conv_net

March 10, 2019

1 Convolutional Networks

We have talked about convolutional neural networks. We will implement convolutional operations and max-pooling operation in this task to get a deeper understanding of the network.

```
In [4]: # As usual, a bit of setup
        import numpy as np
        import tensorflow as tf
        import matplotlib.pyplot as plt
        from implementations.layers import *
        from data_utils import get_CIFAR10_data

        %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))))
```

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

```
In [5]: # Load the (preprocessed) CIFAR10 data.

        data = get_CIFAR10_data()
        for k, v in data.items():
          print('%s: ' % k, v.shape)
```

```
y_test:  (1000,)
y_val:  (1000,)
```

```
X_train:  (49000, 3, 32, 32)
X_test:  (1000, 3, 32, 32)
y_train:  (49000,)
X_val:  (1000, 3, 32, 32)
```

2 Convolution Operation

We will implement a convolutional operation with numpy and compare it against an existing convolutional operation.

In [23]:
```
# shape is NCHW
x_shape = (2, 3, 4, 4)

# shape is FCHW
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)

# permute dimensions to NHWC
x = np.transpose(x, [0, 2, 3, 1])
# permute dimensions to HWCF
w = np.transpose(w, [2, 3, 1, 0])

conv_param = {'stride': 2, 'pad': 1}

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]]]])
correct_out = np.transpose(correct_out, [0, 2, 3, 1])


tf_out = tf.nn.conv2d(
    tf.constant(x, dtype=tf.float32),
    tf.constant(w, dtype=tf.float32),
    strides=[1, 2, 2, 1],
```

```
    padding='SAME',
    use_cudnn_on_gpu=False,
    data_format='NHWC' # NHWC is the default setting of tensorflow
)

tf_conv = tf.nn.bias_add(
    tf_out,
    tf.constant(b, dtype=tf.float32),
    data_format='NHWC')


print('Difference between correct output and tf calculation:', \
                                       rel_error(tf.Session().run(tf_conv), correct_ou

# Compare your output to ours; difference should be around e-8
out = conv_forward_naive(x, w, b, conv_param)
print('Difference between my implementation and correct output:', rel_error(out, corre

print('Difference between my implementation and tf calculation:', rel_error(out, tf.Se
```

```
Difference between correct output and tf calculation: 4.427582433439594e-08
Difference between my implementation and correct output: 2.212147649671884e-08
Difference between my implementation and tf calculation: 4.5275181161989593e-08
```

3 Aside: Image processing via convolutions

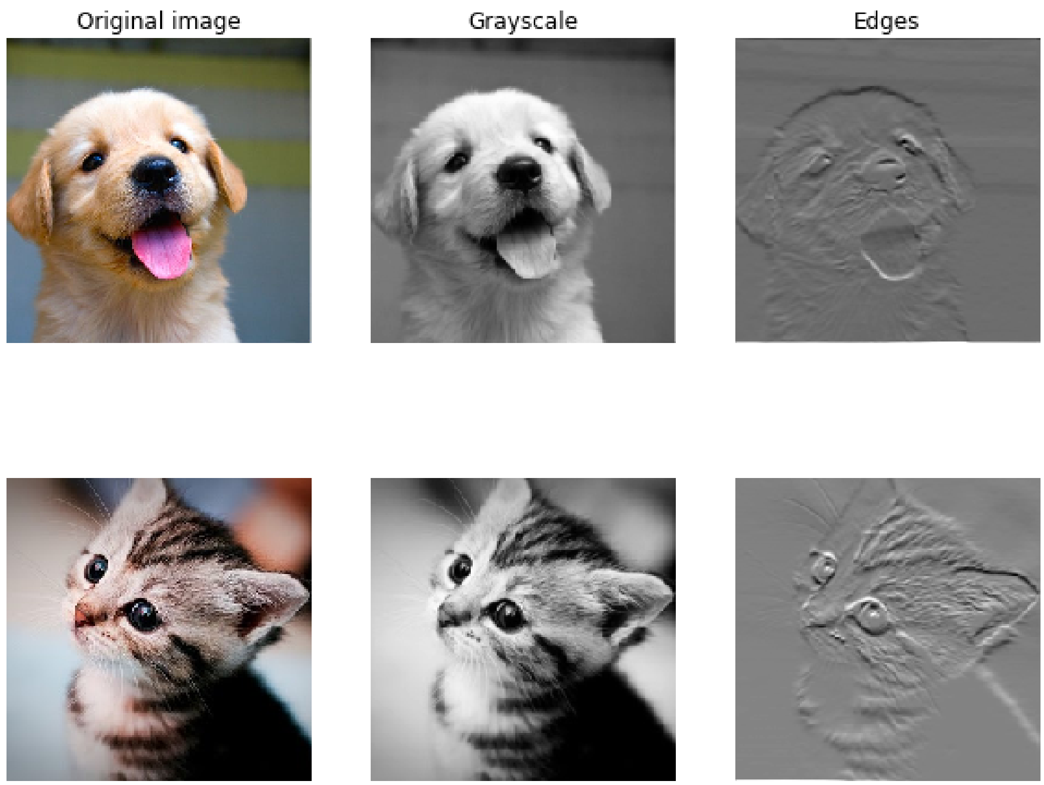
As fun way to both check your implementation and gain a better understanding of the type of operation that convolutional layers can perform, we will set up an input containing two images and manually set up filters that perform common image processing operations (grayscale conversion and edge detection). 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 [28]:
```
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, img_size, img_size, 3))
x[0, :, :, :] = imresize(puppy, (img_size, img_size))
x[1, :, :, :] = imresize(kitten_cropped, (img_size, img_size))

# 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]]

w = np.transpose(w, [2, 3, 1, 0])

# 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()
```

```
/usr/lib/python3.5/site-packages/ipykernel_launcher.py:3: DeprecationWarning: `imread` is depre
`imread` is deprecated in SciPy 1.0.0, and will be removed in 1.2.0.
```

```
Use ``imageio.imread`` instead.
  This is separate from the ipykernel package so we can avoid doing imports until
/usr/lib/python3.5/site-packages/ipykernel_launcher.py:10: DeprecationWarning: `imresize` is de
`imresize` is deprecated in SciPy 1.0.0, and will be removed in 1.2.0.
Use ``skimage.transform.resize`` instead.
  # Remove the CWD from sys.path while we load stuff.
/usr/lib/python3.5/site-packages/ipykernel_launcher.py:11: DeprecationWarning: `imresize` is de
`imresize` is deprecated in SciPy 1.0.0, and will be removed in 1.2.0.
Use ``skimage.transform.resize`` instead.
  # This is added back by InteractiveShellApp.init_path()
```



4 Max-Pooling: Naive forward

Implement the forward pass for the max-pooling operation in the function `max_pool_forward_naive` in the file `implementations/layers.py`. Again, don't worry too much about computational efficiency.

Check your implementation by running the following:

```
In [30]: # shape is NCHW
         x_shape = (2, 3, 4, 4)
```

```
x = np.linspace(-0.3, 0.4, num=np.prod(x_shape)).reshape(x_shape)
x = np.transpose(x, [0, 2, 3, 1])

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       ]]]])
correct_out = np.transpose(correct_out, [0, 2, 3, 1])

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

```
Testing max_pool_forward_naive function:
difference:  4.1666665157267834e-08
```

5 Multilayer Convolutional Network

You need to build a convolutional network with tensorflow operations: tf.nn.conv2d, tf.nn.relu, and tf.pool. You may want to do so by modifying the fully connected network provided in this assignment.

5.1 Overfit small data

A nice trick is to train your model with just a few training samples. You should be able to overfit small datasets, which will result in very high training accuracy and comparatively low validation accuracy.

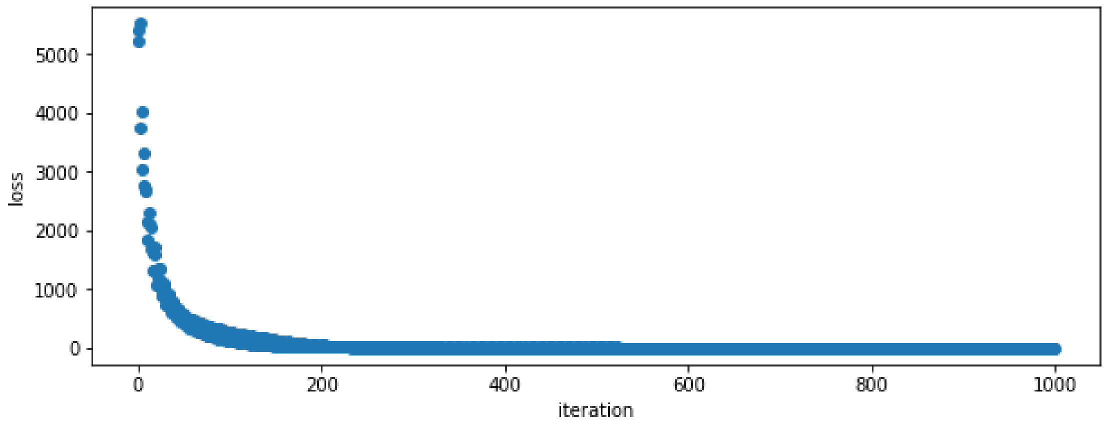
In [58]:
```
np.random.seed(15009)

from implementations.conv_net import ConvNet

num_train = 100
X_train = data['X_train'][:num_train].transpose([0, 2, 3, 1])
y_train = data['y_train'][:num_train]
```

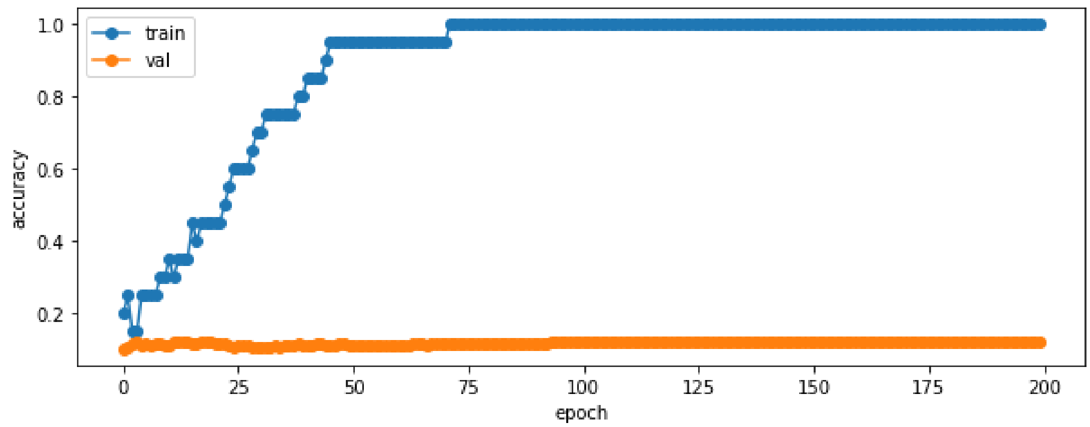
```
X_val = data['X_val'].transpose([0, 2, 3, 1])
y_val = data['y_val']



model = ConvNet(input_size=[32, 32, 3],
                output_size=10,
                filter_size=[[3, 3, 5], [3, 3, 5], [3, 3, 5], [3, 3, 2]],
                pooling_schedule=[1, 3],
                fc_hidden_size=[50])


trace = model.train(X_train, y_train, X_val, y_val,
            learning_rate=1e-3,
            reg=np.float32(5e-6),
            num_iters=1000,
            batch_size=20,
            verbose=True)
```

```
iteration 0 / 1000: objective 5397.040039
iteration 100 / 1000: objective 169.385483
iteration 200 / 1000: objective 20.961233
iteration 300 / 1000: objective 5.682499
iteration 400 / 1000: objective 0.759406
iteration 500 / 1000: objective 0.373937
iteration 600 / 1000: objective 0.254695
iteration 700 / 1000: objective 0.186426
iteration 800 / 1000: objective 0.138188
iteration 900 / 1000: objective 0.107499
```

Plotting the loss, training accuracy, and validation accuracy should show clear overfitting:

```
In [61]: plt.subplot(2, 1, 1)
         plt.plot(trace['objective_history'], 'o')
         plt.xlabel('iteration')
         plt.ylabel('loss')

         plt.subplot(2, 1, 2)
         plt.plot(trace['train_acc_history'], '-o')
         plt.plot(trace['val_acc_history'], '-o')
         plt.legend(['train', 'val'], loc='upper left')
         plt.xlabel('epoch')
         plt.ylabel('accuracy')
         plt.show()
```





5.2 Train the net

By training the three-layer convolutional network for one epoch, you should achieve greater than 40% accuracy on the training set:

```
In [ ]: X_train = data['X_train'].transpose([0, 2, 3, 1])
        y_train = data['y_train']
        X_val = data['X_val'].transpose([0, 2, 3, 1])
        y_val = data['y_val']

        num_train = X_train.shape[0]
        batch_size = 16

        model = ConvNet(input_size=[32, 32, 3],
                        output_size=10,
                        filter_size=[[9, 9, 8], [7, 7, 16], [5, 5, 32]],
                        pooling_schedule=[0, 1, 2],
                        fc_hidden_size=[32],
                       use_bn=True)
```

```
trace = model.train(X_train, y_train, X_val, y_val,
            learning_rate=1e-3,
            reg=np.float32(5e-6),
            num_iters=(num_train * 2 // batch_size + 1),
            batch_size=batch_size,
            verbose=True)
```

```
In [ ]: plt.subplot(2, 1, 1)
        plt.plot(trace['objective_history'], 'o')
        plt.xlabel('iteration')
        plt.ylabel('loss')

        plt.subplot(2, 1, 2)
        plt.plot(trace['train_acc_history'], '-o')
        plt.plot(trace['val_acc_history'], '-o')
        plt.legend(['train', 'val'], loc='upper left')
        plt.xlabel('epoch')
        plt.ylabel('accuracy')
        plt.show()
```

5.3 Visualize Filters

You can visualize the first-layer convolutional filters from the trained network by running the following:

```
In [ ]: from vis_utils import visualize_grid

        grid = visualize_grid(model.get_params()['filter'].transpose(3, 0, 1, 2))
        plt.imshow(grid.astype('uint8'))
        plt.axis('off')
        plt.gcf().set_size_inches(5, 5)
        plt.show()
```