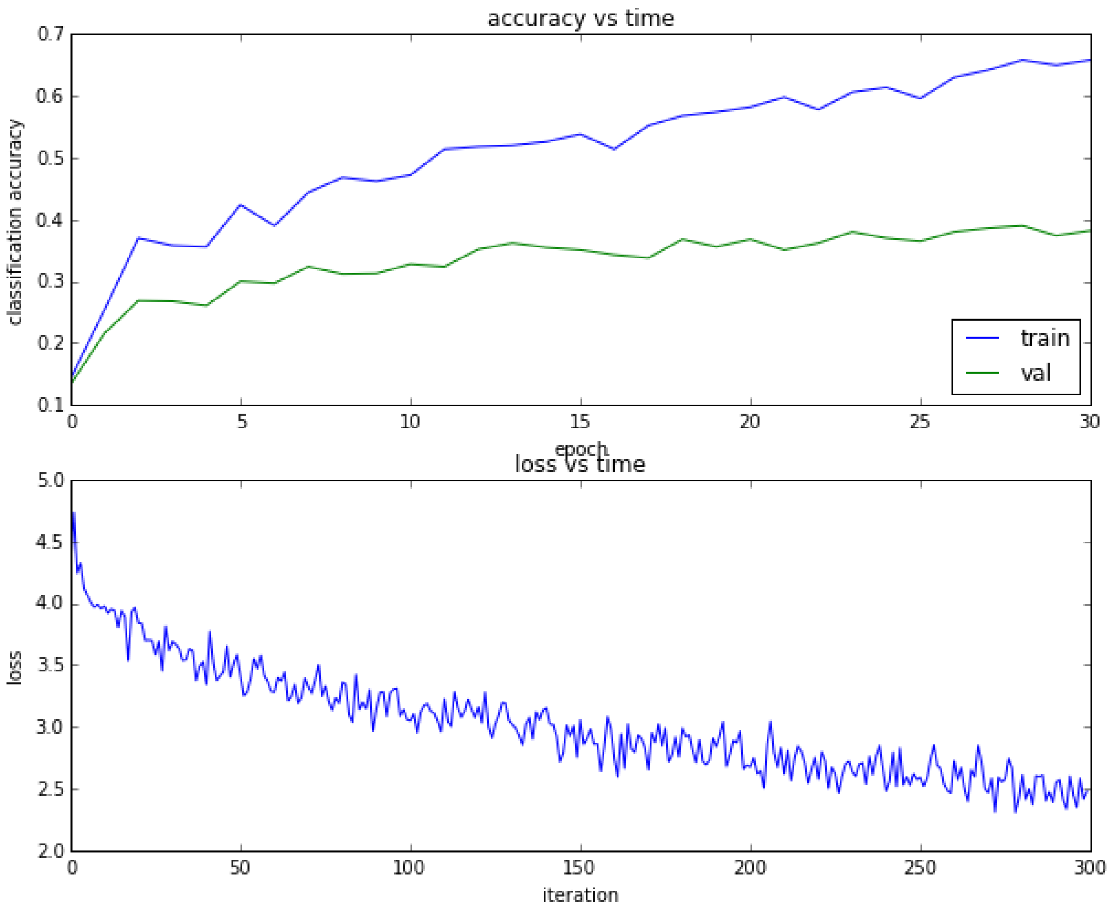
```
starting iteration  0
Finished epoch 0 / 30: cost 4.289228, train: 0.142000, val 0.133000, lr 5.000000e-05
Finished epoch 1 / 30: cost 3.954218, train: 0.254000, val 0.216000, lr 5.000000e-05
starting iteration  10
Finished epoch 2 / 30: cost 3.962945, train: 0.370000, val 0.269000, lr 5.000000e-05
starting iteration  20
Finished epoch 3 / 30: cost 3.614963, train: 0.358000, val 0.268000, lr 5.000000e-05
starting iteration  30
Finished epoch 4 / 30: cost 3.521684, train: 0.356000, val 0.261000, lr 5.000000e-05
starting iteration  40
Finished epoch 5 / 30: cost 3.581431, train: 0.424000, val 0.300000, lr 5.000000e-05
starting iteration  50
Finished epoch 6 / 30: cost 3.285557, train: 0.390000, val 0.297000, lr 5.000000e-05
starting iteration  60
Finished epoch 7 / 30: cost 3.393622, train: 0.444000, val 0.324000, lr 5.000000e-05
starting iteration  70
Finished epoch 8 / 30: cost 3.187727, train: 0.468000, val 0.312000, lr 5.000000e-05
starting iteration  80
Finished epoch 9 / 30: cost 2.966608, train: 0.462000, val 0.313000, lr 5.000000e-05
starting iteration  90
Finished epoch 10 / 30: cost 3.059312, train: 0.472000, val 0.328000, lr 5.000000e-05
starting iteration  100
Finished epoch 11 / 30: cost 2.960930, train: 0.514000, val 0.324000, lr 5.000000e-05
starting iteration  110
Finished epoch 12 / 30: cost 3.073169, train: 0.518000, val 0.352000, lr 5.000000e-05
starting iteration  120
Finished epoch 13 / 30: cost 3.052548, train: 0.520000, val 0.362000, lr 5.000000e-05
starting iteration  130
Finished epoch 14 / 30: cost 3.133880, train: 0.526000, val 0.355000, lr 5.000000e-05
starting iteration  140
Finished epoch 15 / 30: cost 2.752860, train: 0.538000, val 0.351000, lr 5.000000e-05
starting iteration  150
Finished epoch 16 / 30: cost 2.987047, train: 0.514000, val 0.343000, lr 5.000000e-05
starting iteration  160
Finished epoch 17 / 30: cost 2.827745, train: 0.552000, val 0.338000, lr 5.000000e-05
starting iteration  170
Finished epoch 18 / 30: cost 2.755957, train: 0.568000, val 0.368000, lr 5.000000e-05
starting iteration  180
Finished epoch 19 / 30: cost 2.905574, train: 0.574000, val 0.356000, lr 5.000000e-05
starting iteration  190
Finished epoch 20 / 30: cost 2.688496, train: 0.582000, val 0.368000, lr 5.000000e-05
starting iteration  200
Finished epoch 21 / 30: cost 2.829382, train: 0.598000, val 0.351000, lr 5.000000e-05
starting iteration  210
Finished epoch 22 / 30: cost 2.749677, train: 0.578000, val 0.362000, lr 5.000000e-05
```

```
starting iteration  220
Finished epoch 23 / 30: cost 2.720162, train: 0.606000, val 0.380000, lr 5.000000e-05
starting iteration  230
Finished epoch 24 / 30: cost 2.658037, train: 0.614000, val 0.370000, lr 5.000000e-05
starting iteration  240
Finished epoch 25 / 30: cost 2.573758, train: 0.596000, val 0.365000, lr 5.000000e-05
starting iteration  250
Finished epoch 26 / 30: cost 2.462394, train: 0.630000, val 0.380000, lr 5.000000e-05
starting iteration  260
Finished epoch 27 / 30: cost 2.498918, train: 0.642000, val 0.386000, lr 5.000000e-05
starting iteration  270
Finished epoch 28 / 30: cost 2.422930, train: 0.658000, val 0.390000, lr 5.000000e-05
starting iteration  280
Finished epoch 29 / 30: cost 2.388771, train: 0.650000, val 0.374000, lr 5.000000e-05
starting iteration  290
Finished epoch 30 / 30: cost 2.476037, train: 0.658000, val 0.382000, lr 5.000000e-05
finished optimization. best validation accuracy: 0.390000
```

In [9]:
```python
# Visualize the loss and accuracy for our network trained with dropout and data augmentation.
# You should see less overfitting, and you may also see slightly better performance on the
# validation set.

plt.subplot(2, 1, 1)
plt.plot(train_acc_history)
plt.plot(val_acc_history)
plt.title('accuracy vs time')
plt.legend(['train', 'val'], loc=4)
plt.xlabel('epoch')
plt.ylabel('classification accuracy')

plt.subplot(2, 1, 2)
plt.plot(loss_history)
plt.title('loss vs time')
plt.xlabel('iteration')
plt.ylabel('loss')
plt.show()
```


accuracy vs time
classification accuracy
epoch
train
val
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
5
10
15
20
25
30
loss vs time
loss
iteration
5.0
4.5
4.0
3.5
3.0
2.5
2.0
0
50
100
150
200
250
300

```
In [ ]:
```