conv_net

March 12, 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 [1]: # 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))))
```

```
In [2]: # Load the (preprocessed) CIFAR10 data.

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

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

2 Convolution Operation

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

```
In [3]: # 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: 5.5281856741780156e-08
Difference between my implementation and correct output: 2.212147649671884e-08
Difference between my implementation and tf calculation: 4.816658052696488e-08
```

3 Aside: Image processing via convolutions

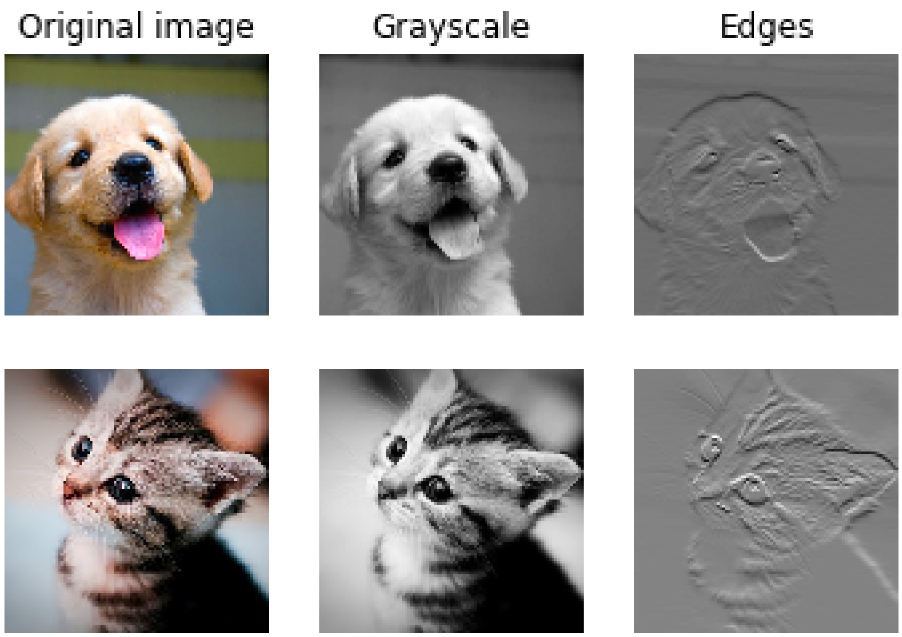
As fun way to both check your implementation and gain a better understanding of the type of operation that convolutional layers can perform, we will set up an input containing two images and manually set up filters that perform common image processing operations (grayscale conversion and edge detection). 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 [4]: 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.
```

```python
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()
```

```
C:\Users\Alan\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: DeprecationWarning: `imread
`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
C:\Users\Alan\Anaconda3\lib\site-packages\ipykernel_launcher.py:10: DeprecationWarning: `imres
`imresize` is deprecated in SciPy 1.0.0, and will be removed in 1.3.0.
Use Pillow instead: ``numpy.array(Image.fromarray(arr).resize())``.
  # Remove the CWD from sys.path while we load stuff.
C:\Users\Alan\Anaconda3\lib\site-packages\ipykernel_launcher.py:11: DeprecationWarning: `imres
```

```
`imresize` is deprecated in SciPy 1.0.0, and will be removed in 1.3.0.
Use Pillow instead: ``numpy.array(Image.fromarray(arr).resize())``.
  # 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 [5]: # 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.

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

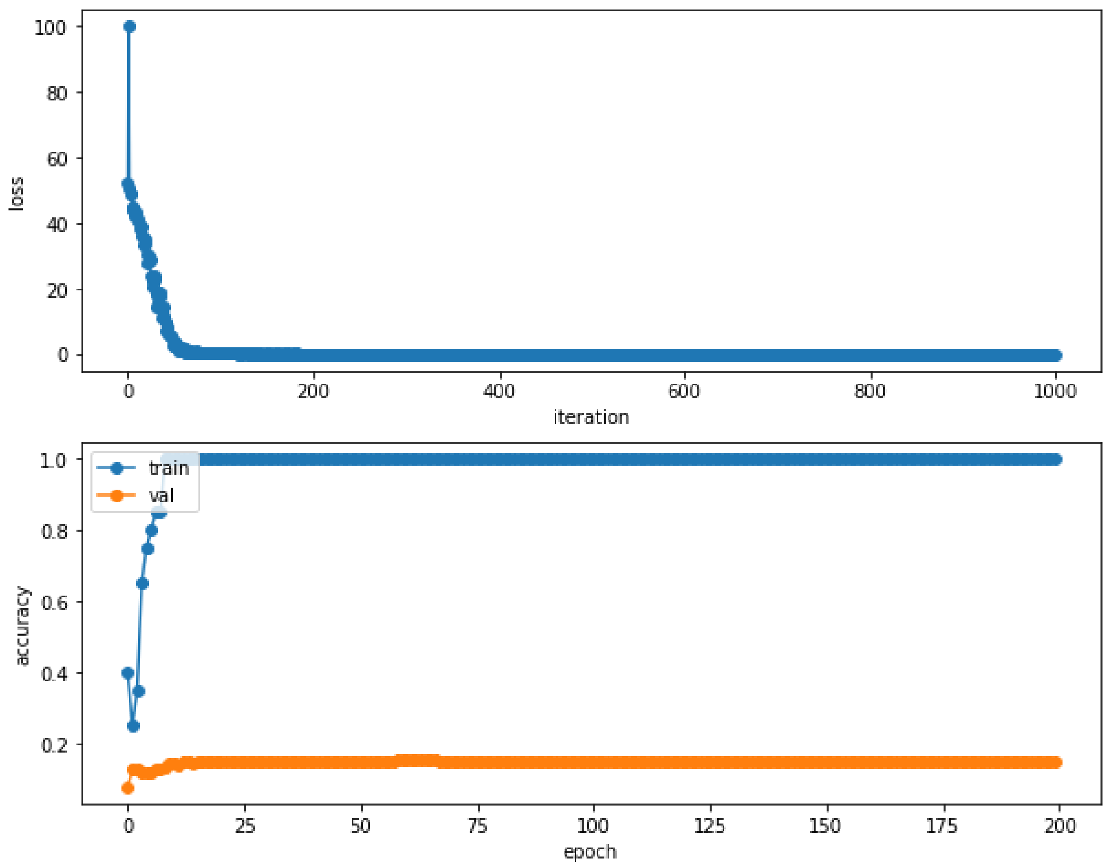
5.2 Testing

```
In [123]: 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 52.289539
iteration 100 / 1000: objective 0.114442
iteration 200 / 1000: objective 0.030320
iteration 300 / 1000: objective 0.016737
iteration 400 / 1000: objective 0.011316
iteration 500 / 1000: objective 0.008441
iteration 600 / 1000: objective 0.006695
iteration 700 / 1000: objective 0.005529
iteration 800 / 1000: objective 0.004687
iteration 900 / 1000: objective 0.004059
```

In [109]:
```
plt.figure(figsize = (10,8))

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()
```



5.2.1 Train the net

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

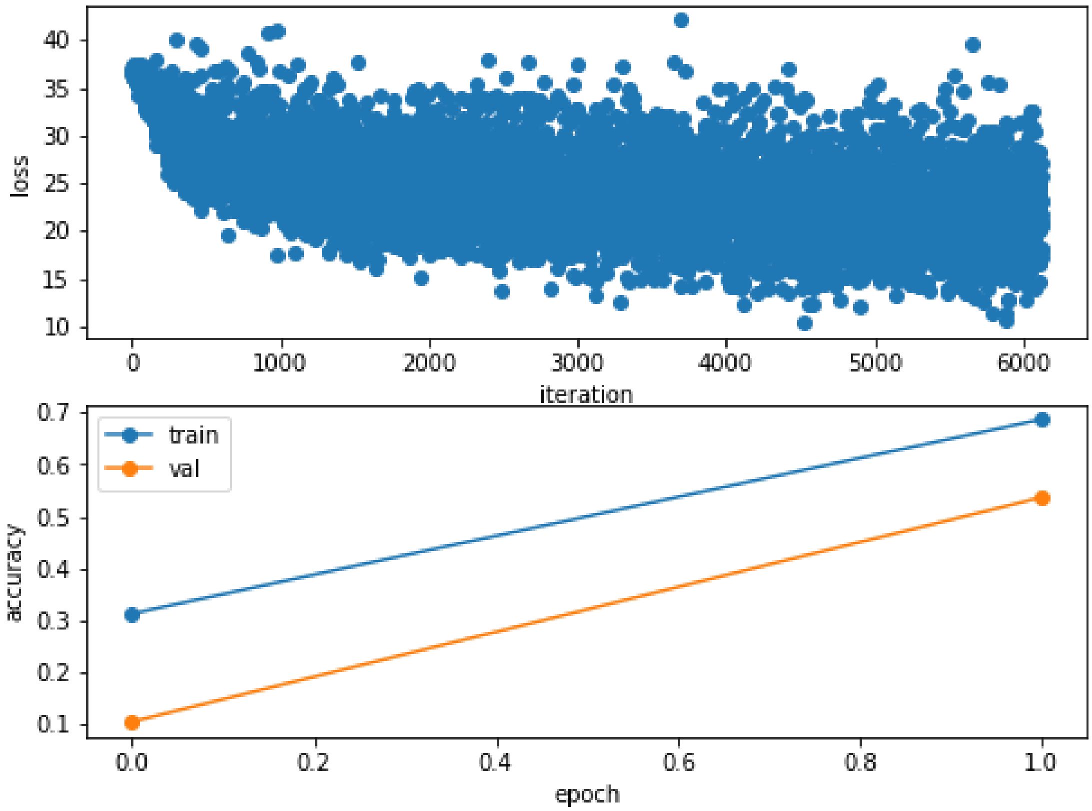
```
In [171]: X_train = data['X_train'].transpose([0, 2, 3, 1])
          y_train = data['y_train']
          X_val = data['X_val'].transpose([0, 2, 3, 1])
          y_val = data['y_val']

          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)
```

```python
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)
```

```
iteration 0 / 6126: objective 36.541039
iteration 100 / 6126: objective 33.299915
iteration 200 / 6126: objective 34.462852
iteration 300 / 6126: objective 27.580877
iteration 400 / 6126: objective 26.855225
iteration 500 / 6126: objective 28.849806
iteration 600 / 6126: objective 28.925531
iteration 700 / 6126: objective 29.797802
iteration 800 / 6126: objective 27.540171
iteration 900 / 6126: objective 27.949398
iteration 1000 / 6126: objective 31.845381
iteration 1100 / 6126: objective 27.359459
iteration 1200 / 6126: objective 27.495857
iteration 1300 / 6126: objective 27.791265
iteration 1400 / 6126: objective 26.921722
iteration 1500 / 6126: objective 18.375010
iteration 1600 / 6126: objective 26.275381
iteration 1700 / 6126: objective 26.950394
iteration 1800 / 6126: objective 24.624851
iteration 1900 / 6126: objective 27.502792
iteration 2000 / 6126: objective 23.300999
iteration 2100 / 6126: objective 26.692835
iteration 2200 / 6126: objective 28.848381
iteration 2300 / 6126: objective 21.204998
iteration 2400 / 6126: objective 23.804800
iteration 2500 / 6126: objective 27.583363
iteration 2600 / 6126: objective 22.888187
iteration 2700 / 6126: objective 25.038359
iteration 2800 / 6126: objective 23.852272
iteration 2900 / 6126: objective 19.906765
iteration 3000 / 6126: objective 28.078136
iteration 3100 / 6126: objective 29.400469
iteration 3200 / 6126: objective 16.505518
iteration 3300 / 6126: objective 27.615196
iteration 3400 / 6126: objective 26.245054
iteration 3500 / 6126: objective 20.717768
iteration 3600 / 6126: objective 17.678864
iteration 3700 / 6126: objective 26.732271
iteration 3800 / 6126: objective 21.548248
iteration 3900 / 6126: objective 19.598434
```

```
iteration 4000 / 6126: objective 20.261570
iteration 4100 / 6126: objective 23.761156
iteration 4200 / 6126: objective 23.640272
iteration 4300 / 6126: objective 22.726273
iteration 4400 / 6126: objective 22.954666
iteration 4500 / 6126: objective 21.733789
iteration 4600 / 6126: objective 25.869289
iteration 4700 / 6126: objective 14.544167
iteration 4800 / 6126: objective 22.928875
iteration 4900 / 6126: objective 22.056343
iteration 5000 / 6126: objective 27.416588
iteration 5100 / 6126: objective 25.131821
iteration 5200 / 6126: objective 16.925447
iteration 5300 / 6126: objective 20.341845
iteration 5400 / 6126: objective 17.449516
iteration 5500 / 6126: objective 20.569796
iteration 5600 / 6126: objective 19.295031
iteration 5700 / 6126: objective 23.034170
iteration 5800 / 6126: objective 22.562328
iteration 5900 / 6126: objective 20.144482
iteration 6000 / 6126: objective 21.638531
iteration 6100 / 6126: objective 22.384182
```

In [175]:
```python
plt.figure(figsize = (8,6))

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()

print('Validation accuracy after 1 epoch: %s' %trace['val_acc_history'][-1])
```




```
Validation accuracy after 1 epoch: 0.537
```

5.3 Visualize Filters

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

```
In [179]: from vis_utils import visualize_grid

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