Modular neural nets

In the previous exercise, we started to build modules/general layers for implementing large neural networks. In this exercise, we will expand on this by implementing a convolutional layer, max pooling layer and a dropout layer. For each layer we will implement `forward` and `backward` functions. The `forward` function will receive data, weights, and other parameters, and will return both an output and a `cache` object that stores data needed for the backward pass. The `backward` function will recieve upstream derivatives and the cache object, and will return gradients with respect to the data and all of the weights. This will allow us to write code that looks like this:

```
def two_layer_net(X, W1, b1, W2, b2, reg):
    # Forward pass; compute scores
    s1, fc1_cache = affine_forward(X, W1, b1)
    a1, relu_cache = relu_forward(s1)
    scores, fc2_cache = affine_forward(a1, W2, b2)

    # Loss functions return data loss and gradients on scores
    data_loss, dscores = svm_loss(scores, y)

    # Compute backward pass
    da1, dW2, db2 = affine_backward(dscores, fc2_cache)
    ds1 = relu_backward(da1, relu_cache)
    dX, dW1, db1 = affine_backward(ds1, fc1_cache)

    # A real network would add regularization here

    # Return loss and gradients
    return loss, dW1, db1, dW2, db2
```

In [1]:

```
# As usual, a bit of setup

import numpy as np
import matplotlib.pyplot as plt
from cs231n.gradient_check import eval_numerical_gradient_array, eval_numerical_gra
from cs231n.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 external 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))))
```

Dropout layer: forward

Open the file `cs231n/layers.py` and implement the `dropout_forward` function. You should implement **inverted dropout** rather than regular dropout. We can check the forward pass by looking at the statistics of the outputs in train and test modes.

In [2]:

```
# 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) # expected to be ~0.25

# Test dropout test mode; all of the elements should be nonzero
print np.mean(out_test != 0) # expected to be = 1
```

```
0.2502
1.0
```

Dropout layer: backward

Open the file `cs231n/layers.py` and implement the `dropout_backward` function. We can check the backward pass using numerical gradient checking.

In [3]:

```
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)[(

_, 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:  7.71642187513e-12
```

Convolution layer: forward naive

We are now ready to implement the forward pass for a convolutional layer. Implement the function `conv_forward_naive` in the file `cs231n/layers.py`.

You don't have to worry too much about efficiency at this point; just write the code in whatever way you find most clear.

You can test your implementation by running the following:

In [4]:

```
x_shape = (2, 3, 4, 4)
w_shape = (3, 3, 4, 4)
x = np.linspace(-0.1, 0.5, num=np.prod(x_shape)).reshape(x_shape)
w = np.linspace(-0.2, 0.3, num=np.prod(w_shape)).reshape(w_shape)
b = np.linspace(-0.1, 0.2, num=3)

conv_param = {'stride': 2, 'pad': 1}
out, _ = conv_forward_naive(x, w, b, conv_param)
correct_out = np.array([[[[[-0.08759809, -0.10987781],
                           [-0.18387192, -0.2109216 ]],
                          [[ 0.21027089,  0.21661097],
                           [ 0.22847626,  0.23004637]],
                          [[ 0.50813986,  0.54309974],
                           [ 0.64082444,  0.67101435]]],
                         [[[-0.98053589, -1.03143541],
                           [-1.19128892, -1.24695841]],
                          [[ 0.69108355,  0.66880383],
                           [ 0.59480972,  0.56776003]],
                          [[ 2.36270298,  2.36904306],
                           [ 2.38090835,  2.38247847]]]]])

# Compare your output to ours; difference should be around 1e-8
print 'Testing conv_forward_naive'
print 'difference: ', rel_error(out, correct_out)
```

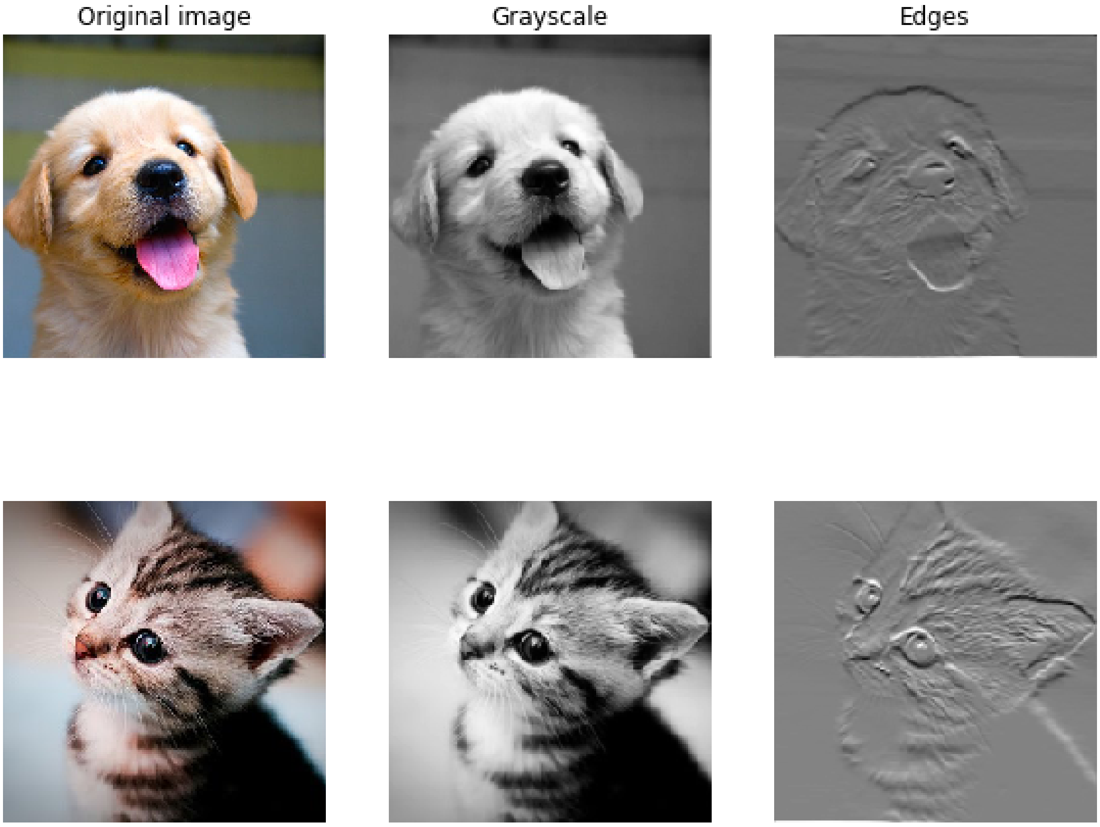
```
Testing conv_forward_naive
difference:  2.21214764175e-08
```

Aside: Image processing via convolutions

As fun way to both check your implementation and gain a better understanding of the type of operation that convolutional layers can perform, we will set up an input containing two images and manually set up filters that perform common image processing operations (grayscale conversion and edge detection). The convolution forward pass will apply these operations to each of the input images. We can then visualize the results as a sanity check.

In [5]:

```
from scipy.misc import imread, imresize

kitten, puppy = imread('kitten.jpg'), imread('puppy.jpg')
# kitten is wide, and puppy is already square
d = kitten.shape[1] - kitten.shape[0]
kitten_cropped = kitten[:, d/2:-d/2, :]

img_size = 200   # Make this smaller if it runs too slow
x = np.zeros((2, 3, img_size, img_size))
x[0, :, :, :] = imresize(puppy, (img_size, img_size)).transpose((2, 0, 1))
x[1, :, :, :] = imresize(kitten_cropped, (img_size, img_size)).transpose((2, 0, 1))

# Set up a convolutional weights holding 2 filters, each 3x3
w = np.zeros((2, 3, 3, 3))

# The first filter converts the image to grayscale.
# Set up the red, green, and blue channels of the filter.
w[0, 0, :, :] = [[0, 0, 0], [0, 0.3, 0], [0, 0, 0]]
w[0, 1, :, :] = [[0, 0, 0], [0, 0.6, 0], [0, 0, 0]]
w[0, 2, :, :] = [[0, 0, 0], [0, 0.1, 0], [0, 0, 0]]

# Second filter detects horizontal edges in the blue channel.
w[1, 2, :, :] = [[1, 2, 1], [0, 0, 0], [-1, -2, -1]]

# Vector of biases. We don't need any bias for the grayscale
# filter, but for the edge detection filter we want to add 128
# to each output so that nothing is negative.
b = np.array([0, 128])

# Compute the result of convolving each input in x with each filter in w,
# offsetting by b, and storing the results in out.
out, _ = conv_forward_naive(x, w, b, {'stride': 1, 'pad': 1})

def imshow_noax(img, normalize=True):
    """ Tiny helper to show images as uint8 and remove axis labels """
    if normalize:
        img_max, img_min = np.max(img), np.min(img)
        img = 255.0 * (img - img_min) / (img_max - img_min)
    plt.imshow(img.astype('uint8'))
    plt.gca().axis('off')

# Show the original images and the results of the conv operation
plt.subplot(2, 3, 1)
imshow_noax(puppy, normalize=False)
plt.title('Original image')
plt.subplot(2, 3, 2)
imshow_noax(out[0, 0])
plt.title('Grayscale')
plt.subplot(2, 3, 3)
imshow_noax(out[0, 1])
plt.title('Edges')
plt.subplot(2, 3, 4)
imshow_noax(kitten_cropped, normalize=False)
plt.subplot(2, 3, 5)
imshow_noax(out[1, 0])
plt.subplot(2, 3, 6)
imshow_noax(out[1, 1])
plt.show()
```



Convolution layer: backward naive

Next you need to implement the function `conv_backward_naive` in the file `cs231n/layers.py`. As usual, we will check your implementation with numeric gradient checking.

In [6]:

```
x = np.random.randn(4, 3, 5, 5)
w = np.random.randn(2, 3, 3, 3)
b = np.random.randn(2,)
dout = np.random.randn(4, 2, 5, 5)
conv_param = {'stride': 1, 'pad': 1}

dx_num = eval_numerical_gradient_array(lambda x: conv_forward_naive(x, w, b, conv_pa
dw_num = eval_numerical_gradient_array(lambda w: conv_forward_naive(x, w, b, conv_pa
db_num = eval_numerical_gradient_array(lambda b: conv_forward_naive(x, w, b, conv_pa

out, cache = conv_forward_naive(x, w, b, conv_param)
dx, dw, db = conv_backward_naive(dout, cache)

# Your errors should be around 1e-9'
print 'Testing conv_backward_naive function'
print 'dx error: ', rel_error(dx, dx_num)
print 'dw error: ', rel_error(dw, dw_num)
print 'db error: ', rel_error(db, db_num)
```

```
Testing conv_backward_naive function
dx error:  1.42918515583e-09
dw error:  3.24894092112e-10
db error:  4.93456965076e-12
```

Max pooling layer: forward naive

The last layer we need for a basic convolutional neural network is the max pooling layer. First implement the forward pass in the function `max_pool_forward_naive` in the file `cs231n/layers.py`.

In [7]:

```
x_shape = (2, 3, 4, 4)
x = np.linspace(-0.3, 0.4, num=np.prod(x_shape)).reshape(x_shape)
pool_param = {'pool_width': 2, 'pool_height': 2, 'stride': 2}

out, _ = max_pool_forward_naive(x, pool_param)

correct_out = np.array([[[[-0.26315789, -0.24842105],
                          [-0.20421053, -0.18947368]],
                         [[-0.14526316, -0.13052632],
                          [-0.08631579, -0.07157895]],
                         [[-0.02736842, -0.01263158],
                          [ 0.03157895,  0.04631579]]],
                        [[[ 0.09052632,  0.10526316],
                          [ 0.14947368,  0.16421053]],
                         [[ 0.20842105,  0.22315789],
                          [ 0.26736842,  0.28210526]],
                         [[ 0.32631579,  0.34105263],
                          [ 0.38526316,  0.4       ]]]])

# Compare your output with ours. Difference should be around 1e-8.
print 'Testing max_pool_forward_naive function:'
print 'difference: ', rel_error(out, correct_out)
```

```
Testing max_pool_forward_naive function:
difference:  4.16666651573e-08
```

Max pooling layer: backward naive

Implement the backward pass for a max pooling layer in the function `max_pool_backward_naive` in the file `cs231n/layers.py`. As always we check the correctness of the backward pass using numerical gradient checking.

In [8]:

```
x = np.random.randn(3, 2, 8, 8)
dout = np.random.randn(3, 2, 4, 4)
pool_param = {'pool_height': 2, 'pool_width': 2, 'stride': 2}

dx_num = eval_numerical_gradient_array(lambda x: max_pool_forward_naive(x, pool_par

out, cache = max_pool_forward_naive(x, pool_param)
dx = max_pool_backward_naive(dout, cache)

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

```
Testing max_pool_backward_naive function:
dx error:  3.27563758008e-12
```

Fast layers

Making convolution and pooling layers fast can be challenging. To spare you the pain, we've provided fast implementations of the forward and backward passes for convolution and pooling layers in the file `cs231n/fast_layers.py`.

The fast convolution implementation depends on a Cython extension; to compile it you need to run the following from the `cs231n` directory:

```
python setup.py build_ext --inplace
```

The API for the fast versions of the convolution and pooling layers is exactly the same as the naive versions that you implemented above: the forward pass receives data, weights, and parameters and produces outputs and a cache object; the backward pass recieves upstream derivatives and the cache object and produces gradients with respect to the data and weights.

NOTE: The fast implementation for pooling will only perform optimally if the pooling regions are non-overlapping and tile the input. If these conditions are not met then the fast pooling implementation will not be much faster than the naive implementation.

You can compare the performance of the naive and fast versions of these layers by running the following:

In [9]:

```
from cs231n.fast_layers import conv_forward_fast, conv_backward_fast
from time import time

x = np.random.randn(100, 3, 31, 31)
w = np.random.randn(25, 3, 3, 3)
b = np.random.randn(25,)
dout = np.random.randn(100, 25, 16, 16)
conv_param = {'stride': 2, 'pad': 1}

t0 = time()
out_naive, cache_naive = conv_forward_naive(x, w, b, conv_param)
t1 = time()
out_fast, cache_fast = conv_forward_fast(x, w, b, conv_param)
t2 = time()

print 'Testing conv_forward_fast:'
print 'Naive: %fs' % (t1 - t0)
print 'Fast: %fs' % (t2 - t1)
print 'Speedup: %fx' % ((t1 - t0) / (t2 - t1))
print 'Difference: ', rel_error(out_naive, out_fast)

t0 = time()
dx_naive, dw_naive, db_naive = conv_backward_naive(dout, cache_naive)
t1 = time()
dx_fast, dw_fast, db_fast = conv_backward_fast(dout, cache_fast)
t2 = time()

print '\nTesting conv_backward_fast:'
print 'Naive: %fs' % (t1 - t0)
print 'Fast: %fs' % (t2 - t1)
print 'Speedup: %fx' % ((t1 - t0) / (t2 - t1))
print 'dx difference: ', rel_error(dx_naive, dx_fast)
print 'dw difference: ', rel_error(dw_naive, dw_fast)
print 'db difference: ', rel_error(db_naive, db_fast)
```

```
Testing conv_forward_fast:
Naive: 4.706545s
Fast: 0.025513s
Speedup: 184.476820x
Difference:  5.76441667407e-11

Testing conv_backward_fast:
Naive: 5.707568s
Fast: 0.011451s
Speedup: 498.433759x
dx difference:  1.37522088985e-11
dw difference:  4.97269198917e-13
db difference:  8.05806780804e-14
```

In [10]:

```
from cs231n.fast_layers import max_pool_forward_fast, max_pool_backward_fast

x = np.random.randn(100, 3, 32, 32)
dout = np.random.randn(100, 3, 16, 16)
pool_param = {'pool_height': 2, 'pool_width': 2, 'stride': 2}

t0 = time()
out_naive, cache_naive = max_pool_forward_naive(x, pool_param)
t1 = time()
out_fast, cache_fast = max_pool_forward_fast(x, pool_param)
t2 = time()

print 'Testing pool_forward_fast:'
print 'Naive: %fs' % (t1 - t0)
print 'fast: %fs' % (t2 - t1)
print 'speedup: %fx' % ((t1 - t0) / (t2 - t1))
print 'difference: ', rel_error(out_naive, out_fast)

t0 = time()
dx_naive = max_pool_backward_naive(dout, cache_naive)
t1 = time()
dx_fast = max_pool_backward_fast(dout, cache_fast)
t2 = time()

print '\nTesting pool_backward_fast:'
print 'Naive: %fs' % (t1 - t0)
print 'speedup: %fx' % ((t1 - t0) / (t2 - t1))
print 'dx difference: ', rel_error(dx_naive, dx_fast)
```

```
Testing pool_forward_fast:
Naive: 0.162692s
fast: 0.003355s
speedup: 48.495487x
difference:  0.0

Testing pool_backward_fast:
Naive: 0.939352s
speedup: 69.151874x
dx difference:  0.0
```

Sandwich layers

There are a couple common layer "sandwiches" that frequently appear in ConvNets. For example convolutional layers are frequently followed by ReLU and pooling, and affine layers are frequently followed by ReLU. To make it more convenient to use these common patterns, we have defined several convenience layers in the file `cs231n/layer_utils.py`. Lets grad-check them to make sure that they work correctly:

In [12]:

```
from cs231n.layer_utils import conv_relu_pool_forward, conv_relu_pool_backward

x = np.random.randn(2, 3, 16, 16)
w = np.random.randn(3, 3, 3, 3)
b = np.random.randn(3,)
dout = np.random.randn(2, 3, 8, 8)
conv_param = {'stride': 1, 'pad': 1}
pool_param = {'pool_height': 2, 'pool_width': 2, 'stride': 2}

out, cache = conv_relu_pool_forward(x, w, b, conv_param, pool_param)
dx, dw, db = conv_relu_pool_backward(dout, cache)

dx_num = eval_numerical_gradient_array(lambda x: conv_relu_pool_forward(x, w, b, co
dw_num = eval_numerical_gradient_array(lambda w: conv_relu_pool_forward(x, w, b, co
db_num = eval_numerical_gradient_array(lambda b: conv_relu_pool_forward(x, w, b, co

print 'Testing conv_relu_pool_forward:'
print 'dx error: ', rel_error(dx_num, dx)
print 'dw error: ', rel_error(dw_num, dw)
print 'db error: ', rel_error(db_num, db)
```

```
Testing conv_relu_pool_forward:
dx error:  1.08746124512e-07
dw error:  9.47952395112e-10
db error:  6.53378986613e-11
```

In [17]:

```
from cs231n.layer_utils import conv_relu_forward, conv_relu_backward

x = np.random.randn(2, 3, 8, 8)
w = np.random.randn(3, 3, 3, 3)
b = np.random.randn(3,)
dout = np.random.randn(2, 3, 8, 8)
conv_param = {'stride': 1, 'pad': 1}

out, cache = conv_relu_forward(x, w, b, conv_param)
dx, dw, db = conv_relu_backward(dout, cache)

dx_num = eval_numerical_gradient_array(lambda x: conv_relu_forward(x, w, b, conv_pa
dw_num = eval_numerical_gradient_array(lambda w: conv_relu_forward(x, w, b, conv_pa
db_num = eval_numerical_gradient_array(lambda b: conv_relu_forward(x, w, b, conv_pa

print 'Testing conv_relu_forward:'
print 'dx error: ', rel_error(dx_num, dx)
print 'dw error: ', rel_error(dw_num, dw)
print 'db error: ', rel_error(db_num, db)
```

```
Testing conv_relu_forward:
dx error:  1.05302430612e-07
dw error:  1.4787331483e-09
db error:  1.75838854034e-11
```

In [18]:

```
from cs231n.layer_utils import affine_relu_forward, affine_relu_backward

x = np.random.randn(2, 3, 4)
w = np.random.randn(12, 10)
b = np.random.randn(10)
dout = np.random.randn(2, 10)

out, cache = affine_relu_forward(x, w, b)
dx, dw, db = affine_relu_backward(dout, cache)

dx_num = eval_numerical_gradient_array(lambda x: affine_relu_forward(x, w, b)[0], x
dw_num = eval_numerical_gradient_array(lambda w: affine_relu_forward(x, w, b)[0], w
db_num = eval_numerical_gradient_array(lambda b: affine_relu_forward(x, w, b)[0], b

print 'Testing affine_relu_forward:'
print 'dx error: ', rel_error(dx_num, dx)
print 'dw error: ', rel_error(dw_num, dw)
print 'db error: ', rel_error(db_num, db)
```

```
Testing affine_relu_forward:
dx error:  3.6273940288e-10
dw error:  1.43566723045e-10
db error:  7.82668761908e-12
```

In [ ]:

```

```