CS280 Fall 2021 Assignment 2
Part A

Convolutional Neural Nets

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1. Convolution Cost (10 points)

Assume an input of shape $c_i \times h \times w$ and a convolution kernel of shape $c_o \times c_i \times k_h \times k_w$, padding of (p_h, p_w) , and stride of (s_h, s_w) .

- What is the computational cost (multiplications and additions) for the forward propagation?
- What is the memory footprint?

① given a $C_i \times h \times w$ input,
the output height and width are.

$$h' = (h + 2p_h - k_h)/s_h + 1$$
$$w' = (w + 2p_w - k_w)/s_w + 1$$

Then the output size is
$C_o \times h' \times w'$

For each pixel in output size, there are
$C_i \times k_h \times k_w$ multiplications
$C_i \times k_h \times k_w$ additions

Then the computational cost is
$C_o \times ((h + 2p_h - k_h)/s_h + 1) \times ((w + 2p_w - k_w)/s_w + 1) \times 2 \times C_i \times k_h \times k_w$

② The memory footprint should be the sum of the kernal, input and output.

$$M = C_o \times ((h + 2p_h - k_h)/s_h + 1) \times ((w + 2p_w - k_w)/s_w + 1) +$$
$$C_i \times h \times w +$$
$$C_o \times C_i \times k_h \times k_w$$

2. Residual and Inception blocks (5 points)

What are the major differences between the Inception block and the residual block? After removing some paths in the Inception block, how are they related to each other?

① The main difference between the Inception block and the residual block is that:

The residual block use the function like $F(x)+x$,

The inception block is more like $F_1(x)+F_2(x)+\cdots+x$

residual block only uses one single path,

but inception block use multiple path, which makes the network wider.

② Because inception block uses 1x1 conv, after removing some path, the inception block will be more like to residual block.

So a inception block is a kind of complex version of residual block.

3. Optimization (5 points)

Consider a simple multilayer perceptron with a single hidden layer of, say, d dimensions in the hidden layer and a single output. Show that for any local minimum there are at least $d!$ equivalent solutions that behave identically.

Assume the input is a n-dimensional vector, the weight matrix should be d n-dimensional vectors.

$$\begin{bmatrix} w_1 \\ \vdots \\ w_d \end{bmatrix}$$ where w_i is a n-dimensional vector

For a local minimum, we can change the order of w_i, then adjust the weight of hidden layer to output accordingly. It will behave identically.

There are $A_d^d = d!$ solutions.

FullyConnectedNets

November 15, 2021

1 Fully-Connected Neural Nets

In the previous homework you implemented a fully-connected two-layer neural network on CIFAR-10. The implementation was simple but not very modular since the loss and gradient were computed in a single monolithic function. This is manageable for a simple two-layer network, but would become impractical as we move to bigger models. Ideally we want to build networks using a more modular design so that we can implement different layer types in isolation and then snap them together into models with different architectures.

In this exercise we will implement fully-connected networks using a more modular approach. For each layer we will implement a `forward` and a `backward` function. The `forward` function will receive inputs, weights, and other parameters and will return both an output and a `cache` object storing data needed for the backward pass, like this:

```
def layer_forward(x, w):
  """ Receive inputs x and weights w """
  # Do some computations ...
  z = # ... some intermediate value
  # Do some more computations ...
  out = # the output

  cache = (x, w, z, out) # Values we need to compute gradients

  return out, cache
```

The backward pass will receive upstream derivatives and the `cache` object, and will return gradients with respect to the inputs and weights, like this:

```
def layer_backward(dout, cache):
  """
  Receive dout (derivative of loss with respect to outputs) and cache,
  and compute derivative with respect to inputs.
  """
  # Unpack cache values
  x, w, z, out = cache

  # Use values in cache to compute derivatives
  dx = # Derivative of loss with respect to x
```

```
  dw = # Derivative of loss with respect to w

  return dx, dw
```

After implementing a bunch of layers this way, we will be able to easily combine them to build classifiers with different architectures.

In addition to implementing fully-connected networks of arbitrary depth, we will also explore different update rules for optimization, and introduce Dropout as a regularizer and Batch/Layer Normalization as a tool to more efficiently optimize deep networks.

In [2]:
```
# As usual, a bit of setup
from __future__ import print_function
import time
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient, eval_numerical_gradient_arra
from cs231n.solver import Solver

%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 [3]:
```
# Load the (preprocessed) CIFAR10 data.

data = get_CIFAR10_data()
for k, v in list(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 Affine layer: forward

Open the file `cs231n/layers.py` and implement the `affine_forward` function.

Once you are done you can test your implementaion by running the following:

In [4]:
```
# Test the affine_forward function

num_inputs = 2
input_shape = (4, 5, 6)
output_dim = 3

input_size = num_inputs * np.prod(input_shape)
weight_size = output_dim * np.prod(input_shape)

x = np.linspace(-0.1, 0.5, num=input_size).reshape(num_inputs, *input_shape)
w = np.linspace(-0.2, 0.3, num=weight_size).reshape(np.prod(input_shape), output_dim)
b = np.linspace(-0.3, 0.1, num=output_dim)

out, _ = affine_forward(x, w, b)
correct_out = np.array([[ 1.49834967,  1.70660132,  1.91485297],
                        [ 3.25553199,  3.5141327,   3.77273342]])

# Compare your output with ours. The error should be around e-9 or less.
print('Testing affine_forward function:')
print('difference: ', rel_error(out, correct_out))
```

```
Testing affine_forward function:
difference:  9.769849468192957e-10
```

3 Affine layer: backward

Now implement the `affine_backward` function and test your implementation using numeric gradient checking.

In [5]:
```
# Test the affine_backward function
np.random.seed(231)
x = np.random.randn(10, 2, 3)
w = np.random.randn(6, 5)
b = np.random.randn(5)
dout = np.random.randn(10, 5)

dx_num = eval_numerical_gradient_array(lambda x: affine_forward(x, w, b)[0], x, dout)
dw_num = eval_numerical_gradient_array(lambda w: affine_forward(x, w, b)[0], w, dout)
```

```
db_num = eval_numerical_gradient_array(lambda b: affine_forward(x, w, b)[0], b, dout)

_, cache = affine_forward(x, w, b)
dx, dw, db = affine_backward(dout, cache)

# The error should be around e-10 or less
print('Testing affine_backward function:')
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_backward function:
dx error:  5.399100368651805e-11
dw error:  9.904211865398145e-11
db error:  2.4122867568119087e-11
```

4 ReLU activation: forward

Implement the forward pass for the ReLU activation function in the `relu_forward` function and test your implementation using the following:

```
In [6]: # Test the relu_forward function

        x = np.linspace(-0.5, 0.5, num=12).reshape(3, 4)

        out, _ = relu_forward(x)
        correct_out = np.array([[ 0.,          0.,          0.,          0.,        ],
                                [ 0.,          0.,          0.04545455,  0.13636364,],
                                [ 0.22727273,  0.31818182,  0.40909091,  0.5,       ]])

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

```
Testing relu_forward function:
difference:  4.999999798022158e-08
```

5 ReLU activation: backward

Now implement the backward pass for the ReLU activation function in the `relu_backward` function and test your implementation using numeric gradient checking:

```
In [7]: np.random.seed(231)
        x = np.random.randn(10, 10)
        dout = np.random.randn(*x.shape)
```

```
dx_num = eval_numerical_gradient_array(lambda x: relu_forward(x)[0], x, dout)

_, cache = relu_forward(x)
dx = relu_backward(dout, cache)

# The error should be on the order of e-12
print('Testing relu_backward function:')
print('dx error: ', rel_error(dx_num, dx))
```

```
Testing relu_backward function:
dx error:  3.2756349136310288e-12
```

5.1 Inline Question 1:

We've only asked you to implement ReLU, but there are a number of different activation functions that one could use in neural networks, each with its pros and cons. In particular, an issue commonly seen with activation functions is getting zero (or close to zero) gradient flow during backpropagation. Which of the following activation functions have this problem? If you consider these functions in the one dimensional case, what types of input would lead to this behaviour? 1. Sigmoid 2. ReLU 3. Leaky ReLU

5.2 Answer:

1. When the input is extremely large, the gradients of sigmoid will be close to zero.
2. When the input is less than zero, the gradients of sigmoid will be zero
3. Even when the input is less than zero, Leaky ReLU gives a small gradient, so leaky relu won't have this problem.

6 "Sandwich" layers

There are some common patterns of layers that are frequently used in neural nets. For example, affine layers are frequently followed by a ReLU nonlinearity. To make these common patterns easy, we define several convenience layers in the file `cs231n/layer_utils.py`.

For now take a look at the `affine_relu_forward` and `affine_relu_backward` functions, and run the following to numerically gradient check the backward pass:

```
In [8]: from cs231n.layer_utils import affine_relu_forward, affine_relu_backward
        np.random.seed(231)
        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, do
dw_num = eval_numerical_gradient_array(lambda w: affine_relu_forward(x, w, b)[0], w, do
db_num = eval_numerical_gradient_array(lambda b: affine_relu_forward(x, w, b)[0], b, do

# Relative error should be around e-10 or less
print('Testing affine_relu_forward and affine_relu_backward:')
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 and affine_relu_backward:
dx error:  2.299579177309368e-11
dw error:  8.162011105764925e-11
db error:  7.826724021458994e-12
```

7 Loss layers: Softmax and SVM

You implemented these loss functions in the last assignment, so we'll give them to you for free here. You should still make sure you understand how they work by looking at the implementations in `cs231n/layers.py`.

You can make sure that the implementations are correct by running the following:

In [9]:
```
np.random.seed(231)
num_classes, num_inputs = 10, 50
x = 0.001 * np.random.randn(num_inputs, num_classes)
y = np.random.randint(num_classes, size=num_inputs)

dx_num = eval_numerical_gradient(lambda x: svm_loss(x, y)[0], x, verbose=False)
loss, dx = svm_loss(x, y)

# Test svm_loss function. Loss should be around 9 and dx error should be around the or
print('Testing svm_loss:')
print('loss: ', loss)
print('dx error: ', rel_error(dx_num, dx))

dx_num = eval_numerical_gradient(lambda x: softmax_loss(x, y)[0], x, verbose=False)
loss, dx = softmax_loss(x, y)

# Test softmax_loss function. Loss should be close to 2.3 and dx error should be aroun
print('\nTesting softmax_loss:')
print('loss: ', loss)
print('dx error: ', rel_error(dx_num, dx))
```

```
Testing svm_loss:
loss:  8.999602749096233
dx error:  1.4021566006651672e-09
```

```
Testing softmax_loss:
loss:  2.302545844500738
dx error:  9.384673161989355e-09
```

8 Two-layer network

In the previous assignment you implemented a two-layer neural network in a single monolithic class. Now that you have implemented modular versions of the necessary layers, you will reimplement the two layer network using these modular implementations.

Open the file `cs231n/classifiers/fc_net.py` and complete the implementation of the `TwoLayerNet` class. This class will serve as a model for the other networks you will implement in this assignment, so read through it to make sure you understand the API. You can run the cell below to test your implementation.

```
In [10]: np.random.seed(231)
         N, D, H, C = 3, 5, 50, 7
         X = np.random.randn(N, D)
         y = np.random.randint(C, size=N)

         std = 1e-3
         model = TwoLayerNet(input_dim=D, hidden_dim=H, num_classes=C, weight_scale=std)

         print('Testing initialization ... ')
         W1_std = abs(model.params['W1'].std() - std)
         b1 = model.params['b1']
         W2_std = abs(model.params['W2'].std() - std)
         b2 = model.params['b2']
         assert W1_std < std / 10, 'First layer weights do not seem right'
         assert np.all(b1 == 0), 'First layer biases do not seem right'
         assert W2_std < std / 10, 'Second layer weights do not seem right'
         assert np.all(b2 == 0), 'Second layer biases do not seem right'

         print('Testing test-time forward pass ... ')
         model.params['W1'] = np.linspace(-0.7, 0.3, num=D*H).reshape(D, H)
         model.params['b1'] = np.linspace(-0.1, 0.9, num=H)
         model.params['W2'] = np.linspace(-0.3, 0.4, num=H*C).reshape(H, C)
         model.params['b2'] = np.linspace(-0.9, 0.1, num=C)
         X = np.linspace(-5.5, 4.5, num=N*D).reshape(D, N).T
         scores = model.loss(X)
         correct_scores = np.asarray(
           [[11.53165108,  12.2917344,   13.05181771,  13.81190102,  14.57198434, 15.33206765,
            [12.05769098,  12.74614105,  13.43459113,  14.1230412,   14.81149128, 15.49994135,
            [12.58373087,  13.20054771,  13.81736455,  14.43418138,  15.05099822, 15.66781506,
         scores_diff = np.abs(scores - correct_scores).sum()
         assert scores_diff < 1e-6, 'Problem with test-time forward pass'
```

```
print('Testing training loss (no regularization)')
y = np.asarray([0, 5, 1])
loss, grads = model.loss(X, y)
correct_loss = 3.4702243556
assert abs(loss - correct_loss) < 1e-10, 'Problem with training-time loss'

model.reg = 1.0
loss, grads = model.loss(X, y)
correct_loss = 26.5948426952
assert abs(loss - correct_loss) < 1e-10, 'Problem with regularization loss'

# Errors should be around e-7 or less
for reg in [0.0, 0.7]:
  print('Running numeric gradient check with reg = ', reg)
  model.reg = reg
  loss, grads = model.loss(X, y)

  for name in sorted(grads):
    f = lambda _: model.loss(X, y)[0]
    grad_num = eval_numerical_gradient(f, model.params[name], verbose=False)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[name])))
```

```
Testing initialization ...
Testing test-time forward pass ...
Testing training loss (no regularization)
Running numeric gradient check with reg =  0.0
W1 relative error: 1.83e-08
W2 relative error: 3.12e-10
b1 relative error: 9.83e-09
b2 relative error: 4.33e-10
Running numeric gradient check with reg =  0.7
W1 relative error: 2.53e-07
W2 relative error: 2.85e-08
b1 relative error: 1.56e-08
b2 relative error: 7.76e-10
```

9 Solver

In the previous assignment, the logic for training models was coupled to the models themselves. Following a more modular design, for this assignment we have split the logic for training models into a separate class.

Open the file `cs231n/solver.py` and read through it to familiarize yourself with the API. After doing so, use a `Solver` instance to train a `TwoLayerNet` that achieves at least `50%` accuracy on the validation set.

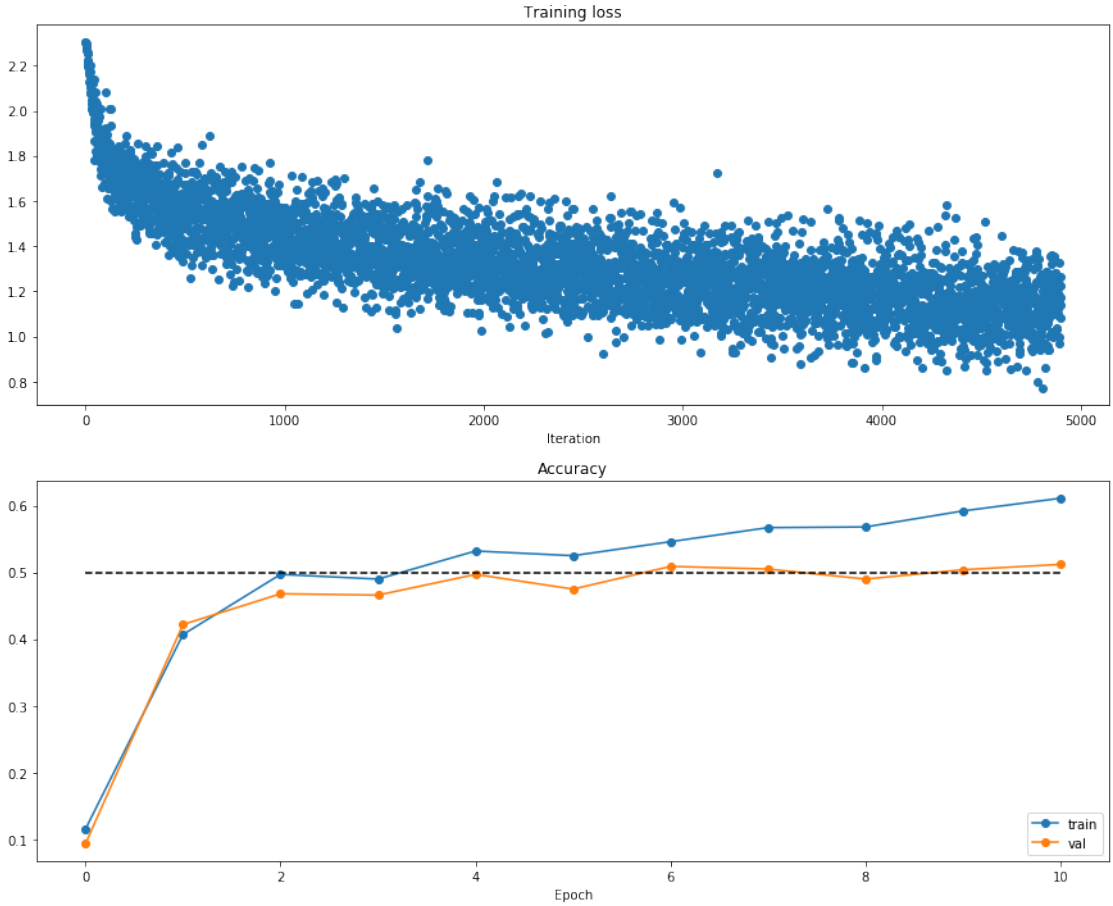
In [11]:
```
model = TwoLayerNet()
solver = None
```

```
        ################################################################################
        # TODO: Use a Solver instance to train a TwoLayerNet that achieves at least  #
        # 50% accuracy on the validation set.                                          #
        ################################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

        solver = Solver(model, data,
                        update_rule='sgd',
                        optim_config={
                            'learning_rate': 1e-3,
                        },
                        lr_decay=0.95,
                        num_epochs=10, batch_size=100,
                        print_every=500)
        solver.train()

        scores = model.loss(data['X_test'])
        pred = np.argmax(scores, axis = 1)
        accuracy = np.sum(pred == data['y_test']) / pred.shape[0]
        print('test accuracy:', accuracy)
        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ################################################################################
        #                              END OF YOUR CODE                                #
        ################################################################################
```

```
(Iteration 1 / 4900) loss: 2.304060
(Epoch 0 / 10) train acc: 0.116000; val_acc: 0.094000
(Epoch 1 / 10) train acc: 0.407000; val_acc: 0.422000
(Iteration 501 / 4900) loss: 1.565913
(Epoch 2 / 10) train acc: 0.497000; val_acc: 0.468000
(Iteration 1001 / 4900) loss: 1.385772
(Epoch 3 / 10) train acc: 0.490000; val_acc: 0.466000
(Iteration 1501 / 4900) loss: 1.346286
(Epoch 4 / 10) train acc: 0.532000; val_acc: 0.497000
(Iteration 2001 / 4900) loss: 1.343165
(Epoch 5 / 10) train acc: 0.525000; val_acc: 0.475000
(Iteration 2501 / 4900) loss: 1.390234
(Epoch 6 / 10) train acc: 0.546000; val_acc: 0.509000
(Iteration 3001 / 4900) loss: 1.304489
(Epoch 7 / 10) train acc: 0.567000; val_acc: 0.505000
(Iteration 3501 / 4900) loss: 1.319024
(Epoch 8 / 10) train acc: 0.568000; val_acc: 0.490000
(Iteration 4001 / 4900) loss: 1.191735
(Epoch 9 / 10) train acc: 0.592000; val_acc: 0.504000
(Iteration 4501 / 4900) loss: 0.963330
(Epoch 10 / 10) train acc: 0.611000; val_acc: 0.512000
test accuracy: 0.502
```

In [12]: *# Run this cell to visualize training loss and train / val accuracy*

```
plt.subplot(2, 1, 1)
plt.title('Training loss')
plt.plot(solver.loss_history, 'o')
plt.xlabel('Iteration')

plt.subplot(2, 1, 2)
plt.title('Accuracy')
plt.plot(solver.train_acc_history, '-o', label='train')
plt.plot(solver.val_acc_history, '-o', label='val')
plt.plot([0.5] * len(solver.val_acc_history), 'k--')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.gcf().set_size_inches(15, 12)
plt.show()
```



10 Multilayer network

Next you will implement a fully-connected network with an arbitrary number of hidden layers.

Read through the `FullyConnectedNet` class in the file `cs231n/classifiers/fc_net.py`.

Implement the initialization, the forward pass, and the backward pass. For the moment don't worry about implementing dropout or batch/layer normalization; we will add those features soon.

10.1 Initial loss and gradient check

As a sanity check, run the following to check the initial loss and to gradient check the network both with and without regularization. Do the initial losses seem reasonable?

For gradient checking, you should expect to see errors around 1e-7 or less.

```
In [13]: np.random.seed(231)
         N, D, H1, H2, C = 2, 15, 20, 30, 10
         X = np.random.randn(N, D)
         y = np.random.randint(C, size=(N,))

         for reg in [0, 3.14]:
           print('Running check with reg = ', reg)
           model = FullyConnectedNet([H1, H2], input_dim=D, num_classes=C,
                                     reg=reg, weight_scale=5e-2, dtype=np.float64)

           loss, grads = model.loss(X, y)
           print('Initial loss: ', loss)

           # Most of the errors should be on the order of e-7 or smaller.
           # NOTE: It is fine however to see an error for W2 on the order of e-5
           # for the check when reg = 0.0

           for name in sorted(grads):
             f = lambda _: model.loss(X, y)[0]
             grad_num = eval_numerical_gradient(f, model.params[name], verbose=False, h=1e-5)
             print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[name])))
```

```
Running check with reg =  0
Initial loss:  2.3004790897684924
W1 relative error: 1.48e-07
W2 relative error: 2.21e-05
W3 relative error: 3.53e-07
b1 relative error: 5.38e-09
b2 relative error: 2.09e-09
b3 relative error: 5.80e-11
Running check with reg =  3.14
Initial loss:  7.052114776533016
W1 relative error: 7.36e-09
W2 relative error: 6.87e-08
```

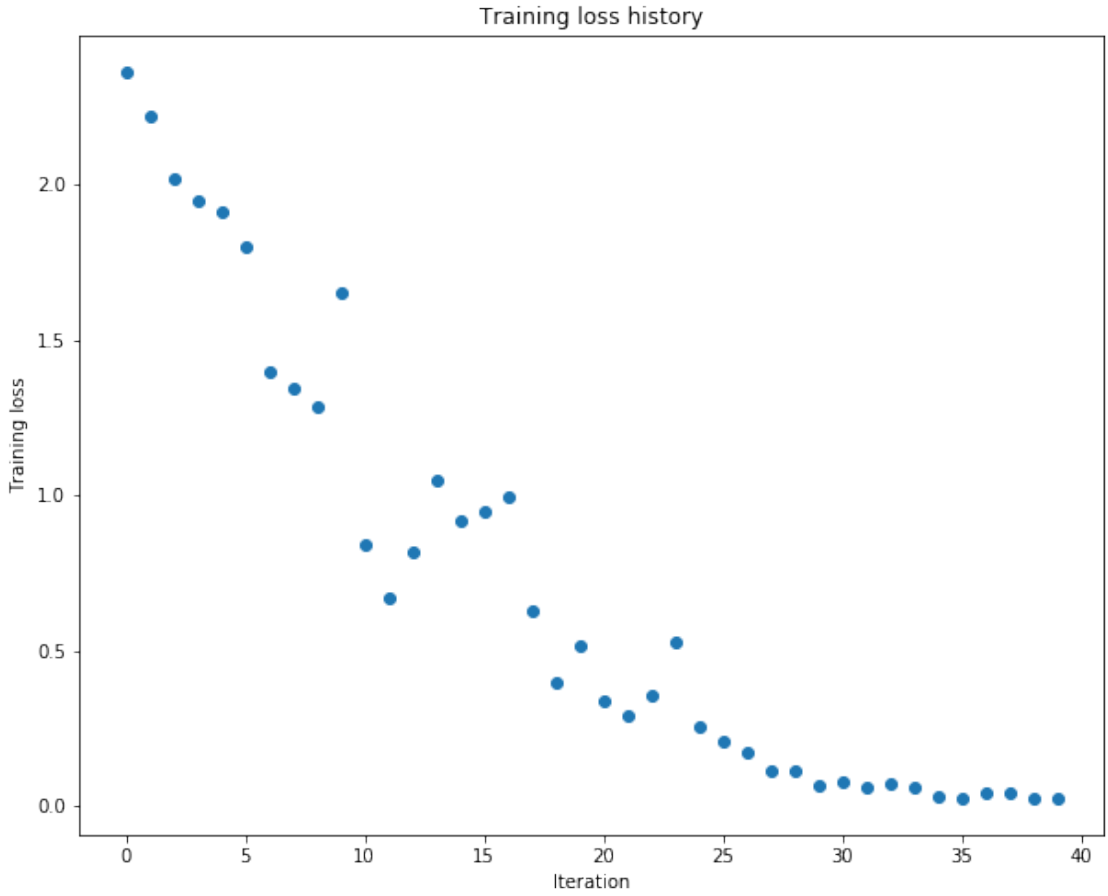
```
W3 relative error: 3.48e-08
b1 relative error: 1.48e-08
b2 relative error: 1.72e-09
b3 relative error: 1.80e-10
```

As another sanity check, make sure you can overfit a small dataset of 50 images. First we will try a three-layer network with 100 units in each hidden layer. In the following cell, tweak the **learning rate** and **weight initialization scale** to overfit and achieve 100% training accuracy within 20 epochs.

In [14]:
```
# TODO: Use a three-layer Net to overfit 50 training examples by
# tweaking just the learning rate and initialization scale.

num_train = 50
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

weight_scale = 1e-2   # Experiment with this!
learning_rate = 1e-2  # Experiment with this!
model = FullyConnectedNet([100, 100],
              weight_scale=weight_scale, dtype=np.float64)
solver = Solver(model, small_data,
                print_every=10, num_epochs=20, batch_size=25,
                update_rule='sgd',
                optim_config={
                  'learning_rate': learning_rate,
                }
         )
solver.train()

plt.plot(solver.loss_history, 'o')
plt.title('Training loss history')
plt.xlabel('Iteration')
plt.ylabel('Training loss')
plt.show()
```

```
(Iteration 1 / 40) loss: 2.363364
(Epoch 0 / 20) train acc: 0.180000; val_acc: 0.108000
(Epoch 1 / 20) train acc: 0.320000; val_acc: 0.127000
(Epoch 2 / 20) train acc: 0.440000; val_acc: 0.172000
(Epoch 3 / 20) train acc: 0.500000; val_acc: 0.184000
(Epoch 4 / 20) train acc: 0.540000; val_acc: 0.181000
(Epoch 5 / 20) train acc: 0.740000; val_acc: 0.190000
```

```
(Iteration 11 / 40) loss: 0.839976
(Epoch 6 / 20) train acc: 0.740000; val_acc: 0.187000
(Epoch 7 / 20) train acc: 0.740000; val_acc: 0.183000
(Epoch 8 / 20) train acc: 0.820000; val_acc: 0.177000
(Epoch 9 / 20) train acc: 0.860000; val_acc: 0.200000
(Epoch 10 / 20) train acc: 0.920000; val_acc: 0.191000
(Iteration 21 / 40) loss: 0.337174
(Epoch 11 / 20) train acc: 0.960000; val_acc: 0.189000
(Epoch 12 / 20) train acc: 0.940000; val_acc: 0.180000
(Epoch 13 / 20) train acc: 1.000000; val_acc: 0.199000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.199000
(Epoch 15 / 20) train acc: 1.000000; val_acc: 0.195000
(Iteration 31 / 40) loss: 0.075911
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.182000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.201000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.207000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.185000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.192000
```

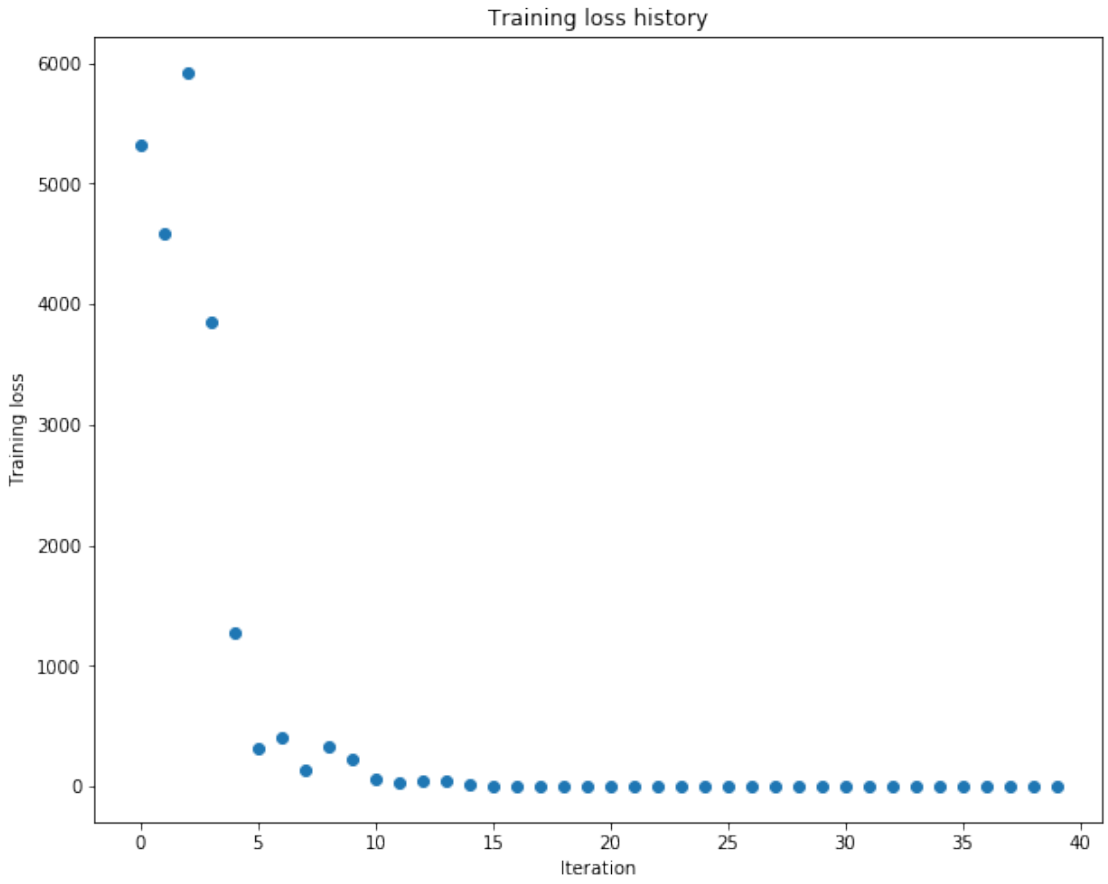


Now try to use a five-layer network with 100 units on each layer to overfit 50 training examples. Again, you will have to adjust the learning rate and weight initialization scale, but you should be able to achieve 100% training accuracy within 20 epochs.

In [15]:
```
# TODO: Use a five-layer Net to overfit 50 training examples by
# tweaking just the learning rate and initialization scale.

num_train = 50
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

learning_rate = 2e-4  # Experiment with this!
weight_scale = 2e-1   # Experiment with this!
model = FullyConnectedNet([100, 100, 100, 100],
                weight_scale=weight_scale, dtype=np.float64)
solver = Solver(model, small_data,
                print_every=10, num_epochs=20, batch_size=25,
                update_rule='sgd',
                optim_config={
                  'learning_rate': learning_rate,
                }
         )
solver.train()

plt.plot(solver.loss_history, 'o')
plt.title('Training loss history')
plt.xlabel('Iteration')
plt.ylabel('Training loss')
plt.show()
```

```
(Iteration 1 / 40) loss: 5327.907224
(Epoch 0 / 20) train acc: 0.160000; val_acc: 0.111000
(Epoch 1 / 20) train acc: 0.240000; val_acc: 0.086000
(Epoch 2 / 20) train acc: 0.280000; val_acc: 0.126000
(Epoch 3 / 20) train acc: 0.420000; val_acc: 0.129000
(Epoch 4 / 20) train acc: 0.680000; val_acc: 0.120000
(Epoch 5 / 20) train acc: 0.720000; val_acc: 0.096000
(Iteration 11 / 40) loss: 64.746154
(Epoch 6 / 20) train acc: 0.860000; val_acc: 0.112000
(Epoch 7 / 20) train acc: 0.900000; val_acc: 0.123000
(Epoch 8 / 20) train acc: 0.900000; val_acc: 0.120000
(Epoch 9 / 20) train acc: 0.980000; val_acc: 0.114000
(Epoch 10 / 20) train acc: 1.000000; val_acc: 0.114000
(Iteration 21 / 40) loss: 0.000000
```

```
(Epoch 11 / 20) train acc: 1.000000; val_acc: 0.114000
(Epoch 12 / 20) train acc: 1.000000; val_acc: 0.114000
(Epoch 13 / 20) train acc: 1.000000; val_acc: 0.114000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.114000
(Epoch 15 / 20) train acc: 1.000000; val_acc: 0.114000
(Iteration 31 / 40) loss: 0.000000
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.114000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.114000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.114000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.114000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.114000
```



10.2 Inline Question 2:

Did you notice anything about the comparative difficulty of training the three-layer net vs training the five layer net? In particular, based on your experience, which network seemed more sensitive to the initialization scale? Why do you think that is the case?

10.3 Answer:

Five layer network is more difficult to adjust hyperparameters. Five layer network will be more sensitive to the initialization scale. That is because deeper network will make loss function more complex, which is more difficult to reach optimal state.

11 Update rules

So far we have used vanilla stochastic gradient descent (SGD) as our update rule. More sophisticated update rules can make it easier to train deep networks. We will implement a few of the most commonly used update rules and compare them to vanilla SGD.

12 SGD+Momentum

Stochastic gradient descent with momentum is a widely used update rule that tends to make deep networks converge faster than vanilla stochastic gradient descent. See the Momentum Update section at http://cs231n.github.io/neural-networks-3/#sgd for more information.

Open the file `cs231n/optim.py` and read the documentation at the top of the file to make sure you understand the API. Implement the SGD+momentum update rule in the function `sgd_momentum` and run the following to check your implementation. You should see errors less than e-8.

In [16]:
```
from cs231n.optim import sgd_momentum

N, D = 4, 5
w = np.linspace(-0.4, 0.6, num=N*D).reshape(N, D)
dw = np.linspace(-0.6, 0.4, num=N*D).reshape(N, D)
v = np.linspace(0.6, 0.9, num=N*D).reshape(N, D)

config = {'learning_rate': 1e-3, 'velocity': v}
next_w, _ = sgd_momentum(w, dw, config=config)

expected_next_w = np.asarray([
  [ 0.1406,      0.20738947,  0.27417895,  0.34096842,  0.40775789],
  [ 0.47454737,  0.54133684,  0.60812632,  0.67491579,  0.74170526],
  [ 0.80849474,  0.87528421,  0.94207368,  1.00886316,  1.07565263],
  [ 1.14244211,  1.20923158,  1.27602105,  1.34281053,  1.4096    ]])
expected_velocity = np.asarray([
  [ 0.5406,      0.55475789,  0.56891579, 0.58307368,  0.59723158],
  [ 0.61138947,  0.62554737,  0.63970526,  0.65386316,  0.66802105],
  [ 0.68217895,  0.69633684,  0.71049474,  0.72465263,  0.73881053],
  [ 0.75296842,  0.76712632,  0.78128421,  0.79544211,  0.8096    ]])

# Should see relative errors around e-8 or less
print('next_w error: ', rel_error(next_w, expected_next_w))
print('velocity error: ', rel_error(expected_velocity, config['velocity']))
```

```
next_w error:  8.882347033505819e-09
velocity error:  4.269287743278663e-09
```

Once you have done so, run the following to train a six-layer network with both SGD and SGD+momentum. You should see the SGD+momentum update rule converge faster.

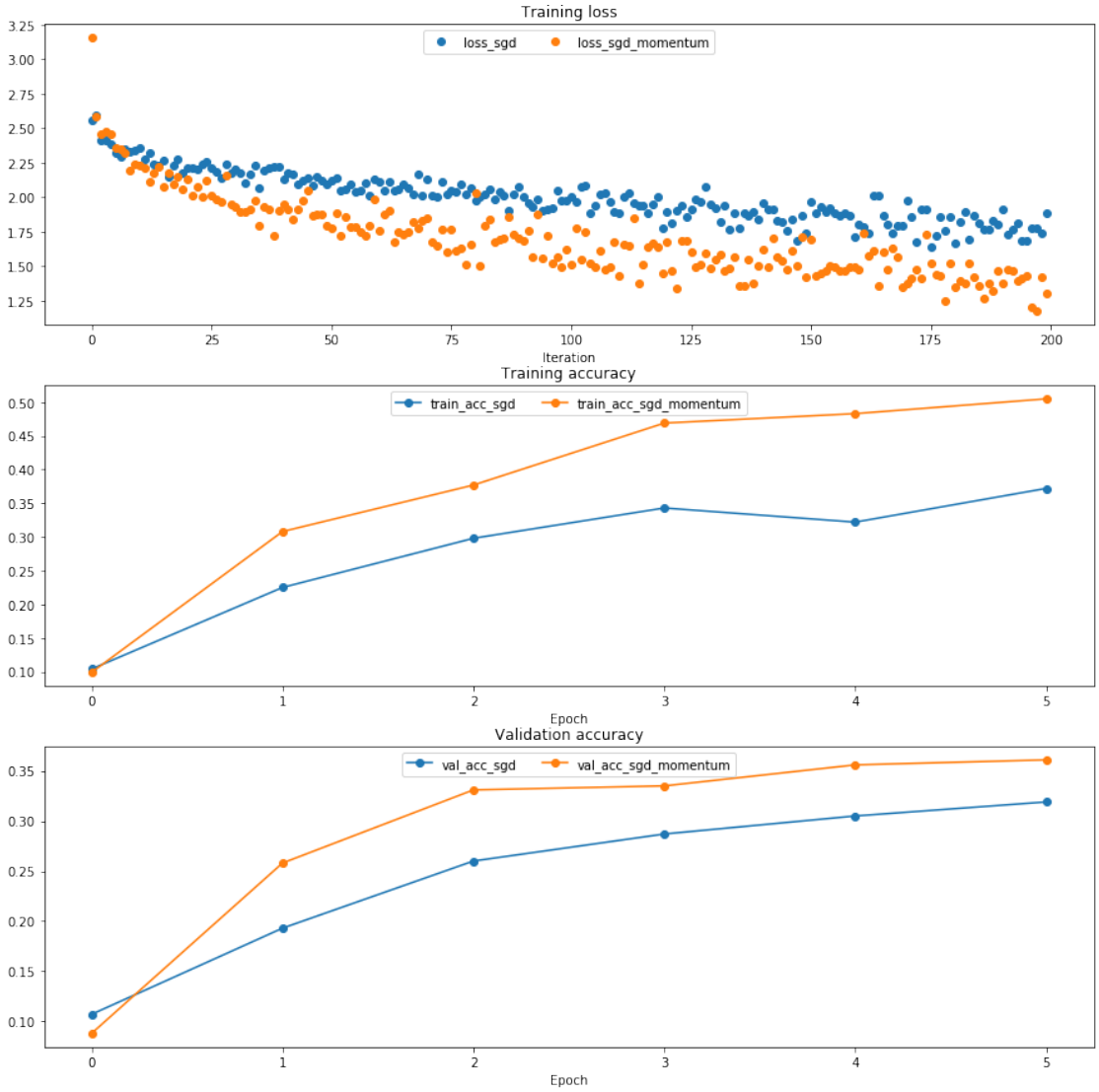
```
In [17]: num_train = 4000
         small_data = {
           'X_train': data['X_train'][:num_train],
           'y_train': data['y_train'][:num_train],
           'X_val': data['X_val'],
           'y_val': data['y_val'],
         }

         solvers = {}

         for update_rule in ['sgd', 'sgd_momentum']:
           print('running with ', update_rule)
           model = FullyConnectedNet([100, 100, 100, 100, 100], weight_scale=5e-2)

           solver = Solver(model, small_data,
                           num_epochs=5, batch_size=100,
                           update_rule=update_rule,
                           optim_config={
                             'learning_rate': 5e-3,
                           },
                           verbose=True)
           solvers[update_rule] = solver
           solver.train()
           print()

         plt.subplot(3, 1, 1)
         plt.title('Training loss')
         plt.xlabel('Iteration')

         plt.subplot(3, 1, 2)
         plt.title('Training accuracy')
         plt.xlabel('Epoch')

         plt.subplot(3, 1, 3)
         plt.title('Validation accuracy')
         plt.xlabel('Epoch')

         for update_rule, solver in solvers.items():
           plt.subplot(3, 1, 1)
           plt.plot(solver.loss_history, 'o', label="loss_%s" % update_rule)
```

```
            plt.subplot(3, 1, 2)
            plt.plot(solver.train_acc_history, '-o', label="train_acc_%s" % update_rule)

            plt.subplot(3, 1, 3)
            plt.plot(solver.val_acc_history, '-o', label="val_acc_%s" % update_rule)

          for i in [1, 2, 3]:
            plt.subplot(3, 1, i)
            plt.legend(loc='upper center', ncol=4)
          plt.gcf().set_size_inches(15, 15)
          plt.show()
```

```
running with  sgd
(Iteration 1 / 200) loss: 2.559978
(Epoch 0 / 5) train acc: 0.104000; val_acc: 0.107000
(Iteration 11 / 200) loss: 2.356069
(Iteration 21 / 200) loss: 2.214091
(Iteration 31 / 200) loss: 2.205928
(Epoch 1 / 5) train acc: 0.225000; val_acc: 0.193000
(Iteration 41 / 200) loss: 2.132095
(Iteration 51 / 200) loss: 2.118950
(Iteration 61 / 200) loss: 2.116443
(Iteration 71 / 200) loss: 2.132549
(Epoch 2 / 5) train acc: 0.298000; val_acc: 0.260000
(Iteration 81 / 200) loss: 1.977227
(Iteration 91 / 200) loss: 2.007528
(Iteration 101 / 200) loss: 2.004762
(Iteration 111 / 200) loss: 1.885342
(Epoch 3 / 5) train acc: 0.343000; val_acc: 0.287000
(Iteration 121 / 200) loss: 1.891517
(Iteration 131 / 200) loss: 1.923677
(Iteration 141 / 200) loss: 1.957744
(Iteration 151 / 200) loss: 1.966736
(Epoch 4 / 5) train acc: 0.322000; val_acc: 0.305000
(Iteration 161 / 200) loss: 1.801483
(Iteration 171 / 200) loss: 1.973779
(Iteration 181 / 200) loss: 1.666572
(Iteration 191 / 200) loss: 1.909494
(Epoch 5 / 5) train acc: 0.372000; val_acc: 0.319000

running with  sgd_momentum
(Iteration 1 / 200) loss: 3.153777
(Epoch 0 / 5) train acc: 0.099000; val_acc: 0.088000
(Iteration 11 / 200) loss: 2.227203
(Iteration 21 / 200) loss: 2.125706
(Iteration 31 / 200) loss: 1.932679
(Epoch 1 / 5) train acc: 0.308000; val_acc: 0.258000
(Iteration 41 / 200) loss: 1.946329
```

```
(Iteration 51 / 200) loss: 1.780464
(Iteration 61 / 200) loss: 1.753502
(Iteration 71 / 200) loss: 1.844626
(Epoch 2 / 5) train acc: 0.377000; val_acc: 0.331000
(Iteration 81 / 200) loss: 2.028389
(Iteration 91 / 200) loss: 1.685416
(Iteration 101 / 200) loss: 1.513204
(Iteration 111 / 200) loss: 1.431671
(Epoch 3 / 5) train acc: 0.469000; val_acc: 0.335000
(Iteration 121 / 200) loss: 1.678510
(Iteration 131 / 200) loss: 1.544807
(Iteration 141 / 200) loss: 1.620010
(Iteration 151 / 200) loss: 1.691080
(Epoch 4 / 5) train acc: 0.483000; val_acc: 0.356000
(Iteration 161 / 200) loss: 1.474016
(Iteration 171 / 200) loss: 1.374763
(Iteration 181 / 200) loss: 1.350309
(Iteration 191 / 200) loss: 1.377182
(Epoch 5 / 5) train acc: 0.505000; val_acc: 0.361000
```

```
/home/mpl/anaconda3/envs/cs231n/lib/python3.7/site-packages/matplotlib/figure.py:98: Matplotlib
Adding an axes using the same arguments as a previous axes currently reuses the earlier instanc
  "Adding an axes using the same arguments as a previous axes "
```



13 RMSProp and Adam

RMSProp [1] and Adam [2] are update rules that set per-parameter learning rates by using a running average of the second moments of gradients.

In the file `cs231n/optim.py`, implement the RMSProp update rule in the `rmsprop` function and implement the Adam update rule in the `adam` function, and check your implementations using the tests below.

NOTE: Please implement the *complete* Adam update rule (with the bias correction mechanism), not the first simplified version mentioned in the course notes.

[1] Tijmen Tieleman and Geoffrey Hinton. "Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude." COURSERA: Neural Networks for Machine Learning 4 (2012).

[2] Diederik Kingma and Jimmy Ba, "Adam: A Method for Stochastic Optimization", ICLR 2015.

```
In [18]: # Test RMSProp implementation
         from cs231n.optim import rmsprop

         N, D = 4, 5
         w = np.linspace(-0.4, 0.6, num=N*D).reshape(N, D)
         dw = np.linspace(-0.6, 0.4, num=N*D).reshape(N, D)
         cache = np.linspace(0.6, 0.9, num=N*D).reshape(N, D)

         config = {'learning_rate': 1e-2, 'cache': cache}
         next_w, _ = rmsprop(w, dw, config=config)

         expected_next_w = np.asarray([
           [-0.39223849, -0.34037513, -0.28849239, -0.23659121, -0.18467247],
           [-0.132737,   -0.08078555, -0.02881884,  0.02316247,  0.07515774],
           [ 0.12716641,  0.17918792,  0.23122175,  0.28326742,  0.33532447],
           [ 0.38739248,  0.43947102,  0.49155973,  0.54365823,  0.59576619]])
         expected_cache = np.asarray([
           [ 0.5976,      0.6126277,   0.6277108,   0.64284931,  0.65804321],
           [ 0.67329252,  0.68859723,  0.70395734,  0.71937285,  0.73484377],
           [ 0.75037008,  0.7659518,   0.78158892,  0.79728144,  0.81302936],
           [ 0.82883269,  0.84469141,  0.86060554,  0.87657507,  0.8926    ]])

         # You should see relative errors around e-7 or less
         print('next_w error: ', rel_error(expected_next_w, next_w))
         print('cache error: ', rel_error(expected_cache, config['cache']))
```

```
next_w error:  9.524687511038133e-08
cache error:  2.6477955807156126e-09
```

```
In [19]: # Test Adam implementation
         from cs231n.optim import adam

         N, D = 4, 5
         w = np.linspace(-0.4, 0.6, num=N*D).reshape(N, D)
         dw = np.linspace(-0.6, 0.4, num=N*D).reshape(N, D)
         m = np.linspace(0.6, 0.9, num=N*D).reshape(N, D)
         v = np.linspace(0.7, 0.5, num=N*D).reshape(N, D)

         config = {'learning_rate': 1e-2, 'm': m, 'v': v, 't': 5}
         next_w, _ = adam(w, dw, config=config)

         expected_next_w = np.asarray([
           [-0.40094747, -0.34836187, -0.29577703, -0.24319299, -0.19060977],
           [-0.1380274,  -0.08544591, -0.03286534,  0.01971428,  0.0722929],
```

```
    [ 0.1248705,   0.17744702,  0.23002243,  0.28259667,  0.33516969],
    [ 0.38774145,  0.44031188,  0.49288093,  0.54544852,  0.59801459]])
expected_v = np.asarray([
    [ 0.69966,     0.68908382,  0.67851319,  0.66794809,  0.65738853,],
    [ 0.64683452,  0.63628604,  0.6257431,   0.61520571,  0.60467385,],
    [ 0.59414753,  0.58362676,  0.57311152,  0.56260183,  0.55209767,],
    [ 0.54159906,  0.53110598,  0.52061845,  0.51013645,  0.49966,   ]])
expected_m = np.asarray([
    [ 0.48,        0.49947368,  0.51894737,  0.53842105,  0.55789474],
    [ 0.57736842,  0.59684211,  0.61631579,  0.63578947,  0.65526316],
    [ 0.67473684,  0.69421053,  0.71368421,  0.73315789,  0.75263158],
    [ 0.77210526,  0.79157895,  0.81105263,  0.83052632,  0.85      ]])

# You should see relative errors around e-7 or less
print('next_w error: ', rel_error(expected_next_w, next_w))
print('v error: ', rel_error(expected_v, config['v']))
print('m error: ', rel_error(expected_m, config['m']))
```

```
next_w error:  1.1395691798535431e-07
v error:  4.208314038113071e-09
m error:  4.214963193114416e-09
```

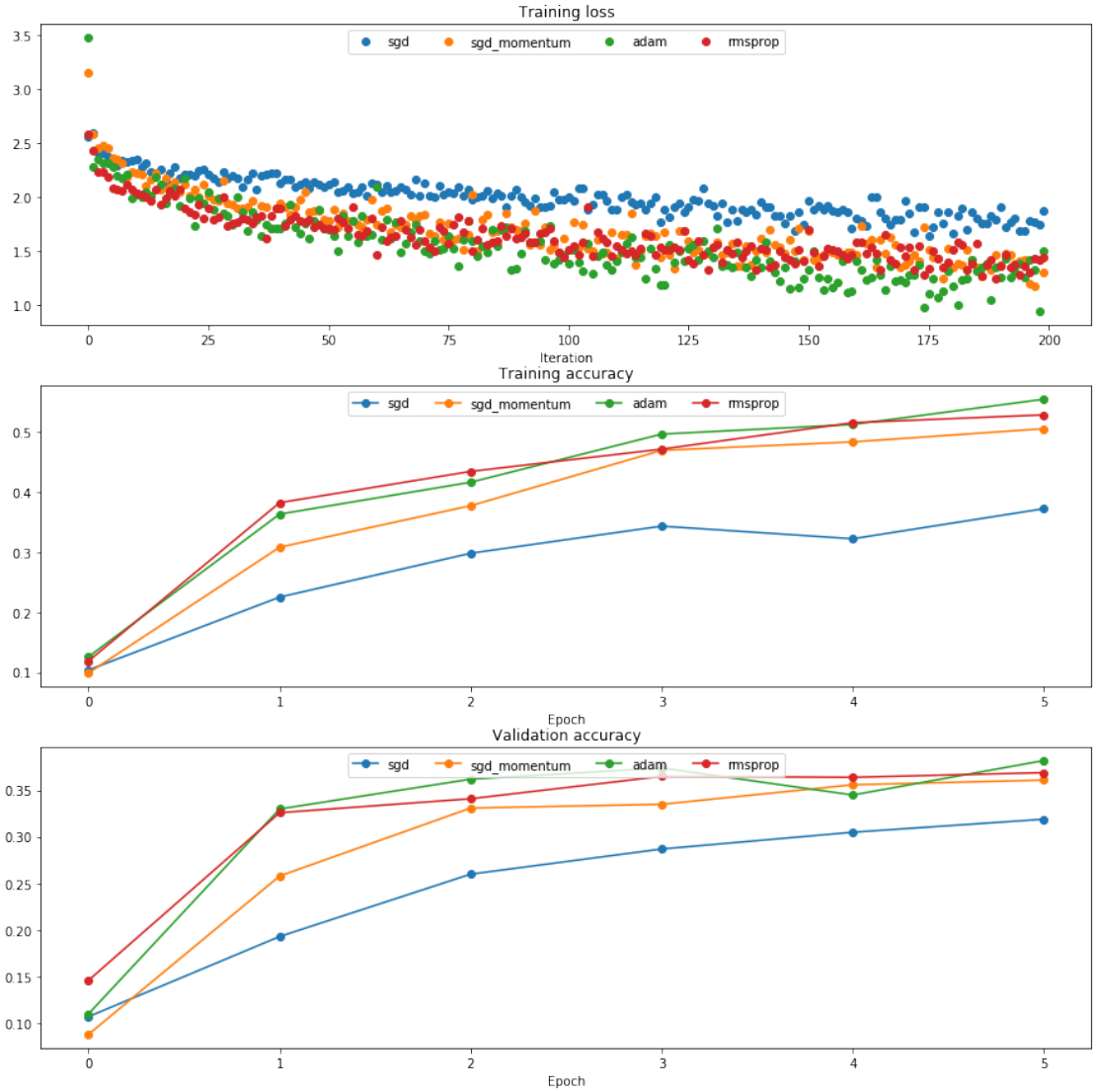
Once you have debugged your RMSProp and Adam implementations, run the following to train a pair of deep networks using these new update rules:

```
In [20]: learning_rates = {'rmsprop': 1e-4, 'adam': 1e-3}
         for update_rule in ['adam', 'rmsprop']:
           print('running with ', update_rule)
           model = FullyConnectedNet([100, 100, 100, 100, 100], weight_scale=5e-2)

           solver = Solver(model, small_data,
                           num_epochs=5, batch_size=100,
                           update_rule=update_rule,
                           optim_config={
                             'learning_rate': learning_rates[update_rule]
                           },
                           verbose=True)
           solvers[update_rule] = solver
           solver.train()
           print()

         plt.subplot(3, 1, 1)
         plt.title('Training loss')
         plt.xlabel('Iteration')

         plt.subplot(3, 1, 2)
         plt.title('Training accuracy')
```

```
        plt.xlabel('Epoch')

        plt.subplot(3, 1, 3)
        plt.title('Validation accuracy')
        plt.xlabel('Epoch')

        for update_rule, solver in list(solvers.items()):
          plt.subplot(3, 1, 1)
          plt.plot(solver.loss_history, 'o', label=update_rule)

          plt.subplot(3, 1, 2)
          plt.plot(solver.train_acc_history, '-o', label=update_rule)

          plt.subplot(3, 1, 3)
          plt.plot(solver.val_acc_history, '-o', label=update_rule)

        for i in [1, 2, 3]:
          plt.subplot(3, 1, i)
          plt.legend(loc='upper center', ncol=4)
        plt.gcf().set_size_inches(15, 15)
        plt.show()
```

```
running with  adam
(Iteration 1 / 200) loss: 3.476928
(Epoch 0 / 5) train acc: 0.126000; val_acc: 0.110000
(Iteration 11 / 200) loss: 2.027712
(Iteration 21 / 200) loss: 2.183358
(Iteration 31 / 200) loss: 1.744257
(Epoch 1 / 5) train acc: 0.363000; val_acc: 0.330000
(Iteration 41 / 200) loss: 1.707951
(Iteration 51 / 200) loss: 1.703835
(Iteration 61 / 200) loss: 2.094758
(Iteration 71 / 200) loss: 1.505514
(Epoch 2 / 5) train acc: 0.416000; val_acc: 0.362000
(Iteration 81 / 200) loss: 1.594391
(Iteration 91 / 200) loss: 1.483393
(Iteration 101 / 200) loss: 1.391985
(Iteration 111 / 200) loss: 1.410419
(Epoch 3 / 5) train acc: 0.496000; val_acc: 0.374000
(Iteration 121 / 200) loss: 1.190327
(Iteration 131 / 200) loss: 1.446230
(Iteration 141 / 200) loss: 1.358681
(Iteration 151 / 200) loss: 1.324699
(Epoch 4 / 5) train acc: 0.512000; val_acc: 0.345000
(Iteration 161 / 200) loss: 1.411795
(Iteration 171 / 200) loss: 1.208069
(Iteration 181 / 200) loss: 1.174987
(Iteration 191 / 200) loss: 1.255647
```

```
(Epoch 5 / 5) train acc: 0.554000; val_acc: 0.382000

running with  rmsprop
(Iteration 1 / 200) loss: 2.589166
(Epoch 0 / 5) train acc: 0.119000; val_acc: 0.146000
(Iteration 11 / 200) loss: 2.039570
(Iteration 21 / 200) loss: 1.897350
(Iteration 31 / 200) loss: 1.763338
(Epoch 1 / 5) train acc: 0.382000; val_acc: 0.326000
(Iteration 41 / 200) loss: 1.893851
(Iteration 51 / 200) loss: 1.715672
(Iteration 61 / 200) loss: 1.473092
(Iteration 71 / 200) loss: 1.602196
(Epoch 2 / 5) train acc: 0.434000; val_acc: 0.341000
(Iteration 81 / 200) loss: 1.501205
(Iteration 91 / 200) loss: 1.629006
(Iteration 101 / 200) loss: 1.516101
(Iteration 111 / 200) loss: 1.555156
(Epoch 3 / 5) train acc: 0.471000; val_acc: 0.365000
(Iteration 121 / 200) loss: 1.511333
(Iteration 131 / 200) loss: 1.543257
(Iteration 141 / 200) loss: 1.530261
(Iteration 151 / 200) loss: 1.700269
(Epoch 4 / 5) train acc: 0.515000; val_acc: 0.364000
(Iteration 161 / 200) loss: 1.591097
(Iteration 171 / 200) loss: 1.453837
(Iteration 181 / 200) loss: 1.519405
(Iteration 191 / 200) loss: 1.362337
(Epoch 5 / 5) train acc: 0.528000; val_acc: 0.369000
```



13.1 Inline Question 3:

AdaGrad, like Adam, is a per-parameter optimization method that uses the following update rule:

```
cache += dw**2
w += - learning_rate * dw / (np.sqrt(cache) + eps)
```

John notices that when he was training a network with AdaGrad that the updates became very small, and that his network was learning slowly. Using your knowledge of the AdaGrad update rule, why do you think the updates would become very small? Would Adam have the same issue?

13.2 Answer:

The reason might be that, cache keeps adding the power of the gradient, which will get larger, then the update is that the gradient divide the cache, will become very small.

Adam keeps the advantage of rmsprop which is the decay rate. This solved the problem.

14 Train a good model!

Train the best fully-connected model that you can on CIFAR-10, storing your best model in the `best_model` variable. We require you to get at least 50% accuracy on the validation set using a fully-connected net.

If you are careful it should be possible to get accuracies above 55%, but we don't require it for this part and won't assign extra credit for doing so. Later in the assignment we will ask you to train the best convolutional network that you can on CIFAR-10, and we would prefer that you spend your effort working on convolutional nets rather than fully-connected nets.

You might find it useful to complete the `BatchNormalization.ipynb` and `Dropout.ipynb` notebooks before completing this part, since those techniques can help you train powerful models.

```
In [21]: best_model = None
         ################################################################################
         # TODO: Train the best FullyConnectedNet that you can on CIFAR-10. You might   #
         # find batch/layer normalization and dropout useful. Store your best model in  #
         # the best_model variable.                                                     #
         ################################################################################
         # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
         best_val_acc = 0
         best_lr = None
         best_reg = None

         lrs = [1e-4, 5e-4, 1e-3, 5e-3]
         regs = [1e-3, 3e-3, 5e-3, 1e-2]

         for lr in lrs:
             for reg in regs:
                 model = FullyConnectedNet([100, 100, 100, 100, 100], reg=reg, weight_scale=0.

                 solver = Solver(model, data, num_epochs=25, batch_size=100, update_rule='adam
                                 optim_config={ 'learning_rate' : lr }, verbose=False)

                 solver.train()

                 y_train_pred = np.argmax(model.loss(data['X_train']), axis=1)
                 model_train_acc = (y_train_pred == data['y_train']).mean()

                 y_val_pred = np.argmax(model.loss(data['X_val']), axis=1)
                 model_val_acc = (y_val_pred == data['y_val']).mean()

                 print('lr :', lr, 'reg:', reg, 'train_acc : ', model_train_acc,'va_acc : ', m
                 if best_val_acc < model_val_acc:
                     best_model, best_val_acc = model, model_val_acc
                     best_lr, best_reg = lr, reg
```

```
        print('best_lr : ', best_lr, 'best_reg : ', best_reg, 'best_val_acc : ', best_val_acc)

        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ################################################################################
        #                                END OF YOUR CODE                              #
        ################################################################################
```

```
lr : 0.0001 reg: 0.001 train_acc :  0.5472244897959183 va_acc :  0.459
lr : 0.0001 reg: 0.003 train_acc :  0.5500204081632653 va_acc :  0.468
lr : 0.0001 reg: 0.005 train_acc :  0.6555102040816326 va_acc :  0.508
lr : 0.0001 reg: 0.01 train_acc :  0.5054081632653061 va_acc :  0.437
lr : 0.0005 reg: 0.001 train_acc :  0.6635102040816326 va_acc :  0.518
lr : 0.0005 reg: 0.003 train_acc :  0.6398775510204081 va_acc :  0.541
lr : 0.0005 reg: 0.005 train_acc :  0.6304285714285714 va_acc :  0.538
lr : 0.0005 reg: 0.01 train_acc :  0.5153673469387755 va_acc :  0.499
lr : 0.001 reg: 0.001 train_acc :  0.5798163265306122 va_acc :  0.523
lr : 0.001 reg: 0.003 train_acc :  0.5436122448979592 va_acc :  0.514
lr : 0.001 reg: 0.005 train_acc :  0.48512244897959184 va_acc :  0.466
lr : 0.001 reg: 0.01 train_acc :  0.49718367346938774 va_acc :  0.464
lr : 0.005 reg: 0.001 train_acc :  0.11957142857142856 va_acc :  0.112
lr : 0.005 reg: 0.003 train_acc :  0.1113469387755102 va_acc :  0.12
lr : 0.005 reg: 0.005 train_acc :  0.081 va_acc :  0.07
lr : 0.005 reg: 0.01 train_acc :  0.11118367346938776 va_acc :  0.106
best_lr :  0.0005 best_reg :  0.003 best_val_acc :  0.541
```

15 Test your model!

Run your best model on the validation and test sets. You should achieve above 50% accuracy on the validation set.

```
In [22]: y_test_pred = np.argmax(best_model.loss(data['X_test']), axis=1)
         y_val_pred = np.argmax(best_model.loss(data['X_val']), axis=1)
         print('Validation set accuracy: ', (y_val_pred == data['y_val']).mean())
         print('Test set accuracy: ', (y_test_pred == data['y_test']).mean())
```

```
Validation set accuracy:  0.541
Test set accuracy:  0.524
```

BatchNormalization

November 15, 2021

1 Batch Normalization

One way to make deep networks easier to train is to use more sophisticated optimization procedures such as SGD+momentum, RMSProp, or Adam. Another strategy is to change the architecture of the network to make it easier to train. One idea along these lines is batch normalization which was proposed by [1] in 2015.

The idea is relatively straightforward. Machine learning methods tend to work better when their input data consists of uncorrelated features with zero mean and unit variance. When training a neural network, we can preprocess the data before feeding it to the network to explicitly decorrelate its features; this will ensure that the first layer of the network sees data that follows a nice distribution. However, even if we preprocess the input data, the activations at deeper layers of the network will likely no longer be decorrelated and will no longer have zero mean or unit variance since they are output from earlier layers in the network. Even worse, during the training process the distribution of features at each layer of the network will shift as the weights of each layer are updated.

The authors of [1] hypothesize that the shifting distribution of features inside deep neural networks may make training deep networks more difficult. To overcome this problem, [1] proposes to insert batch normalization layers into the network. At training time, a batch normalization layer uses a minibatch of data to estimate the mean and standard deviation of each feature. These estimated means and standard deviations are then used to center and normalize the features of the minibatch. A running average of these means and standard deviations is kept during training, and at test time these running averages are used to center and normalize features.

It is possible that this normalization strategy could reduce the representational power of the network, since it may sometimes be optimal for certain layers to have features that are not zero-mean or unit variance. To this end, the batch normalization layer includes learnable shift and scale parameters for each feature dimension.

[1] Sergey Ioffe and Christian Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015.

```
In [87]: # As usual, a bit of setup
         import time
         import numpy as np
         import matplotlib.pyplot as plt
         from cs231n.classifiers.fc_net import *
         from cs231n.data_utils import get_CIFAR10_data
         from cs231n.gradient_check import eval_numerical_gradient, eval_numerical_gradient_ar
         from cs231n.solver import Solver
```

```
%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))))

def print_mean_std(x,axis=0):
    print('  means: ', x.mean(axis=axis))
    print('  stds:  ', x.std(axis=axis))
    print()
```

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

In [51]:
```
# 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,)
```

1.1 Batch normalization: forward

In the file `cs231n/layers.py`, implement the batch normalization forward pass in the function `batchnorm_forward`. Once you have done so, run the following to test your implementation.

Referencing the paper linked to above in [1] may be helpful!

In [52]:
```
# Check the training-time forward pass by checking means and variances
# of features both before and after batch normalization

# Simulate the forward pass for a two-layer network
np.random.seed(231)
N, D1, D2, D3 = 200, 50, 60, 3
```

```
X = np.random.randn(N, D1)
W1 = np.random.randn(D1, D2)
W2 = np.random.randn(D2, D3)
a = np.maximum(0, X.dot(W1)).dot(W2)

print('Before batch normalization:')
print_mean_std(a,axis=0)

gamma = np.ones((D3,))
beta = np.zeros((D3,))
# Means should be close to zero and stds close to one
print('After batch normalization (gamma=1, beta=0)')
a_norm, _ = batchnorm_forward(a, gamma, beta, {'mode': 'train'})
print_mean_std(a_norm,axis=0)

gamma = np.asarray([1.0, 2.0, 3.0])
beta = np.asarray([11.0, 12.0, 13.0])
# Now means should be close to beta and stds close to gamma
print('After batch normalization (gamma=', gamma, ', beta=', beta, ')')
a_norm, _ = batchnorm_forward(a, gamma, beta, {'mode': 'train'})
print_mean_std(a_norm,axis=0)
```

```
Before batch normalization:
  means:  [ -2.3814598  -13.18038246   1.91780462]
  stds:   [27.18502186 34.21455511 37.68611762]

After batch normalization (gamma=1, beta=0)
  means:  [5.32907052e-17 7.04991621e-17 1.85962357e-17]
  stds:   [0.99999999 1.         1.        ]

After batch normalization (gamma= [1. 2. 3.] , beta= [11. 12. 13.] )
  means:  [11. 12. 13.]
  stds:   [0.99999999 1.99999999 2.99999999]
```

In [53]:
```
# Check the test-time forward pass by running the training-time
# forward pass many times to warm up the running averages, and then
# checking the means and variances of activations after a test-time
# forward pass.

np.random.seed(231)
N, D1, D2, D3 = 200, 50, 60, 3
W1 = np.random.randn(D1, D2)
W2 = np.random.randn(D2, D3)

bn_param = {'mode': 'train'}
gamma = np.ones(D3)
```

```
beta = np.zeros(D3)

for t in range(50):
  X = np.random.randn(N, D1)
  a = np.maximum(0, X.dot(W1)).dot(W2)
  batchnorm_forward(a, gamma, beta, bn_param)

bn_param['mode'] = 'test'
X = np.random.randn(N, D1)
a = np.maximum(0, X.dot(W1)).dot(W2)
a_norm, _ = batchnorm_forward(a, gamma, beta, bn_param)

# Means should be close to zero and stds close to one, but will be
# noisier than training-time forward passes.
print('After batch normalization (test-time):')
print_mean_std(a_norm,axis=0)
```

```
After batch normalization (test-time):
  means:  [-0.03927354 -0.04349152 -0.10452688]
  stds:   [1.01531428 1.01238373 0.97819988]
```

1.2 Batch normalization: backward

Now implement the backward pass for batch normalization in the function `batchnorm_backward`.

To derive the backward pass you should write out the computation graph for batch normalization and backprop through each of the intermediate nodes. Some intermediates may have multiple outgoing branches; make sure to sum gradients across these branches in the backward pass.

Once you have finished, run the following to numerically check your backward pass.

In [54]:
```
# Gradient check batchnorm backward pass
np.random.seed(231)
N, D = 4, 5
x = 5 * np.random.randn(N, D) + 12
gamma = np.random.randn(D)
beta = np.random.randn(D)
dout = np.random.randn(N, D)

bn_param = {'mode': 'train'}
fx = lambda x: batchnorm_forward(x, gamma, beta, bn_param)[0]
fg = lambda a: batchnorm_forward(x, a, beta, bn_param)[0]
fb = lambda b: batchnorm_forward(x, gamma, b, bn_param)[0]

dx_num = eval_numerical_gradient_array(fx, x, dout)
da_num = eval_numerical_gradient_array(fg, gamma.copy(), dout)
db_num = eval_numerical_gradient_array(fb, beta.copy(), dout)
```

Dropout

November 15, 2021

1 Dropout

Dropout [1] is a technique for regularizing neural networks by randomly setting some output activations to zero during the forward pass. In this exercise you will implement a dropout layer and modify your fully-connected network to optionally use dropout.

[1] Geoffrey E. Hinton et al, "Improving neural networks by preventing co-adaptation of feature detectors", arXiv 2012

In [2]:
```
# As usual, a bit of setup
from __future__ import print_function
import time
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient, eval_numerical_gradient_arra
from cs231n.solver import Solver

%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 [3]:
```
# 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 Dropout forward pass

In the file `cs231n/layers.py`, implement the forward pass for dropout. Since dropout behaves differently during training and testing, make sure to implement the operation for both modes.

Once you have done so, run the cell below to test your implementation.

```
In [7]: np.random.seed(231)
        x = np.random.randn(500, 500) + 10

        for p in [0.25, 0.4, 0.7]:
          out, _ = dropout_forward(x, {'mode': 'train', 'p': p})
          out_test, _ = dropout_forward(x, {'mode': 'test', 'p': p})

          print('Running tests with p = ', p)
          print('Mean of input: ', x.mean())
          print('Mean of train-time output: ', out.mean())
          print('Mean of test-time output: ', out_test.mean())
          print('Fraction of train-time output set to zero: ', (out == 0).mean())
          print('Fraction of test-time output set to zero: ', (out_test == 0).mean())
          print()
```

```
Running tests with p =  0.25
Mean of input:  10.000207878477502
Mean of train-time output:  10.014059116977283
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.749784
Fraction of test-time output set to zero:  0.0

Running tests with p =  0.4
Mean of input:  10.000207878477502
Mean of train-time output:  9.977917658761159
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.600796
Fraction of test-time output set to zero:  0.0

Running tests with p =  0.7
```

```
Mean of input:  10.000207878477502
Mean of train-time output:  9.987811912159426
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.30074
Fraction of test-time output set to zero:  0.0
```

3 Dropout backward pass

In the file `cs231n/layers.py`, implement the backward pass for dropout. After doing so, run the following cell to numerically gradient-check your implementation.

```
In [9]: np.random.seed(231)
        x = np.random.randn(10, 10) + 10
        dout = np.random.randn(*x.shape)

        dropout_param = {'mode': 'train', 'p': 0.2, 'seed': 123}
        out, cache = dropout_forward(x, dropout_param)
        dx = dropout_backward(dout, cache)
        dx_num = eval_numerical_gradient_array(lambda xx: dropout_forward(xx, dropout_param)[0]

        # Error should be around e-10 or less
        print('dx relative error: ', rel_error(dx, dx_num))
```

```
dx relative error:  5.44560814873387e-11
```

3.1 Inline Question 1:

What happens if we do not divide the values being passed through inverse dropout by `p` in the dropout layer? Why does that happen?

3.2 Answer:

If we don't dive the value by p, the mean output value will be p times larger. But we want the mean to be the same.

4 Fully-connected nets with Dropout

In the file `cs231n/classifiers/fc_net.py`, modify your implementation to use dropout. Specifically, if the constructor of the network receives a value that is not 1 for the `dropout` parameter, then the net should add a dropout layer immediately after every ReLU nonlinearity. After doing so, run the following to numerically gradient-check your implementation.

```
In [12]: np.random.seed(231)
         N, D, H1, H2, C = 2, 15, 20, 30, 10
         X = np.random.randn(N, D)
```

```
y = np.random.randint(C, size=(N,))

for dropout in [1, 0.75, 0.5]:
  print('Running check with dropout = ', dropout)
  model = FullyConnectedNet([H1, H2], input_dim=D, num_classes=C,
                            weight_scale=5e-2, dtype=np.float64,
                            dropout=dropout, seed=123)

  loss, grads = model.loss(X, y)
  print('Initial loss: ', loss)

  # Relative errors should be around e-6 or less; Note that it's fine
  # if for dropout=1 you have W2 error be on the order of e-5.
  for name in sorted(grads):
    f = lambda _: model.loss(X, y)[0]
    grad_num = eval_numerical_gradient(f, model.params[name], verbose=False, h=1e-5)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[name])))
  print()
```

```
Running check with dropout =  1
Initial loss:  2.3004790897684924
W1 relative error: 1.48e-07
W2 relative error: 2.21e-05
W3 relative error: 3.53e-07
b1 relative error: 5.38e-09
b2 relative error: 2.09e-09
b3 relative error: 5.80e-11

Running check with dropout =  0.75
Initial loss:  2.302371489704412
W1 relative error: 1.90e-07
W2 relative error: 4.76e-06
W3 relative error: 2.60e-08
b1 relative error: 4.73e-09
b2 relative error: 1.82e-09
b3 relative error: 1.70e-10

Running check with dropout =  0.5
Initial loss:  2.3042759220785896
W1 relative error: 3.11e-07
W2 relative error: 1.84e-08
W3 relative error: 5.35e-08
b1 relative error: 5.37e-09
b2 relative error: 2.99e-09
b3 relative error: 1.13e-10
```

5 Regularization experiment

As an experiment, we will train a pair of two-layer networks on 500 training examples: one will use no dropout, and one will use a keep probability of 0.25. We will then visualize the training and validation accuracies of the two networks over time.

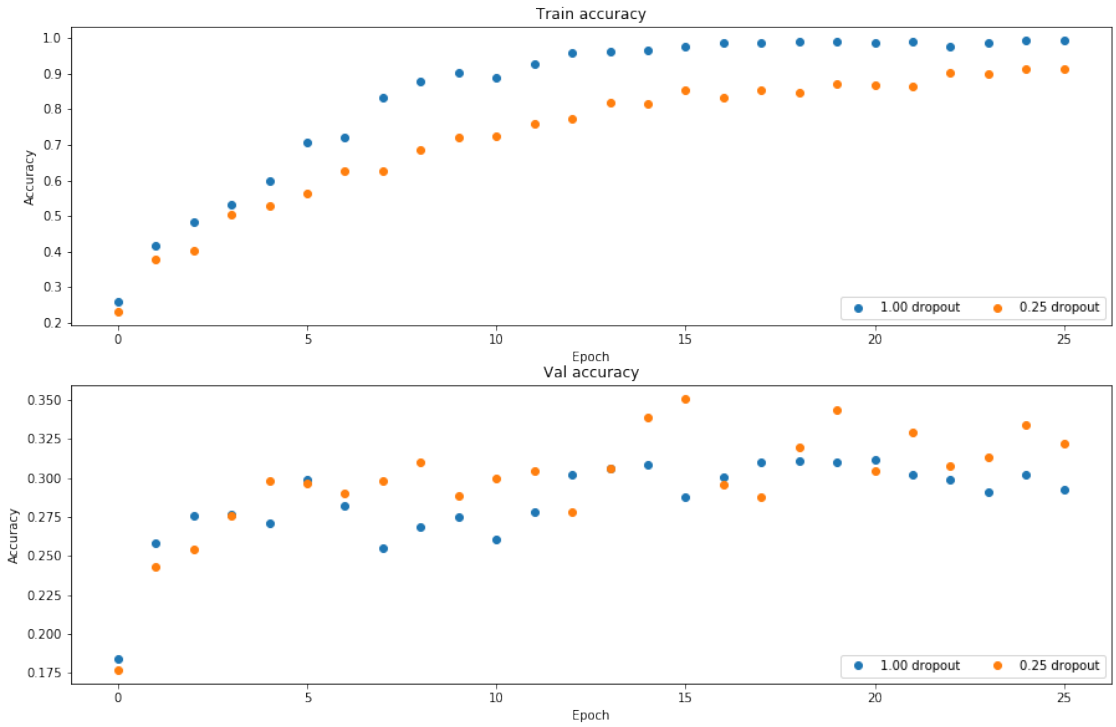
In [13]:
```
# Train two identical nets, one with dropout and one without
np.random.seed(231)
num_train = 500
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

solvers = {}
dropout_choices = [1, 0.25]
for dropout in dropout_choices:
  model = FullyConnectedNet([500], dropout=dropout)
  print(dropout)

  solver = Solver(model, small_data,
                  num_epochs=25, batch_size=100,
                  update_rule='adam',
                  optim_config={
                    'learning_rate': 5e-4,
                  },
                  verbose=True, print_every=100)
  solver.train()
  solvers[dropout] = solver
  print()
```

```
1
(Iteration 1 / 125) loss: 7.856643
(Epoch 0 / 25) train acc: 0.260000; val_acc: 0.184000
(Epoch 1 / 25) train acc: 0.416000; val_acc: 0.258000
(Epoch 2 / 25) train acc: 0.482000; val_acc: 0.276000
(Epoch 3 / 25) train acc: 0.532000; val_acc: 0.277000
(Epoch 4 / 25) train acc: 0.600000; val_acc: 0.271000
(Epoch 5 / 25) train acc: 0.708000; val_acc: 0.299000
(Epoch 6 / 25) train acc: 0.722000; val_acc: 0.282000
(Epoch 7 / 25) train acc: 0.832000; val_acc: 0.255000
(Epoch 8 / 25) train acc: 0.878000; val_acc: 0.269000
(Epoch 9 / 25) train acc: 0.902000; val_acc: 0.275000
(Epoch 10 / 25) train acc: 0.888000; val_acc: 0.261000
(Epoch 11 / 25) train acc: 0.926000; val_acc: 0.278000
(Epoch 12 / 25) train acc: 0.960000; val_acc: 0.302000
```

```
(Epoch 13 / 25) train acc: 0.964000; val_acc: 0.306000
(Epoch 14 / 25) train acc: 0.966000; val_acc: 0.309000
(Epoch 15 / 25) train acc: 0.976000; val_acc: 0.288000
(Epoch 16 / 25) train acc: 0.988000; val_acc: 0.301000
(Epoch 17 / 25) train acc: 0.988000; val_acc: 0.310000
(Epoch 18 / 25) train acc: 0.990000; val_acc: 0.311000
(Epoch 19 / 25) train acc: 0.990000; val_acc: 0.310000
(Epoch 20 / 25) train acc: 0.988000; val_acc: 0.312000
(Iteration 101 / 125) loss: 0.084611
(Epoch 21 / 25) train acc: 0.990000; val_acc: 0.302000
(Epoch 22 / 25) train acc: 0.978000; val_acc: 0.299000
(Epoch 23 / 25) train acc: 0.986000; val_acc: 0.291000
(Epoch 24 / 25) train acc: 0.994000; val_acc: 0.302000
(Epoch 25 / 25) train acc: 0.994000; val_acc: 0.293000

0.25
(Iteration 1 / 125) loss: 17.318478
(Epoch 0 / 25) train acc: 0.230000; val_acc: 0.177000
(Epoch 1 / 25) train acc: 0.378000; val_acc: 0.243000
(Epoch 2 / 25) train acc: 0.402000; val_acc: 0.254000
(Epoch 3 / 25) train acc: 0.502000; val_acc: 0.276000
(Epoch 4 / 25) train acc: 0.528000; val_acc: 0.298000
(Epoch 5 / 25) train acc: 0.562000; val_acc: 0.297000
(Epoch 6 / 25) train acc: 0.626000; val_acc: 0.290000
(Epoch 7 / 25) train acc: 0.628000; val_acc: 0.298000
(Epoch 8 / 25) train acc: 0.686000; val_acc: 0.310000
(Epoch 9 / 25) train acc: 0.722000; val_acc: 0.289000
(Epoch 10 / 25) train acc: 0.724000; val_acc: 0.300000
(Epoch 11 / 25) train acc: 0.760000; val_acc: 0.305000
(Epoch 12 / 25) train acc: 0.772000; val_acc: 0.278000
(Epoch 13 / 25) train acc: 0.818000; val_acc: 0.306000
(Epoch 14 / 25) train acc: 0.816000; val_acc: 0.339000
(Epoch 15 / 25) train acc: 0.854000; val_acc: 0.351000
(Epoch 16 / 25) train acc: 0.832000; val_acc: 0.296000
(Epoch 17 / 25) train acc: 0.854000; val_acc: 0.288000
(Epoch 18 / 25) train acc: 0.846000; val_acc: 0.320000
(Epoch 19 / 25) train acc: 0.872000; val_acc: 0.344000
(Epoch 20 / 25) train acc: 0.868000; val_acc: 0.305000
(Iteration 101 / 125) loss: 5.472347
(Epoch 21 / 25) train acc: 0.866000; val_acc: 0.329000
(Epoch 22 / 25) train acc: 0.902000; val_acc: 0.308000
(Epoch 23 / 25) train acc: 0.898000; val_acc: 0.313000
(Epoch 24 / 25) train acc: 0.912000; val_acc: 0.334000
(Epoch 25 / 25) train acc: 0.914000; val_acc: 0.322000
```

In [14]: *# Plot train and validation accuracies of the two models*

```
train_accs = []
val_accs = []
for dropout in dropout_choices:
  solver = solvers[dropout]
  train_accs.append(solver.train_acc_history[-1])
  val_accs.append(solver.val_acc_history[-1])

plt.subplot(3, 1, 1)
for dropout in dropout_choices:
  plt.plot(solvers[dropout].train_acc_history, 'o', label='%.2f dropout' % dropout)
plt.title('Train accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(ncol=2, loc='lower right')

plt.subplot(3, 1, 2)
for dropout in dropout_choices:
  plt.plot(solvers[dropout].val_acc_history, 'o', label='%.2f dropout' % dropout)
plt.title('Val accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(ncol=2, loc='lower right')

plt.gcf().set_size_inches(15, 15)
plt.show()
```



5.1 Inline Question 2:

Compare the validation and training accuracies with and without dropout – what do your results suggest about dropout as a regularizer?

5.2 Answer:

It seems that dropout reduce the convergence during training. But in test, the dropout can make a slightly better performance.

5.3 Inline Question 3:

Suppose we are training a deep fully-connected network for image classification, with dropout after hidden layers (parameterized by keep probability p). If we are concerned about overfitting, how should we modify p (if at all) when we decide to decrease the size of the hidden layers (that is, the number of nodes in each layer)?

5.4 Answer:

We should increase p, so that we won't lose too many hidden layers.

ConvolutionalNetworks

November 15, 2021

1 Convolutional Networks

So far we have worked with deep fully-connected networks, using them to explore different optimization strategies and network architectures. Fully-connected networks are a good testbed for experimentation because they are very computationally efficient, but in practice all state-of-the-art results use convolutional networks instead.

First you will implement several layer types that are used in convolutional networks. You will then use these layers to train a convolutional network on the CIFAR-10 dataset.

In [1]:
```
# As usual, a bit of setup
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.cnn import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient_array, eval_numerical_gradie
from cs231n.layers import *
from cs231n.fast_layers import *
from cs231n.solver import Solver

%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: Naive forward pass

The core of a convolutional network is the convolution operation. In the file `cs231n/layers.py`, implement the forward pass for the convolution layer in the function `conv_forward_naive`.

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 [3]: 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 e-8
        print('Testing conv_forward_naive')
        print('difference: ', rel_error(out, correct_out))
```

```
Testing conv_forward_naive
difference:  2.2121476417505994e-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.

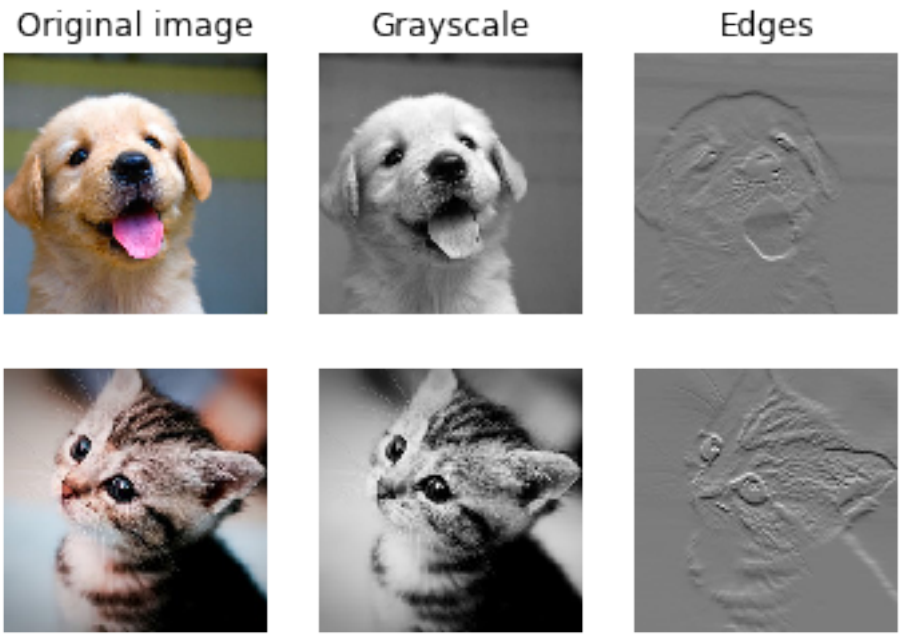
3.1 Colab Users Only

Please execute the below cell to copy two cat images to the Colab VM.

In [ ]:
```
# Colab users only!
%mkdir -p cs231n/notebook_images
%cd drive/My\ Drive/$FOLDERNAME/cs231n
%cp -r notebook_images/ /content/cs231n/
%cd /content/
```

In [4]:
```
from imageio import imread
from PIL import Image

kitten = imread('cs231n/notebook_images/kitten.jpg')
puppy = imread('cs231n/notebook_images/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
resized_puppy = np.array(Image.fromarray(puppy).resize((img_size, img_size)))
resized_kitten = np.array(Image.fromarray(kitten_cropped).resize((img_size, img_size)))
x = np.zeros((2, 3, img_size, img_size))
x[0, :, :, :] = resized_puppy.transpose((2, 0, 1))
x[1, :, :, :] = resized_kitten.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_no_ax(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_no_ax(puppy, normalize=False)
plt.title('Original image')
plt.subplot(2, 3, 2)
imshow_no_ax(out[0, 0])
plt.title('Grayscale')
plt.subplot(2, 3, 3)
imshow_no_ax(out[0, 1])
plt.title('Edges')
plt.subplot(2, 3, 4)
imshow_no_ax(kitten_cropped, normalize=False)
plt.subplot(2, 3, 5)
imshow_no_ax(out[1, 0])
plt.subplot(2, 3, 6)
imshow_no_ax(out[1, 1])
plt.show()
```



4 Convolution: Naive backward pass

Implement the backward pass for the convolution operation in the function `conv_backward_naive` in the file `cs231n/layers.py`. Again, you don't need to worry too much about computational efficiency.

When you are done, run the following to check your backward pass with a numeric gradient check.

```
In [5]: np.random.seed(231)
        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_para
        dw_num = eval_numerical_gradient_array(lambda w: conv_forward_naive(x, w, b, conv_para
        db_num = eval_numerical_gradient_array(lambda b: conv_forward_naive(x, w, b, conv_para

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

        # Your errors should be around e-8 or less.
        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:  1.159803161159293e-08
dw error:  2.2471264748452487e-10
db error:  3.37264006649648e-11
```

5 Max-Pooling: Naive forward

Implement the forward pass for the max-pooling operation in the function `max_pool_forward_naive` in the file `cs231n/layers.py`. Again, don't worry too much about computational efficiency.

Check your implementation by running the following:

```
In [6]: 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 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
```

6 Max-Pooling: Naive backward

Implement the backward pass for the max-pooling operation in the function `max_pool_backward_naive` in the file `cs231n/layers.py`. You don't need to worry about

computational efficiency.

Check your implementation with numeric gradient checking by running the following:

```
In [7]: np.random.seed(231)
        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_param)

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

        # Your error should be on the order of e-12
        print('Testing max_pool_backward_naive function:')
        print('dx error: ', rel_error(dx, dx_num))

Testing max_pool_backward_naive function:
dx error:  3.27562514223145e-12
```

7 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 either execute the local development cell (option A) if you are developing locally, or the Colab cell (option B) if you are running this assignment in Colab.

Very Important, Please Read. For **both** option A and B, you have to **restart** the notebook after compiling the cython extension. In Colab, please save the notebook `File -> Save`, then click `Runtime -> Restart Runtime -> Yes`. This will restart the kernel which means local variables will be lost. Just re-execute the cells from top to bottom and skip the cell below as you only need to run it once for the compilation step.

7.1 Option A: Local Development

Go to the cs231n directory and execute the following in your terminal:

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

7.2 Option B: Colab

Execute the cell below only only **ONCE**.

```
In [ ]: %cd drive/My\ Drive/$FOLDERNAME/cs231n/
        !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 [8]: # Rel errors should be around e-9 or less
        from cs231n.fast_layers import conv_forward_fast, conv_backward_fast
        from time import time
        np.random.seed(231)
        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: 3.414206s
Fast: 0.008868s
Speedup: 385.024548x
Difference:  4.926407851494105e-11

Testing conv_backward_fast:
Naive: 5.083464s
Fast: 0.009075s
Speedup: 560.151114x
dx difference:  1.949764775345631e-11
dw difference:  3.681156828004736e-13
db difference:  0.0
```

In [10]:
```
# Relative errors should be close to 0.0
from cs231n.fast_layers import max_pool_forward_fast, max_pool_backward_fast
np.random.seed(231)
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('fast: %fs' % (t2 - t1))
print('speedup: %fx' % ((t1 - t0) / (t2 - t1)))
print('dx difference: ', rel_error(dx_naive, dx_fast))
```

```
Testing pool_forward_fast:
Naive: 0.276309s
fast: 0.001920s
speedup: 143.912207x
difference:  0.0

Testing pool_backward_fast:
Naive: 0.230199s
fast: 0.007489s
speedup: 30.736415x
dx difference:  0.0
```

8 Convolutional "sandwich" layers

Previously we introduced the concept of "sandwich" layers that combine multiple operations into commonly used patterns. In the file `cs231n/layer_utils.py` you will find sandwich layers that implement a few commonly used patterns for convolutional networks. Run the cells below to sanity check they're working.

```
In [11]: from cs231n.layer_utils import conv_relu_pool_forward, conv_relu_pool_backward
         np.random.seed(231)
         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, conv
         dw_num = eval_numerical_gradient_array(lambda w: conv_relu_pool_forward(x, w, b, conv
         db_num = eval_numerical_gradient_array(lambda b: conv_relu_pool_forward(x, w, b, conv

         # Relative errors should be around e-8 or less
         print('Testing conv_relu_pool')
         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
dx error:  9.591132621921372e-09
dw error:  5.802391137330214e-09
db error:  1.0146343411762047e-09
```

```
In [12]: from cs231n.layer_utils import conv_relu_forward, conv_relu_backward
         np.random.seed(231)
         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_para
         dw_num = eval_numerical_gradient_array(lambda w: conv_relu_forward(x, w, b, conv_para
         db_num = eval_numerical_gradient_array(lambda b: conv_relu_forward(x, w, b, conv_para

         # Relative errors should be around e-8 or less
         print('Testing conv_relu:')
         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:
dx error:  1.5218619980349303e-09
dw error:  2.702022646099404e-10
db error:  1.451272393591721e-10
```

9 Three-layer ConvNet

Now that you have implemented all the necessary layers, we can put them together into a simple convolutional network.

Open the file `cs231n/classifiers/cnn.py` and complete the implementation of the `ThreeLayerConvNet` class. Remember you can use the fast/sandwich layers (already imported for you) in your implementation. Run the following cells to help you debug:

9.1 Sanity check loss

After you build a new network, one of the first things you should do is sanity check the loss. When we use the softmax loss, we expect the loss for random weights (and no regularization) to be about `log(C)` for `C` classes. When we add regularization the loss should go up slightly.

```
In [13]: model = ThreeLayerConvNet()

         N = 50
         X = np.random.randn(N, 3, 32, 32)
         y = np.random.randint(10, size=N)

         loss, grads = model.loss(X, y)
```

```
        print('Initial loss (no regularization): ', loss)

        model.reg = 0.5
        loss, grads = model.loss(X, y)
        print('Initial loss (with regularization): ', loss)
```

```
Initial loss (no regularization):  2.302586071243987
Initial loss (with regularization):  2.508255635671795
```

9.2 Gradient check

After the loss looks reasonable, use numeric gradient checking to make sure that your backward pass is correct. When you use numeric gradient checking you should use a small amount of artifical data and a small number of neurons at each layer. Note: correct implementations may still have relative errors up to the order of e-2.

```
In [14]: num_inputs = 2
         input_dim = (3, 16, 16)
         reg = 0.0
         num_classes = 10
         np.random.seed(231)
         X = np.random.randn(num_inputs, *input_dim)
         y = np.random.randint(num_classes, size=num_inputs)

         model = ThreeLayerConvNet(num_filters=3, filter_size=3,
                                   input_dim=input_dim, hidden_dim=7,
                                   dtype=np.float64)
         loss, grads = model.loss(X, y)
         # Errors should be small, but correct implementations may have
         # relative errors up to the order of e-2
         for param_name in sorted(grads):
             f = lambda _: model.loss(X, y)[0]
             param_grad_num = eval_numerical_gradient(f, model.params[param_name], verbose=Fals
             e = rel_error(param_grad_num, grads[param_name])
             print('%s max relative error: %e' % (param_name, rel_error(param_grad_num, grads[p
```

```
W1 max relative error: 1.380104e-04
W2 max relative error: 1.822723e-02
W3 max relative error: 3.064049e-04
```

9.3 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 [16]:
```
np.random.seed(231)

num_train = 100
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

model = ThreeLayerConvNet(weight_scale=1e-2)

solver = Solver(model, small_data,
                num_epochs=15, batch_size=50,
                update_rule='adam',
                optim_config={
                  'learning_rate': 1e-3,
                },
                verbose=True, print_every=1)
solver.train()
```

```
(Iteration 1 / 30) loss: 2.414060
(Epoch 0 / 15) train acc: 0.200000; val_acc: 0.137000
(Iteration 2 / 30) loss: 3.102925
(Epoch 1 / 15) train acc: 0.140000; val_acc: 0.087000
(Iteration 3 / 30) loss: 2.270330
(Iteration 4 / 30) loss: 2.096705
(Epoch 2 / 15) train acc: 0.240000; val_acc: 0.094000
(Iteration 5 / 30) loss: 1.838880
(Iteration 6 / 30) loss: 1.934188
(Epoch 3 / 15) train acc: 0.510000; val_acc: 0.173000
(Iteration 7 / 30) loss: 1.827912
(Iteration 8 / 30) loss: 1.639574
(Epoch 4 / 15) train acc: 0.520000; val_acc: 0.188000
(Iteration 9 / 30) loss: 1.330082
(Iteration 10 / 30) loss: 1.756115
(Epoch 5 / 15) train acc: 0.630000; val_acc: 0.167000
(Iteration 11 / 30) loss: 1.024162
(Iteration 12 / 30) loss: 1.041826
(Epoch 6 / 15) train acc: 0.750000; val_acc: 0.229000
(Iteration 13 / 30) loss: 1.142777
(Iteration 14 / 30) loss: 0.835706
(Epoch 7 / 15) train acc: 0.790000; val_acc: 0.247000
(Iteration 15 / 30) loss: 0.587786
(Iteration 16 / 30) loss: 0.645509
(Epoch 8 / 15) train acc: 0.820000; val_acc: 0.252000
(Iteration 17 / 30) loss: 0.786844
(Iteration 18 / 30) loss: 0.467054
```

```
(Epoch 9 / 15) train acc: 0.820000; val_acc: 0.178000
(Iteration 19 / 30) loss: 0.429880
(Iteration 20 / 30) loss: 0.635498
(Epoch 10 / 15) train acc: 0.900000; val_acc: 0.206000
(Iteration 21 / 30) loss: 0.365807
(Iteration 22 / 30) loss: 0.284220
(Epoch 11 / 15) train acc: 0.820000; val_acc: 0.201000
(Iteration 23 / 30) loss: 0.469343
(Iteration 24 / 30) loss: 0.509369
(Epoch 12 / 15) train acc: 0.920000; val_acc: 0.211000
(Iteration 25 / 30) loss: 0.111638
(Iteration 26 / 30) loss: 0.145388
(Epoch 13 / 15) train acc: 0.930000; val_acc: 0.213000
(Iteration 27 / 30) loss: 0.155575
(Iteration 28 / 30) loss: 0.143398
(Epoch 14 / 15) train acc: 0.960000; val_acc: 0.212000
(Iteration 29 / 30) loss: 0.158160
(Iteration 30 / 30) loss: 0.118934
(Epoch 15 / 15) train acc: 0.990000; val_acc: 0.220000
```

In [17]:
```
# Print final training accuracy
print(
    "Small data training accuracy:",
    solver.check_accuracy(small_data['X_train'], small_data['y_train'])
)
```

```
Small data training accuracy: 0.82
```

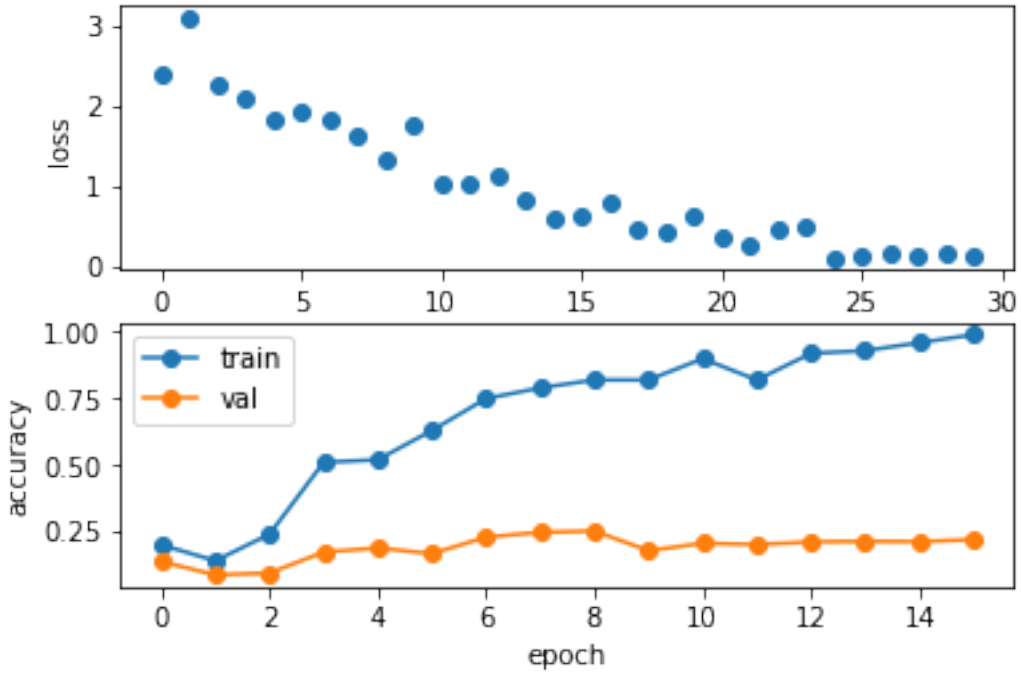
In [18]:
```
# Print final validation accuracy
print(
    "Small data validation accuracy:",
    solver.check_accuracy(small_data['X_val'], small_data['y_val'])
)
```

```
Small data validation accuracy: 0.252
```

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

In [19]:
```
plt.subplot(2, 1, 1)
plt.plot(solver.loss_history, 'o')
plt.xlabel('iteration')
plt.ylabel('loss')

plt.subplot(2, 1, 2)
plt.plot(solver.train_acc_history, '-o')
plt.plot(solver.val_acc_history, '-o')
```

```
plt.legend(['train', 'val'], loc='upper left')
plt.xlabel('epoch')
plt.ylabel('accuracy')
plt.show()
```



9.4 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 [20]: model = ThreeLayerConvNet(weight_scale=0.001, hidden_dim=500, reg=0.001)

         solver = Solver(model, data,
                         num_epochs=1, batch_size=50,
                         update_rule='adam',
                         optim_config={
                           'learning_rate': 1e-3,
                         },
                         verbose=True, print_every=20)
         solver.train()
```

```
(Iteration 1 / 980) loss: 2.304740
(Epoch 0 / 1) train acc: 0.103000; val_acc: 0.107000
(Iteration 21 / 980) loss: 2.098229
(Iteration 41 / 980) loss: 1.949788
```

```
(Iteration 61 / 980) loss: 1.888398
(Iteration 81 / 980) loss: 1.877093
(Iteration 101 / 980) loss: 1.851877
(Iteration 121 / 980) loss: 1.859353
(Iteration 141 / 980) loss: 1.800181
(Iteration 161 / 980) loss: 2.143292
(Iteration 181 / 980) loss: 1.830573
(Iteration 201 / 980) loss: 2.037280
(Iteration 221 / 980) loss: 2.020304
(Iteration 241 / 980) loss: 1.823728
(Iteration 261 / 980) loss: 1.692679
(Iteration 281 / 980) loss: 1.882594
(Iteration 301 / 980) loss: 1.798261
(Iteration 321 / 980) loss: 1.851960
(Iteration 341 / 980) loss: 1.716323
(Iteration 361 / 980) loss: 1.897655
(Iteration 381 / 980) loss: 1.319744
(Iteration 401 / 980) loss: 1.738790
(Iteration 421 / 980) loss: 1.488866
(Iteration 441 / 980) loss: 1.718409
(Iteration 461 / 980) loss: 1.744440
(Iteration 481 / 980) loss: 1.605460
(Iteration 501 / 980) loss: 1.494847
(Iteration 521 / 980) loss: 1.835179
(Iteration 541 / 980) loss: 1.483923
(Iteration 561 / 980) loss: 1.676871
(Iteration 581 / 980) loss: 1.438325
(Iteration 601 / 980) loss: 1.443469
(Iteration 621 / 980) loss: 1.529369
(Iteration 641 / 980) loss: 1.763475
(Iteration 661 / 980) loss: 1.790329
(Iteration 681 / 980) loss: 1.693343
(Iteration 701 / 980) loss: 1.637078
(Iteration 721 / 980) loss: 1.644564
(Iteration 741 / 980) loss: 1.708919
(Iteration 761 / 980) loss: 1.494252
(Iteration 781 / 980) loss: 1.901751
(Iteration 801 / 980) loss: 1.898991
(Iteration 821 / 980) loss: 1.489988
(Iteration 841 / 980) loss: 1.377615
(Iteration 861 / 980) loss: 1.763751
(Iteration 881 / 980) loss: 1.540284
(Iteration 901 / 980) loss: 1.525582
(Iteration 921 / 980) loss: 1.674166
(Iteration 941 / 980) loss: 1.714316
(Iteration 961 / 980) loss: 1.534668
(Epoch 1 / 1) train acc: 0.504000; val_acc: 0.499000
```

```
In [21]: # Print final training accuracy
         print(
             "Full data training accuracy:",
             solver.check_accuracy(small_data['X_train'], small_data['y_train'])
         )
```

```
Full data training accuracy: 0.4
```

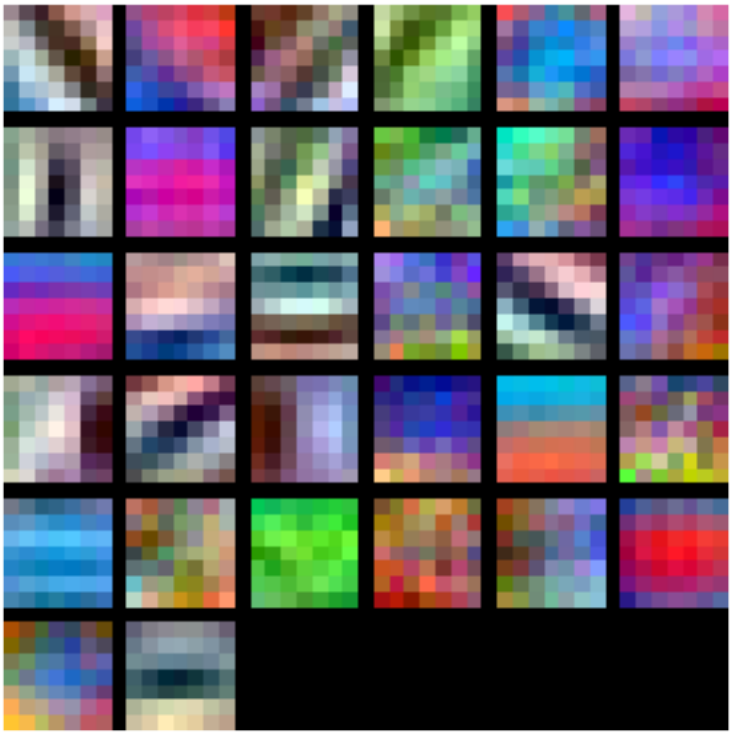
```
In [22]: # Print final validation accuracy
         print(
             "Full data validation accuracy:",
             solver.check_accuracy(data['X_val'], data['y_val'])
         )
```

```
Full data validation accuracy: 0.499
```

9.5 Visualize Filters

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

```
In [23]: from cs231n.vis_utils import visualize_grid

         grid = visualize_grid(model.params['W1'].transpose(0, 2, 3, 1))
         plt.imshow(grid.astype('uint8'))
         plt.axis('off')
         plt.gcf().set_size_inches(5, 5)
         plt.show()
```



10 Spatial Batch Normalization

We already saw that batch normalization is a very useful technique for training deep fully-connected networks. As proposed in the original paper (link in `BatchNormalization.ipynb`), batch normalization can also be used for convolutional networks, but we need to tweak it a bit; the modification will be called "spatial batch normalization."

Normally batch-normalization accepts inputs of shape `(N, D)` and produces outputs of shape `(N, D)`, where we normalize across the minibatch dimension `N`. For data coming from convolutional layers, batch normalization needs to accept inputs of shape `(N, C, H, W)` and produce outputs of shape `(N, C, H, W)` where the `N` dimension gives the minibatch size and the `(H, W)` dimensions give the spatial size of the feature map.

If the feature map was produced using convolutions, then we expect every feature channel's statistics e.g. mean, variance to be relatively consistent both between different images, and different locations within the same image – after all, every feature channel is produced by the same convolutional filter! Therefore spatial batch normalization computes a mean and variance for each of the `C` feature channels by computing statistics over the minibatch dimension `N` as well the spatial dimensions `H` and `W`.

[1] Sergey Ioffe and Christian Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015.

10.1 Spatial batch normalization: forward

In the file `cs231n/layers.py`, implement the forward pass for spatial batch normalization in the function `spatial_batchnorm_forward`. Check your implementation by running the following:

```
In [32]: np.random.seed(231)
         # Check the training-time forward pass by checking means and variances
         # of features both before and after spatial batch normalization

         N, C, H, W = 2, 3, 4, 5
         x = 4 * np.random.randn(N, C, H, W) + 10

         print('Before spatial batch normalization:')
         print('  Shape: ', x.shape)
         print('  Means: ', x.mean(axis=(0, 2, 3)))
         print('  Stds: ', x.std(axis=(0, 2, 3)))

         # Means should be close to zero and stds close to one
         gamma, beta = np.ones(C), np.zeros(C)
         bn_param = {'mode': 'train'}
         out, _ = spatial_batchnorm_forward(x, gamma, beta, bn_param)
         print('After spatial batch normalization:')
         print('  Shape: ', out.shape)
         print('  Means: ', out.mean(axis=(0, 2, 3)))
         print('  Stds: ', out.std(axis=(0, 2, 3)))

         # Means should be close to beta and stds close to gamma
         gamma, beta = np.asarray([3, 4, 5]), np.asarray([6, 7, 8])
         out, _ = spatial_batchnorm_forward(x, gamma, beta, bn_param)
         print('After spatial batch normalization (nontrivial gamma, beta):')
         print('  Shape: ', out.shape)
         print('  Means: ', out.mean(axis=(0, 2, 3)))
         print('  Stds: ', out.std(axis=(0, 2, 3)))
```

```
Before spatial batch normalization:
  Shape:  (2, 3, 4, 5)
  Means:  [9.33463814 8.90909116 9.11056338]
  Stds:  [3.61447857 3.19347686 3.5168142 ]
After spatial batch normalization:
  Shape:  (2, 3, 4, 5)
  Means:  [ 1.38777878e-16  1.94289029e-17 -9.43689571e-17]
  Stds:  [0.99999962 0.99999951 0.9999996 ]
After spatial batch normalization (nontrivial gamma, beta):
  Shape:  (2, 3, 4, 5)
  Means:  [6. 7. 8.]
  Stds:  [2.99999885 3.99999804 4.99999798]
```

```
In [33]: np.random.seed(231)
         # Check the test-time forward pass by running the training-time
```

```
# forward pass many times to warm up the running averages, and then
# checking the means and variances of activations after a test-time
# forward pass.
N, C, H, W = 10, 4, 11, 12

bn_param = {'mode': 'train'}
gamma = np.ones(C)
beta = np.zeros(C)
for t in range(50):
  x = 2.3 * np.random.randn(N, C, H, W) + 13
  spatial_batchnorm_forward(x, gamma, beta, bn_param)
bn_param['mode'] = 'test'
x = 2.3 * np.random.randn(N, C, H, W) + 13
a_norm, _ = spatial_batchnorm_forward(x, gamma, beta, bn_param)

# Means should be close to zero and stds close to one, but will be
# noisier than training-time forward passes.
print('After spatial batch normalization (test-time):')
print('  means: ', a_norm.mean(axis=(0, 2, 3)))
print('  stds: ', a_norm.std(axis=(0, 2, 3)))
```

```
After spatial batch normalization (test-time):
  means:  [-0.08034406  0.07562881  0.05716371  0.04378383]
  stds:  [0.96718744 1.0299714  1.02887624 1.00585577]
```

10.2 Spatial batch normalization: backward

In the file `cs231n/layers.py`, implement the backward pass for spatial batch normalization in the function `spatial_batchnorm_backward`. Run the following to check your implementation using a numeric gradient check:

In [36]:
```
np.random.seed(231)
N, C, H, W = 2, 3, 4, 5
x = 5 * np.random.randn(N, C, H, W) + 12
gamma = np.random.randn(C)
beta = np.random.randn(C)
dout = np.random.randn(N, C, H, W)

bn_param = {'mode': 'train'}
fx = lambda x: spatial_batchnorm_forward(x, gamma, beta, bn_param)[0]
fg = lambda a: spatial_batchnorm_forward(x, gamma, beta, bn_param)[0]
fb = lambda b: spatial_batchnorm_forward(x, gamma, beta, bn_param)[0]

dx_num = eval_numerical_gradient_array(fx, x, dout)
da_num = eval_numerical_gradient_array(fg, gamma, dout)
db_num = eval_numerical_gradient_array(fb, beta, dout)
```

```
        #You should expect errors of magnitudes between 1e-12~1e-06
        _, cache = spatial_batchnorm_forward(x, gamma, beta, bn_param)
        dx, dgamma, dbeta = spatial_batchnorm_backward(dout, cache)
        print('dx error: ', rel_error(dx_num, dx))
        print('dgamma error: ', rel_error(da_num, dgamma))
        print('dbeta error: ', rel_error(db_num, dbeta))
```

```
dx error:  3.423838608783549e-07
dgamma error:  7.0963199356067174e-12
dbeta error:  3.275380797385891e-12
```

11 Group Normalization

In the previous notebook, we mentioned that Layer Normalization is an alternative normalization technique that mitigates the batch size limitations of Batch Normalization. However, as the authors of [2] observed, Layer Normalization does not perform as well as Batch Normalization when used with Convolutional Layers:

> With fully connected layers, all the hidden units in a layer tend to make similar contributions to the final prediction, and re-centering and rescaling the summed inputs to a layer works well. However, the assumption of similar contributions is no longer true for convolutional neural networks. The large number of the hidden units whose receptive fields lie near the boundary of the image are rarely turned on and thus have very different statistics from the rest of the hidden units within the same layer.

The authors of [3] propose an intermediary technique. In contrast to Layer Normalization, where you normalize over the entire feature per-datapoint, they suggest a consistent splitting of each per-datapoint feature into G groups, and a per-group per-datapoint normalization instead.

Visual comparison of the normalization techniques discussed so far (image edited from [3])

Even though an assumption of equal contribution is still being made within each group, the authors hypothesize that this is not as problematic, as innate grouping arises within features for visual recognition. One example they use to illustrate this is that many high-performance handcrafted features in traditional Computer Vision have terms that are explicitly grouped together. Take for example Histogram of Oriented Gradients [4]– after computing histograms per spatially local block, each per-block histogram is normalized before being concatenated together to form the final feature vector.

You will now implement Group Normalization. Note that this normalization technique that you are to implement in the following cells was introduced and published to ECCV just in 2018 – this truly is still an ongoing and excitingly active field of research!

[2] Ba, Jimmy Lei, Jamie Ryan Kiros, and Geoffrey E. Hinton. "Layer Normalization." stat 1050 (2016): 21.

[3] Wu, Yuxin, and Kaiming He. "Group Normalization." arXiv preprint arXiv:1803.08494 (2018).

[4] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In Computer Vision and Pattern Recognition (CVPR), 2005.

11.1 Group normalization: forward

In the file `cs231n/layers.py`, implement the forward pass for group normalization in the function `spatial_groupnorm_forward`. Check your implementation by running the following:

```
In [58]: np.random.seed(231)
         # Check the training-time forward pass by checking means and variances
         # of features both before and after spatial batch normalization

         N, C, H, W = 2, 6, 4, 5
         G = 2
         x = 4 * np.random.randn(N, C, H, W) + 10
         x_g = x.reshape((N*G,-1))
         print('Before spatial group normalization:')
         print('  Shape: ', x.shape)
         print('  Means: ', x_g.mean(axis=1))
         print('  Stds: ', x_g.std(axis=1))

         # Means should be close to zero and stds close to one
         gamma, beta = np.ones((1,C,1,1)), np.zeros((1,C,1,1))
         bn_param = {'mode': 'train'}

         out, _ = spatial_groupnorm_forward(x, gamma, beta, G, bn_param)
         out_g = out.reshape((N*G,-1))
         print('After spatial group normalization:')
         print('  Shape: ', out.shape)
         print('  Means: ', out_g.mean(axis=1))
         print('  Stds: ', out_g.std(axis=1))
```

```
Before spatial group normalization:
  Shape:  (2, 6, 4, 5)
  Means:  [9.72505327 8.51114185 8.9147544  9.43448077]
  Stds:  [3.67070958 3.09892597 4.27043622 3.97521327]
After spatial group normalization:
  Shape:  (2, 6, 4, 5)
  Means:  [-2.14643118e-16  5.25505565e-16  2.65528340e-16 -3.38618023e-16]
  Stds:  [0.99999963 0.99999948 0.99999973 0.99999968]
```

11.2 Spatial group normalization: backward

In the file `cs231n/layers.py`, implement the backward pass for spatial batch normalization in the function `spatial_groupnorm_backward`. Run the following to check your implementation using a numeric gradient check:

```
In [78]: np.random.seed(231)
         N, C, H, W = 2, 6, 4, 5
         G = 2
         x = 5 * np.random.randn(N, C, H, W) + 12
```

```
gamma = np.random.randn(1,C,1,1)
beta = np.random.randn(1,C,1,1)
dout = np.random.randn(N, C, H, W)

gn_param = {}
fx = lambda x: spatial_groupnorm_forward(x, gamma, beta, G, gn_param)[0]
fg = lambda a: spatial_groupnorm_forward(x, gamma, beta, G, gn_param)[0]
fb = lambda b: spatial_groupnorm_forward(x, gamma, beta, G, gn_param)[0]

dx_num = eval_numerical_gradient_array(fx, x, dout)
da_num = eval_numerical_gradient_array(fg, gamma, dout)
db_num = eval_numerical_gradient_array(fb, beta, dout)

_, cache = spatial_groupnorm_forward(x, gamma, beta, G, gn_param)
dx, dgamma, dbeta = spatial_groupnorm_backward(dout, cache)
#You should expect errors of magnitudes between 1e-12~1e-07
print('dx error: ', rel_error(dx_num, dx))
print('dgamma error: ', rel_error(da_num, dgamma))
print('dbeta error: ', rel_error(db_num, dbeta))
```

```
dx error:  7.413109542981906e-08
dgamma error:  9.468195772749234e-12
dbeta error:  3.354494437653335e-12
```

PyTorch

November 15, 2021

1 What's this PyTorch business?

You've written a lot of code in this assignment to provide a whole host of neural network functionality. Dropout, Batch Norm, and 2D convolutions are some of the workhorses of deep learning in computer vision. You've also worked hard to make your code efficient and vectorized.

For the last part of this assignment, though, we're going to leave behind your beautiful codebase and instead migrate to one of two popular deep learning frameworks: in this instance, PyTorch (or TensorFlow, if you choose to use that notebook).

1.0.1 What is PyTorch?

PyTorch is a system for executing dynamic computational graphs over Tensor objects that behave similarly as numpy ndarray. It comes with a powerful automatic differentiation engine that removes the need for manual back-propagation.

1.0.2 Why?

- Our code will now run on GPUs! Much faster training. When using a framework like PyTorch or TensorFlow you can harness the power of the GPU for your own custom neural network architectures without having to write CUDA code directly (which is beyond the scope of this class).
- We want you to be ready to use one of these frameworks for your project so you can experiment more efficiently than if you were writing every feature you want to use by hand.
- We want you to stand on the shoulders of giants! TensorFlow and PyTorch are both excellent frameworks that will make your lives a lot easier, and now that you understand their guts, you are free to use them :)
- We want you to be exposed to the sort of deep learning code you might run into in academia or industry.

1.0.3 PyTorch versions

This notebook assumes that you are using **PyTorch version 1.4**. In some of the previous versions (e.g. before 0.4), Tensors had to be wrapped in Variable objects to be used in autograd; however Variables have now been deprecated. In addition 1.0+ versions separate a Tensor's datatype from its device, and use numpy-style factories for constructing Tensors rather than directly invoking Tensor constructors.

1.1 How will I learn PyTorch?

Justin Johnson has made an excellent tutorial for PyTorch.

You can also find the detailed API doc here. If you have other questions that are not addressed by the API docs, the PyTorch forum is a much better place to ask than StackOverflow.

1.2 Install PyTorch 1.4 (ONLY IF YOU ARE WORKING LOCALLY)

1. Have the latest version of Anaconda installed on your machine.
2. Create a new conda environment starting from Python 3.7. In this setup example, we'll call it `torch_env`.
3. Run the command: `conda activate torch_env`
4. Run the command: `pip install torch==1.4 torchvision==0.5.0`

2 Table of Contents

This assignment has 5 parts. You will learn PyTorch on **three different levels of abstraction**, which will help you understand it better and prepare you for the final project.

1. Part I, Preparation: we will use CIFAR-10 dataset.
2. Part II, Barebones PyTorch: **Abstraction level 1**, we will work directly with the lowest-level PyTorch Tensors.
3. Part III, PyTorch Module API: **Abstraction level 2**, we will use `nn.Module` to define arbitrary neural network architecture.
4. Part IV, PyTorch Sequential API: **Abstraction level 3**, we will use `nn.Sequential` to define a linear feed-forward network very conveniently.
5. Part V, CIFAR-10 open-ended challenge: please implement your own network to get as high accuracy as possible on CIFAR-10. You can experiment with any layer, optimizer, hyperparameters or other advanced features.

Here is a table of comparison:

API	Flexibility	Convenience
Barebone	High	Low
`nn.Module`	High	Medium
`nn.Sequential`	Low	High

3 Part I. Preparation

First, we load the CIFAR-10 dataset. This might take a couple minutes the first time you do it, but the files should stay cached after that.

In previous parts of the assignment we had to write our own code to download the CIFAR-10 dataset, preprocess it, and iterate through it in minibatches; PyTorch provides convenient tools to automate this process for us.

```
In [1]: import torch
        # assert '.'.join(torch.__version__.split('.')[:2]) == '1.4'
```

```
        import torch.nn as nn
        import torch.optim as optim
        from torch.utils.data import DataLoader
        from torch.utils.data import sampler

        import torchvision.datasets as dset
        import torchvision.transforms as T

        import numpy as np
```

In [2]:
```
NUM_TRAIN = 49000

# The torchvision.transforms package provides tools for preprocessing data
# and for performing data augmentation; here we set up a transform to
# preprocess the data by subtracting the mean RGB value and dividing by the
# standard deviation of each RGB value; we've hardcoded the mean and std.
transform = T.Compose([
                T.ToTensor(),
                T.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010))
            ])

# We set up a Dataset object for each split (train / val / test); Datasets load
# training examples one at a time, so we wrap each Dataset in a DataLoader which
# iterates through the Dataset and forms minibatches. We divide the CIFAR-10
# training set into train and val sets by passing a Sampler object to the
# DataLoader telling how it should sample from the underlying Dataset.
cifar10_train = dset.CIFAR10('./cs231n/datasets', train=True, download=True,
                             transform=transform)
loader_train = DataLoader(cifar10_train, batch_size=64,
                          sampler=sampler.SubsetRandomSampler(range(NUM_TRAIN)))

cifar10_val = dset.CIFAR10('./cs231n/datasets', train=True, download=True,
                           transform=transform)
loader_val = DataLoader(cifar10_val, batch_size=64,
                        sampler=sampler.SubsetRandomSampler(range(NUM_TRAIN, 50000)))

cifar10_test = dset.CIFAR10('./cs231n/datasets', train=False, download=True,
                            transform=transform)
loader_test = DataLoader(cifar10_test, batch_size=64)
```

```
Files already downloaded and verified
Files already downloaded and verified
Files already downloaded and verified
```

You have an option to **use GPU by setting the flag to True below**. It is not necessary to use GPU for this assignment. Note that if your computer does not have CUDA enabled, `torch.cuda.is_available()` will return False and this notebook will fallback to CPU mode.

The global variables `dtype` and `device` will control the data types throughout this assignment.

3.1 Colab Users

If you are using Colab, you need to manually switch to a GPU device. You can do this by clicking `Runtime -> Change runtime type` and selecting `GPU` under `Hardware Accelerator`. Note that you have to rerun the cells from the top since the kernel gets restarted upon switching runtimes.

```
In [3]: USE_GPU = True

        dtype = torch.float32 # we will be using float throughout this tutorial

        if USE_GPU and torch.cuda.is_available():
            device = torch.device('cuda')
        else:
            device = torch.device('cpu')

        # Constant to control how frequently we print train loss
        print_every = 100

        print('using device:', device)
```

```
using device: cuda
```

4 Part II. Barebones PyTorch

PyTorch ships with high-level APIs to help us define model architectures conveniently, which we will cover in Part II of this tutorial. In this section, we will start with the barebone PyTorch elements to understand the autograd engine better. After this exercise, you will come to appreciate the high-level model API more.

We will start with a simple fully-connected ReLU network with two hidden layers and no biases for CIFAR classification. This implementation computes the forward pass using operations on PyTorch Tensors, and uses PyTorch autograd to compute gradients. It is important that you understand every line, because you will write a harder version after the example.

When we create a PyTorch Tensor with `requires_grad=True`, then operations involving that Tensor will not just compute values; they will also build up a computational graph in the background, allowing us to easily backpropagate through the graph to compute gradients of some Tensors with respect to a downstream loss. Concretely if x is a Tensor with `x.requires_grad == True` then after backpropagation `x.grad` will be another Tensor holding the gradient of x with respect to the scalar loss at the end.

4.0.1 PyTorch Tensors: Flatten Function

A PyTorch Tensor is conceptionally similar to a numpy array: it is an n-dimensional grid of numbers, and like numpy PyTorch provides many functions to efficiently operate on Tensors. As a simple example, we provide a `flatten` function below which reshapes image data for use in a fully-connected neural network.

Recall that image data is typically stored in a Tensor of shape N x C x H x W, where:

- N is the number of datapoints

- C is the number of channels
- H is the height of the intermediate feature map in pixels
- W is the height of the intermediate feature map in pixels

This is the right way to represent the data when we are doing something like a 2D convolution, that needs spatial understanding of where the intermediate features are relative to each other. When we use fully connected affine layers to process the image, however, we want each datapoint to be represented by a single vector – it's no longer useful to segregate the different channels, rows, and columns of the data. So, we use a "flatten" operation to collapse the `C x H x W` values per representation into a single long vector. The flatten function below first reads in the N, C, H, and W values from a given batch of data, and then returns a "view" of that data. "View" is analogous to numpy's "reshape" method: it reshapes x's dimensions to be N x ??, where ?? is allowed to be anything (in this case, it will be C x H x W, but we don't need to specify that explicitly).

```
In [4]: def flatten(x):
            N = x.shape[0] # read in N, C, H, W
            return x.view(N, -1)  # "flatten" the C * H * W values into a single vector per im

        def test_flatten():
            x = torch.arange(12).view(2, 1, 3, 2)
            print('Before flattening: ', x)
            print('After flattening: ', flatten(x))

        test_flatten()

Before flattening:  tensor([[[[ 0,  1],
          [ 2,  3],
          [ 4,  5]]],


        [[[ 6,  7],
          [ 8,  9],
          [10, 11]]]])
After flattening:  tensor([[ 0,  1,  2,  3,  4,  5],
        [ 6,  7,  8,  9, 10, 11]])
```

4.0.2 Barebones PyTorch: Two-Layer Network

Here we define a function `two_layer_fc` which performs the forward pass of a two-layer fully-connected ReLU network on a batch of image data. After defining the forward pass we check that it doesn't crash and that it produces outputs of the right shape by running zeros through the network.

You don't have to write any code here, but it's important that you read and understand the implementation.

```
In [5]: import torch.nn.functional as F  # useful stateless functions

        def two_layer_fc(x, params):
```

```
        """
        A fully-connected neural networks; the architecture is:
        NN is fully connected -> ReLU -> fully connected layer.
        Note that this function only defines the forward pass;
        PyTorch will take care of the backward pass for us.

        The input to the network will be a minibatch of data, of shape
        (N, d1, ..., dM) where d1 * ... * dM = D. The hidden layer will have H units,
        and the output layer will produce scores for C classes.

        Inputs:
        - x: A PyTorch Tensor of shape (N, d1, ..., dM) giving a minibatch of
          input data.
        - params: A list [w1, w2] of PyTorch Tensors giving weights for the network;
          w1 has shape (D, H) and w2 has shape (H, C).

        Returns:
        - scores: A PyTorch Tensor of shape (N, C) giving classification scores for
          the input data x.
        """
        # first we flatten the image
        x = flatten(x)  # shape: [batch_size, C x H x W]

        w1, w2 = params

        # Forward pass: compute predicted y using operations on Tensors. Since w1 and
        # w2 have requires_grad=True, operations involving these Tensors will cause
        # PyTorch to build a computational graph, allowing automatic computation of
        # gradients. Since we are no longer implementing the backward pass by hand we
        # don't need to keep references to intermediate values.
        # you can also use `.clamp(min=0)`, equivalent to F.relu()
        x = F.relu(x.mm(w1))
        x = x.mm(w2)
        return x


    def two_layer_fc_test():
        hidden_layer_size = 42
        x = torch.zeros((64, 50), dtype=dtype)  # minibatch size 64, feature dimension 50
        w1 = torch.zeros((50, hidden_layer_size), dtype=dtype)
        w2 = torch.zeros((hidden_layer_size, 10), dtype=dtype)
        scores = two_layer_fc(x, [w1, w2])
        print(scores.size())  # you should see [64, 10]

    two_layer_fc_test()
```

```
torch.Size([64, 10])
```

4.0.3 Barebones PyTorch: Three-Layer ConvNet

Here you will complete the implementation of the function `three_layer_convnet`, which will perform the forward pass of a three-layer convolutional network. Like above, we can immediately test our implementation by passing zeros through the network. The network should have the following architecture:

1. A convolutional layer (with bias) with `channel_1` filters, each with shape `KW1 x KH1`, and zero-padding of two
2. ReLU nonlinearity
3. A convolutional layer (with bias) with `channel_2` filters, each with shape `KW2 x KH2`, and zero-padding of one
4. ReLU nonlinearity
5. Fully-connected layer with bias, producing scores for C classes.

Note that we have **no softmax activation** here after our fully-connected layer: this is because PyTorch's cross entropy loss performs a softmax activation for you, and by bundling that step in makes computation more efficient.

HINT: For convolutions: http://pytorch.org/docs/stable/nn.html#torch.nn.functional.conv2d; pay attention to the shapes of convolutional filters!

```
In [6]: def three_layer_convnet(x, params):
            """
            Performs the forward pass of a three-layer convolutional network with the
            architecture defined above.

            Inputs:
            - x: A PyTorch Tensor of shape (N, 3, H, W) giving a minibatch of images
            - params: A list of PyTorch Tensors giving the weights and biases for the
              network; should contain the following:
              - conv_w1: PyTorch Tensor of shape (channel_1, 3, KH1, KW1) giving weights
                for the first convolutional layer
              - conv_b1: PyTorch Tensor of shape (channel_1,) giving biases for the first
                convolutional layer
              - conv_w2: PyTorch Tensor of shape (channel_2, channel_1, KH2, KW2) giving
                weights for the second convolutional layer
              - conv_b2: PyTorch Tensor of shape (channel_2,) giving biases for the second
                convolutional layer
              - fc_w: PyTorch Tensor giving weights for the fully-connected layer. Can you
                figure out what the shape should be?
              - fc_b: PyTorch Tensor giving biases for the fully-connected layer. Can you
                figure out what the shape should be?

            Returns:
            - scores: PyTorch Tensor of shape (N, C) giving classification scores for x
            """
            conv_w1, conv_b1, conv_w2, conv_b2, fc_w, fc_b = params
            scores = None
            ################################################################################
```

```
        # TODO: Implement the forward pass for the three-layer ConvNet.             #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        x = F.conv2d(x, conv_w1, conv_b1, padding=2)
        x = F.relu(x)
        x = F.conv2d(x, conv_w2, conv_b2, padding=1)
        x = F.relu(x)
        x = flatten(x)
        scores = x.mm(fc_w) + fc_b


        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ############################################################################
        #                                 END OF YOUR CODE                         #
        ############################################################################
        return scores
```

After defining the forward pass of the ConvNet above, run the following cell to test your implementation.

When you run this function, scores should have shape (64, 10).

```
In [7]: def three_layer_convnet_test():
            x = torch.zeros((64, 3, 32, 32), dtype=dtype)  # minibatch size 64, image size [3,

            conv_w1 = torch.zeros((6, 3, 5, 5), dtype=dtype)  # [out_channel, in_channel, kern
            conv_b1 = torch.zeros((6,))  # out_channel
            conv_w2 = torch.zeros((9, 6, 3, 3), dtype=dtype)  # [out_channel, in_channel, kern
            conv_b2 = torch.zeros((9,))  # out_channel

            # you must calculate the shape of the tensor after two conv layers, before the ful
            fc_w = torch.zeros((9 * 32 * 32, 10))
            fc_b = torch.zeros(10)

            scores = three_layer_convnet(x, [conv_w1, conv_b1, conv_w2, conv_b2, fc_w, fc_b])
            print(scores.size())  # you should see [64, 10]
        three_layer_convnet_test()
```

```
torch.Size([64, 10])
```

4.0.4 Barebones PyTorch: Initialization

Let's write a couple utility methods to initialize the weight matrices for our models.

- `random_weight(shape)` initializes a weight tensor with the Kaiming normalization method.
- `zero_weight(shape)` initializes a weight tensor with all zeros. Useful for instantiating bias parameters.

The `random_weight` function uses the Kaiming normal initialization method, described in:

He et al, *Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification*, ICCV 2015, https://arxiv.org/abs/1502.01852

```
In [8]: def random_weight(shape):
            """
            Create random Tensors for weights; setting requires_grad=True means that we
            want to compute gradients for these Tensors during the backward pass.
            We use Kaiming normalization: sqrt(2 / fan_in)
            """
            if len(shape) == 2:  # FC weight
                fan_in = shape[0]
            else:
                fan_in = np.prod(shape[1:]) # conv weight [out_channel, in_channel, kH, kW]
            # randn is standard normal distribution generator.
            w = torch.randn(shape, device=device, dtype=dtype) * np.sqrt(2. / fan_in)
            w.requires_grad = True
            return w

        def zero_weight(shape):
            return torch.zeros(shape, device=device, dtype=dtype, requires_grad=True)

        # create a weight of shape [3 x 5]
        # you should see the type `torch.cuda.FloatTensor` if you use GPU.
        # Otherwise it should be `torch.FloatTensor`
        random_weight((3, 5))
```

```
Out[8]: tensor([[ 1.3586, -0.0806, -1.3676,  1.6422, -1.3466],
                [-0.3656, -0.9110,  0.5515,  0.6721,  0.4290],
                [-0.1892, -0.0787, -0.2862,  0.7963,  0.1780]], device='cuda:0',
               requires_grad=True)
```

4.0.5 Barebones PyTorch: Check Accuracy

When training the model we will use the following function to check the accuracy of our model on the training or validation sets.

When checking accuracy we don't need to compute any gradients; as a result we don't need PyTorch to build a computational graph for us when we compute scores. To prevent a graph from being built we scope our computation under a `torch.no_grad()` context manager.

```
In [11]: def check_accuracy_part2(loader, model_fn, params):
             """
             Check the accuracy of a classification model.

             Inputs:
             - loader: A DataLoader for the data split we want to check
             - model_fn: A function that performs the forward pass of the model,
               with the signature scores = model_fn(x, params)
             - params: List of PyTorch Tensors giving parameters of the model
```

```
    Returns: Nothing, but prints the accuracy of the model
    """
    split = 'val' if loader.dataset.train else 'test'
    print('Checking accuracy on the %s set' % split)
    num_correct, num_samples = 0, 0
    with torch.no_grad():
        for x, y in loader:
            x = x.to(device=device, dtype=dtype)  # move to device, e.g. GPU
            y = y.to(device=device, dtype=torch.int64)
            scores = model_fn(x, params)
            _, preds = scores.max(1)
            num_correct += (preds == y).sum()
            num_samples += preds.size(0)
        acc = float(num_correct) / num_samples
        print('Got %d / %d correct (%.2f%%)' % (num_correct, num_samples, 100 * acc))
```

4.0.6 BareBones PyTorch: Training Loop

We can now set up a basic training loop to train our network. We will train the model using stochastic gradient descent without momentum. We will use `torch.functional.cross_entropy` to compute the loss; you can read about it here.

The training loop takes as input the neural network function, a list of initialized parameters (`[w1, w2]` in our example), and learning rate.

```
In [12]: def train_part2(model_fn, params, learning_rate):
             """
             Train a model on CIFAR-10.

             Inputs:
             - model_fn: A Python function that performs the forward pass of the model.
               It should have the signature scores = model_fn(x, params) where x is a
               PyTorch Tensor of image data, params is a list of PyTorch Tensors giving
               model weights, and scores is a PyTorch Tensor of shape (N, C) giving
               scores for the elements in x.
             - params: List of PyTorch Tensors giving weights for the model
             - learning_rate: Python scalar giving the learning rate to use for SGD

             Returns: Nothing
             """
             for t, (x, y) in enumerate(loader_train):
                 # Move the data to the proper device (GPU or CPU)
                 x = x.to(device=device, dtype=dtype)
                 y = y.to(device=device, dtype=torch.long)

                 # Forward pass: compute scores and loss
                 scores = model_fn(x, params)
                 loss = F.cross_entropy(scores, y)
```

```
            # Backward pass: PyTorch figures out which Tensors in the computational
            # graph has requires_grad=True and uses backpropagation to compute the
            # gradient of the loss with respect to these Tensors, and stores the
            # gradients in the .grad attribute of each Tensor.
            loss.backward()

            # Update parameters. We don't want to backpropagate through the
            # parameter updates, so we scope the updates under a torch.no_grad()
            # context manager to prevent a computational graph from being built.
            with torch.no_grad():
                for w in params:
                    w -= learning_rate * w.grad

                    # Manually zero the gradients after running the backward pass
                    w.grad.zero_()

            if t % print_every == 0:
                print('Iteration %d, loss = %.4f' % (t, loss.item()))
                check_accuracy_part2(loader_val, model_fn, params)
                print()
```

4.0.7 BareBones PyTorch: Train a Two-Layer Network

Now we are ready to run the training loop. We need to explicitly allocate tensors for the fully connected weights, `w1` and `w2`.

Each minibatch of CIFAR has 64 examples, so the tensor shape is `[64, 3, 32, 32]`.

After flattening, `x` shape should be `[64, 3 * 32 * 32]`. This will be the size of the first dimension of `w1`. The second dimension of `w1` is the hidden layer size, which will also be the first dimension of `w2`.

Finally, the output of the network is a 10-dimensional vector that represents the probability distribution over 10 classes.

You don't need to tune any hyperparameters but you should see accuracies above 40% after training for one epoch.

```
In [13]: hidden_layer_size = 4000
         learning_rate = 1e-2

         w1 = random_weight((3 * 32 * 32, hidden_layer_size))
         w2 = random_weight((hidden_layer_size, 10))

         train_part2(two_layer_fc, [w1, w2], learning_rate)
```

```
Iteration 0, loss = 3.3987
Checking accuracy on the val set
Got 135 / 1000 correct (13.50%)

Iteration 100, loss = 2.1900
Checking accuracy on the val set
```

```
Got 331 / 1000 correct (33.10%)

Iteration 200, loss = 2.4096
Checking accuracy on the val set
Got 290 / 1000 correct (29.00%)

Iteration 300, loss = 2.2384
Checking accuracy on the val set
Got 391 / 1000 correct (39.10%)

Iteration 400, loss = 1.8477
Checking accuracy on the val set
Got 382 / 1000 correct (38.20%)

Iteration 500, loss = 1.7592
Checking accuracy on the val set
Got 418 / 1000 correct (41.80%)

Iteration 600, loss = 1.4237
Checking accuracy on the val set
Got 461 / 1000 correct (46.10%)

Iteration 700, loss = 1.6900
Checking accuracy on the val set
Got 429 / 1000 correct (42.90%)
```

4.0.8 BareBones PyTorch: Training a ConvNet

In the below you should use the functions defined above to train a three-layer convolutional network on CIFAR. The network should have the following architecture:

1. Convolutional layer (with bias) with 32 5x5 filters, with zero-padding of 2
2. ReLU
3. Convolutional layer (with bias) with 16 3x3 filters, with zero-padding of 1
4. ReLU
5. Fully-connected layer (with bias) to compute scores for 10 classes

You should initialize your weight matrices using the `random_weight` function defined above, and you should initialize your bias vectors using the `zero_weight` function above.

You don't need to tune any hyperparameters, but if everything works correctly you should achieve an accuracy above 42% after one epoch.

In [27]:
```
learning_rate = 3e-3

channel_1 = 32
channel_2 = 16
```

```
        conv_w1 = None
        conv_b1 = None
        conv_w2 = None
        conv_b2 = None
        fc_w = None
        fc_b = None

        ################################################################################
        # TODO: Initialize the parameters of a three-layer ConvNet.                    #
        ################################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

        conv_w1 = random_weight((channel_1, 3, 5, 5))
        conv_b1 = zero_weight(channel_1)
        conv_w2 = random_weight((channel_2, 32, 3, 3))
        conv_b2 = zero_weight(channel_2)
        fc_w = random_weight((channel_2 * 32 * 32, 10))
        fc_b = zero_weight(10)
        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ################################################################################
        #                                END OF YOUR CODE                              #
        ################################################################################

        params = [conv_w1, conv_b1, conv_w2, conv_b2, fc_w, fc_b]
        train_part2(three_layer_convnet, params, learning_rate)
```

```
Iteration 0, loss = 2.9411
Checking accuracy on the val set
Got 141 / 1000 correct (14.10%)

Iteration 100, loss = 1.9585
Checking accuracy on the val set
Got 346 / 1000 correct (34.60%)

Iteration 200, loss = 1.9592
Checking accuracy on the val set
Got 406 / 1000 correct (40.60%)

Iteration 300, loss = 1.8574
Checking accuracy on the val set
Got 414 / 1000 correct (41.40%)

Iteration 400, loss = 1.5134
Checking accuracy on the val set
Got 466 / 1000 correct (46.60%)

Iteration 500, loss = 1.8140
Checking accuracy on the val set
```

```
Got 454 / 1000 correct (45.40%)

Iteration 600, loss = 1.4908
Checking accuracy on the val set
Got 473 / 1000 correct (47.30%)

Iteration 700, loss = 1.6075
Checking accuracy on the val set
Got 486 / 1000 correct (48.60%)
```

5 Part III. PyTorch Module API

Barebone PyTorch requires that we track all the parameter tensors by hand. This is fine for small networks with a few tensors, but it would be extremely inconvenient and error-prone to track tens or hundreds of tensors in larger networks.

PyTorch provides the `nn.Module` API for you to define arbitrary network architectures, while tracking every learnable parameters for you. In Part II, we implemented SGD ourselves. PyTorch also provides the `torch.optim` package that implements all the common optimizers, such as RMSProp, Adagrad, and Adam. It even supports approximate second-order methods like L-BFGS! You can refer to the doc for the exact specifications of each optimizer.

To use the Module API, follow the steps below:

1. Subclass `nn.Module`. Give your network class an intuitive name like `TwoLayerFC`.
2. In the constructor `__init__()`, define all the layers you need as class attributes. Layer objects like `nn.Linear` and `nn.Conv2d` are themselves `nn.Module` subclasses and contain learnable parameters, so that you don't have to instantiate the raw tensors yourself. `nn.Module` will track these internal parameters for you. Refer to the doc to learn more about the dozens of builtin layers. **Warning**: don't forget to call the `super().__init__()` first!
3. In the `forward()` method, define the *connectivity* of your network. You should use the attributes defined in `__init__` as function calls that take tensor as input and output the "transformed" tensor. Do *not* create any new layers with learnable parameters in `forward()`! All of them must be declared upfront in `__init__`.

After you define your Module subclass, you can instantiate it as an object and call it just like the NN forward function in part II.

5.0.1 Module API: Two-Layer Network

Here is a concrete example of a 2-layer fully connected network:

```
In [28]: class TwoLayerFC(nn.Module):
             def __init__(self, input_size, hidden_size, num_classes):
                 super().__init__()
                 # assign layer objects to class attributes
                 self.fc1 = nn.Linear(input_size, hidden_size)
```

```
            # nn.init package contains convenient initialization methods
            # http://pytorch.org/docs/master/nn.html#torch-nn-init
            nn.init.kaiming_normal_(self.fc1.weight)
            self.fc2 = nn.Linear(hidden_size, num_classes)
            nn.init.kaiming_normal_(self.fc2.weight)

        def forward(self, x):
            # forward always defines connectivity
            x = flatten(x)
            scores = self.fc2(F.relu(self.fc1(x)))
            return scores

    def test_TwoLayerFC():
        input_size = 50
        x = torch.zeros((64, input_size), dtype=dtype)  # minibatch size 64, feature dime
        model = TwoLayerFC(input_size, 42, 10)
        scores = model(x)
        print(scores.size())  # you should see [64, 10]
    test_TwoLayerFC()
```

```
torch.Size([64, 10])
```

5.0.2 Module API: Three-Layer ConvNet

It's your turn to implement a 3-layer ConvNet followed by a fully connected layer. The network architecture should be the same as in Part II:

1. Convolutional layer with `channel_1` 5x5 filters with zero-padding of 2
2. ReLU
3. Convolutional layer with `channel_2` 3x3 filters with zero-padding of 1
4. ReLU
5. Fully-connected layer to `num_classes` classes

You should initialize the weight matrices of the model using the Kaiming normal initialization method.

HINT: http://pytorch.org/docs/stable/nn.html#conv2d

After you implement the three-layer ConvNet, the `test_ThreeLayerConvNet` function will run your implementation; it should print `(64, 10)` for the shape of the output scores.

```
In [29]: class ThreeLayerConvNet(nn.Module):
            def __init__(self, in_channel, channel_1, channel_2, num_classes):
                super().__init__()
                ########################################################################
                # TODO: Set up the layers you need for a three-layer ConvNet with the  #
                # architecture defined above.                                          #
                ########################################################################
                # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
                self.conv1 = nn.Conv2d(in_channel, channel_1, 5, padding=2)
```

```
            self.conv2 = nn.Conv2d(channel_1, channel_2, 3, padding=1)
            self.fc1 = nn.Linear(channel_2*32*32, num_classes)

            nn.init.kaiming_normal_(self.conv1.weight)
            nn.init.kaiming_normal_(self.conv2.weight)
            nn.init.kaiming_normal_(self.fc1.weight)

            # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
            ################################################################################
            #                               END OF YOUR CODE                               #
            ################################################################################

        def forward(self, x):
            scores = None
            ################################################################################
            # TODO: Implement the forward function for a 3-layer ConvNet. you      #
            # should use the layers you defined in __init__ and specify the        #
            # connectivity of those layers in forward()                            #
            ################################################################################
            # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

            conv1_out = F.relu(self.conv1(x))
            conv2_out = F.relu(self.conv2(conv1_out))
            conv2_out = flatten(conv2_out)
            scores = self.fc1(conv2_out)
            # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
            ################################################################################
            #                                 END OF YOUR CODE                             #
            ################################################################################
            return scores


    def test_ThreeLayerConvNet():
        x = torch.zeros((64, 3, 32, 32), dtype=dtype)  # minibatch size 64, image size [3
        model = ThreeLayerConvNet(in_channel=3, channel_1=12, channel_2=8, num_classes=10)
        scores = model(x)
        print(scores.size())  # you should see [64, 10]
    test_ThreeLayerConvNet()
```

```
torch.Size([64, 10])
```

5.0.3 Module API: Check Accuracy

Given the validation or test set, we can check the classification accuracy of a neural network.

This version is slightly different from the one in part II. You don't manually pass in the parameters anymore.

```
In [30]: def check_accuracy_part34(loader, model):
```

```
    if loader.dataset.train:
        print('Checking accuracy on validation set')
    else:
        print('Checking accuracy on test set')
    num_correct = 0
    num_samples = 0
    model.eval()  # set model to evaluation mode
    with torch.no_grad():
        for x, y in loader:
            x = x.to(device=device, dtype=dtype)  # move to device, e.g. GPU
            y = y.to(device=device, dtype=torch.long)
            scores = model(x)
            _, preds = scores.max(1)
            num_correct += (preds == y).sum()
            num_samples += preds.size(0)
        acc = float(num_correct) / num_samples
        print('Got %d / %d correct (%.2f)' % (num_correct, num_samples, 100 * acc))
```

5.0.4 Module API: Training Loop

We also use a slightly different training loop. Rather than updating the values of the weights ourselves, we use an Optimizer object from the `torch.optim` package, which abstract the notion of an optimization algorithm and provides implementations of most of the algorithms commonly used to optimize neural networks.

```
In [31]: def train_part34(model, optimizer, epochs=1):
             """
             Train a model on CIFAR-10 using the PyTorch Module API.

             Inputs:
             - model: A PyTorch Module giving the model to train.
             - optimizer: An Optimizer object we will use to train the model
             - epochs: (Optional) A Python integer giving the number of epochs to train for

             Returns: Nothing, but prints model accuracies during training.
             """
             model = model.to(device=device)  # move the model parameters to CPU/GPU
             for e in range(epochs):
                 for t, (x, y) in enumerate(loader_train):
                     model.train()  # put model to training mode
                     x = x.to(device=device, dtype=dtype)  # move to device, e.g. GPU
                     y = y.to(device=device, dtype=torch.long)

                     scores = model(x)
                     loss = F.cross_entropy(scores, y)

                     # Zero out all of the gradients for the variables which the optimizer
                     # will update.
```

```
        optimizer.zero_grad()

        # This is the backwards pass: compute the gradient of the loss with
        # respect to each  parameter of the model.
        loss.backward()

        # Actually update the parameters of the model using the gradients
        # computed by the backwards pass.
        optimizer.step()

        if t % print_every == 0:
            print('Iteration %d, loss = %.4f' % (t, loss.item()))
            check_accuracy_part34(loader_val, model)
            print()
```

5.0.5 Module API: Train a Two-Layer Network

Now we are ready to run the training loop. In contrast to part II, we don't explicitly allocate parameter tensors anymore.

Simply pass the input size, hidden layer size, and number of classes (i.e. output size) to the constructor of `TwoLayerFC`.

You also need to define an optimizer that tracks all the learnable parameters inside `TwoLayerFC`.

You don't need to tune any hyperparameters, but you should see model accuracies above 40% after training for one epoch.

```
In [32]: hidden_layer_size = 4000
         learning_rate = 1e-2
         model = TwoLayerFC(3 * 32 * 32, hidden_layer_size, 10)
         optimizer = optim.SGD(model.parameters(), lr=learning_rate)

         train_part34(model, optimizer)
```

```
Iteration 0, loss = 3.8131
Checking accuracy on validation set
Got 146 / 1000 correct (14.60)

Iteration 100, loss = 2.3148
Checking accuracy on validation set
Got 334 / 1000 correct (33.40)

Iteration 200, loss = 2.7683
Checking accuracy on validation set
Got 353 / 1000 correct (35.30)

Iteration 300, loss = 1.9656
Checking accuracy on validation set
Got 419 / 1000 correct (41.90)
```

```
Iteration 400, loss = 1.7928
Checking accuracy on validation set
Got 417 / 1000 correct (41.70)

Iteration 500, loss = 1.8043
Checking accuracy on validation set
Got 412 / 1000 correct (41.20)

Iteration 600, loss = 1.6025
Checking accuracy on validation set
Got 438 / 1000 correct (43.80)

Iteration 700, loss = 1.9009
Checking accuracy on validation set
Got 468 / 1000 correct (46.80)
```

5.0.6 Module API: Train a Three-Layer ConvNet

You should now use the Module API to train a three-layer ConvNet on CIFAR. This should look very similar to training the two-layer network! You don't need to tune any hyperparameters, but you should achieve above above 45% after training for one epoch.

You should train the model using stochastic gradient descent without momentum.

```
In [34]: learning_rate = 3e-3
         channel_1 = 32
         channel_2 = 16

         model = None
         optimizer = None
         ################################################################################
         # TODO: Instantiate your ThreeLayerConvNet model and a corresponding optimizer #
         ################################################################################
         # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

         model = ThreeLayerConvNet(3, channel_1, channel_2, 10)
         optimizer = optim.SGD(model.parameters(), lr=learning_rate)

         # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
         ################################################################################
         #                                END OF YOUR CODE
         ################################################################################

         train_part34(model, optimizer)
```

```
Iteration 0, loss = 3.3710
Checking accuracy on validation set
```

```
Got 119 / 1000 correct (11.90)

Iteration 100, loss = 1.9680
Checking accuracy on validation set
Got 328 / 1000 correct (32.80)

Iteration 200, loss = 1.8616
Checking accuracy on validation set
Got 353 / 1000 correct (35.30)

Iteration 300, loss = 1.7252
Checking accuracy on validation set
Got 418 / 1000 correct (41.80)

Iteration 400, loss = 1.7157
Checking accuracy on validation set
Got 452 / 1000 correct (45.20)

Iteration 500, loss = 1.7524
Checking accuracy on validation set
Got 471 / 1000 correct (47.10)

Iteration 600, loss = 1.6890
Checking accuracy on validation set
Got 473 / 1000 correct (47.30)

Iteration 700, loss = 1.6115
Checking accuracy on validation set
Got 491 / 1000 correct (49.10)
```

6 Part IV. PyTorch Sequential API

Part III introduced the PyTorch Module API, which allows you to define arbitrary learnable layers and their connectivity.

For simple models like a stack of feed forward layers, you still need to go through 3 steps: subclass `nn.Module`, assign layers to class attributes in `__init__`, and call each layer one by one in `forward()`. Is there a more convenient way?

Fortunately, PyTorch provides a container Module called `nn.Sequential`, which merges the above steps into one. It is not as flexible as `nn.Module`, because you cannot specify more complex topology than a feed-forward stack, but it's good enough for many use cases.

6.0.1 Sequential API: Two-Layer Network

Let's see how to rewrite our two-layer fully connected network example with `nn.Sequential`, and train it using the training loop defined above.

Again, you don't need to tune any hyperparameters here, but you shoud achieve above 40% accuracy after one epoch of training.

In [35]:
```
# We need to wrap `flatten` function in a module in order to stack it
# in nn.Sequential
class Flatten(nn.Module):
    def forward(self, x):
        return flatten(x)

hidden_layer_size = 4000
learning_rate = 1e-2

model = nn.Sequential(
    Flatten(),
    nn.Linear(3 * 32 * 32, hidden_layer_size),
    nn.ReLU(),
    nn.Linear(hidden_layer_size, 10),
)

# you can use Nesterov momentum in optim.SGD
optimizer = optim.SGD(model.parameters(), lr=learning_rate,
                      momentum=0.9, nesterov=True)

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.4141
Checking accuracy on validation set
Got 199 / 1000 correct (19.90)

Iteration 100, loss = 1.7196
Checking accuracy on validation set
Got 400 / 1000 correct (40.00)

Iteration 200, loss = 1.6357
Checking accuracy on validation set
Got 414 / 1000 correct (41.40)

Iteration 300, loss = 1.9838
Checking accuracy on validation set
Got 392 / 1000 correct (39.20)

Iteration 400, loss = 2.0815
Checking accuracy on validation set
Got 419 / 1000 correct (41.90)

Iteration 500, loss = 1.9829
Checking accuracy on validation set
Got 409 / 1000 correct (40.90)
```

```
Iteration 600, loss = 1.7257
Checking accuracy on validation set
Got 456 / 1000 correct (45.60)

Iteration 700, loss = 1.7982
Checking accuracy on validation set
Got 432 / 1000 correct (43.20)
```

6.0.2 Sequential API: Three-Layer ConvNet

Here you should use `nn.Sequential` to define and train a three-layer ConvNet with the same architecture we used in Part III:

1. Convolutional layer (with bias) with 32 5x5 filters, with zero-padding of 2
2. ReLU
3. Convolutional layer (with bias) with 16 3x3 filters, with zero-padding of 1
4. ReLU
5. Fully-connected layer (with bias) to compute scores for 10 classes

You should initialize your weight matrices using the `random_weight` function defined above, and you should initialize your bias vectors using the `zero_weight` function above.

You should optimize your model using stochastic gradient descent with Nesterov momentum 0.9.

Again, you don't need to tune any hyperparameters but you should see accuracy above 55% after one epoch of training.

```
In [40]: channel_1 = 32
         channel_2 = 16
         learning_rate = 1e-2

         model = None
         optimizer = None

         ################################################################################
         # TODO: Rewrite the 2-layer ConvNet with bias from Part III with the           #
         # Sequential API.                                                              #
         ################################################################################
         # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

         model = nn.Sequential(
             nn.Conv2d(3, channel_1, 5, padding=2),
             nn.ReLU(),
             nn.Conv2d(channel_1, channel_2, 3, padding=1),
             nn.ReLU(),
             Flatten(),
             nn.Linear(channel_2*32*32, 10)
```

```
        )

        # you can use Nesterov momentum in optim.SGD
        optimizer = optim.SGD(model.parameters(), lr=learning_rate,
                              momentum=0.9, nesterov=True)


        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ################################################################################
        #                                  END OF YOUR CODE
        ################################################################################

        train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.2951
Checking accuracy on validation set
Got 104 / 1000 correct (10.40)

Iteration 100, loss = 1.6773
Checking accuracy on validation set
Got 431 / 1000 correct (43.10)

Iteration 200, loss = 1.5041
Checking accuracy on validation set
Got 490 / 1000 correct (49.00)

Iteration 300, loss = 1.4661
Checking accuracy on validation set
Got 512 / 1000 correct (51.20)

Iteration 400, loss = 1.4752
Checking accuracy on validation set
Got 524 / 1000 correct (52.40)

Iteration 500, loss = 1.3723
Checking accuracy on validation set
Got 547 / 1000 correct (54.70)

Iteration 600, loss = 1.4349
Checking accuracy on validation set
Got 557 / 1000 correct (55.70)

Iteration 700, loss = 1.3696
Checking accuracy on validation set
Got 580 / 1000 correct (58.00)
```

7 Part V. CIFAR-10 open-ended challenge

In this section, you can experiment with whatever ConvNet architecture you'd like on CIFAR-10.

Now it's your job to experiment with architectures, hyperparameters, loss functions, and optimizers to train a model that achieves **at least 70%** accuracy on the CIFAR-10 **validation** set within 10 epochs. You can use the check_accuracy and train functions from above. You can use either `nn.Module` or `nn.Sequential` API.

Describe what you did at the end of this notebook.

Here are the official API documentation for each component. One note: what we call in the class "spatial batch norm" is called "BatchNorm2D" in PyTorch.

- Layers in torch.nn package: http://pytorch.org/docs/stable/nn.html
- Activations: http://pytorch.org/docs/stable/nn.html#non-linear-activations
- Loss functions: http://pytorch.org/docs/stable/nn.html#loss-functions
- Optimizers: http://pytorch.org/docs/stable/optim.html

7.0.1 Things you might try:

- **Filter size**: Above we used 5x5; would smaller filters be more efficient?
- **Number of filters**: Above we used 32 filters. Do more or fewer do better?
- **Pooling vs Strided Convolution**: Do you use max pooling or just stride convolutions?
- **Batch normalization**: Try adding spatial batch normalization after convolution layers and vanilla batch normalization after affine layers. Do your networks train faster?
- **Network architecture**: The network above has two layers of trainable parameters. Can you do better with a deep network? Good architectures to try include:
  - [conv-relu-pool]xN -> [affine]xM -> [softmax or SVM]
  - [conv-relu-conv-relu-pool]xN -> [affine]xM -> [softmax or SVM]
  - [batchnorm-relu-conv]xN -> [affine]xM -> [softmax or SVM]
- **Global Average Pooling**: Instead of flattening and then having multiple affine layers, perform convolutions until your image gets small (7x7 or so) and then perform an average pooling operation to get to a 1x1 image picture (1, 1 , Filter#), which is then reshaped into a (Filter#) vector. This is used in Google's Inception Network (See Table 1 for their architecture).
- **Regularization**: Add l2 weight regularization, or perhaps use Dropout.

7.0.2 Tips for training

For each network architecture that you try, you should tune the learning rate and other hyperparameters. When doing this there are a couple important things to keep in mind:

- If the parameters are working well, you should see improvement within a few hundred iterations
- Remember the coarse-to-fine approach for hyperparameter tuning: start by testing a large range of hyperparameters for just a few training iterations to find the combinations of parameters that are working at all.
- Once you have found some sets of parameters that seem to work, search more finely around these parameters. You may need to train for more epochs.
- You should use the validation set for hyperparameter search, and save your test set for evaluating your architecture on the best parameters as selected by the validation set.

7.0.3 Going above and beyond

If you are feeling adventurous there are many other features you can implement to try and improve your performance. You are **not required** to implement any of these, but don't miss the fun if you have time!

- Alternative optimizers: you can try Adam, Adagrad, RMSprop, etc.
- Alternative activation functions such as leaky ReLU, parametric ReLU, ELU, or MaxOut.
- Model ensembles
- Data augmentation
- New Architectures
  - ResNets where the input from the previous layer is added to the output.
  - DenseNets where inputs into previous layers are concatenated together.
  - This blog has an in-depth overview

7.0.4 Have fun and happy training!

In [65]:
```
################################################################################
# TODO:                                                                        #
# Experiment with any architectures, optimizers, and hyperparameters.          #
# Achieve AT LEAST 70% accuracy on the *validation set* within 10 epochs.      #
#                                                                              #
# Note that you can use the check_accuracy function to evaluate on either      #
# the test set or the validation set, by passing either loader_test or         #
# loader_val as the second argument to check_accuracy. You should not touch    #
# the test set until you have finished your architecture and  hyperparameter   #
# tuning, and only run the test set once at the end to report a final value.   #
################################################################################
model = None
optimizer = None

# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

channel_1 = 32
channel_2 = 64
channel_3 = 64
channel_4 = 16
learning_rate = 1e-2

model = nn.Sequential(
    nn.Conv2d(3, channel_1, 5, padding=2),
    nn.ReLU(),
    nn.Conv2d(channel_1, channel_2, 3, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(2),

    nn.Conv2d(channel_2, channel_3, 5, padding=2),
    nn.ReLU(),
```

```
            nn.Conv2d(channel_3, channel_4, 3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2),

            Flatten(),
            nn.Linear(channel_4*8*8, 1000),
            nn.ReLU(),
            nn.Linear(1000, 10)
        )

        # you can use Nesterov momentum in optim.SGD
        optimizer = optim.SGD(model.parameters(), lr=learning_rate,
                              momentum=0.9, nesterov=True)

        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ################################################################################
        #                                  END OF YOUR CODE
        ################################################################################

        # You should get at least 70% accuracy
        train_part34(model, optimizer, epochs=10)
```

```
Iteration 0, loss = 2.3082
Checking accuracy on validation set
Got 89 / 1000 correct (8.90)

Iteration 100, loss = 2.0226
Checking accuracy on validation set
Got 259 / 1000 correct (25.90)

Iteration 200, loss = 1.6904
Checking accuracy on validation set
Got 395 / 1000 correct (39.50)

Iteration 300, loss = 1.5436
Checking accuracy on validation set
Got 452 / 1000 correct (45.20)

Iteration 400, loss = 1.6210
Checking accuracy on validation set
Got 487 / 1000 correct (48.70)

Iteration 500, loss = 1.3310
Checking accuracy on validation set
Got 482 / 1000 correct (48.20)

Iteration 600, loss = 1.6343
Checking accuracy on validation set
```

```
Got 552 / 1000 correct (55.20)

Iteration 700, loss = 1.0314
Checking accuracy on validation set
Got 556 / 1000 correct (55.60)

Iteration 0, loss = 1.5106
Checking accuracy on validation set
Got 571 / 1000 correct (57.10)

Iteration 100, loss = 1.0390
Checking accuracy on validation set
Got 556 / 1000 correct (55.60)

Iteration 200, loss = 1.2015
Checking accuracy on validation set
Got 605 / 1000 correct (60.50)

Iteration 300, loss = 1.1582
Checking accuracy on validation set
Got 644 / 1000 correct (64.40)

Iteration 400, loss = 0.8968
Checking accuracy on validation set
Got 622 / 1000 correct (62.20)

Iteration 500, loss = 0.9961
Checking accuracy on validation set
Got 662 / 1000 correct (66.20)

Iteration 600, loss = 0.8177
Checking accuracy on validation set
Got 689 / 1000 correct (68.90)

Iteration 700, loss = 0.9975
Checking accuracy on validation set
Got 692 / 1000 correct (69.20)

Iteration 0, loss = 1.0271
Checking accuracy on validation set
Got 671 / 1000 correct (67.10)

Iteration 100, loss = 0.6967
Checking accuracy on validation set
Got 688 / 1000 correct (68.80)

Iteration 200, loss = 0.9137
Checking accuracy on validation set
```

```
Got 687 / 1000 correct (68.70)

Iteration 300, loss = 0.7291
Checking accuracy on validation set
Got 680 / 1000 correct (68.00)

Iteration 400, loss = 0.6424
Checking accuracy on validation set
Got 706 / 1000 correct (70.60)

Iteration 500, loss = 0.9416
Checking accuracy on validation set
Got 708 / 1000 correct (70.80)

Iteration 600, loss = 0.8967
Checking accuracy on validation set
Got 714 / 1000 correct (71.40)

Iteration 700, loss = 1.0465
Checking accuracy on validation set
Got 722 / 1000 correct (72.20)

Iteration 0, loss = 0.6171
Checking accuracy on validation set
Got 711 / 1000 correct (71.10)

Iteration 100, loss = 0.7518
Checking accuracy on validation set
Got 731 / 1000 correct (73.10)

Iteration 200, loss = 0.9102
Checking accuracy on validation set
Got 736 / 1000 correct (73.60)

Iteration 300, loss = 0.4874
Checking accuracy on validation set
Got 717 / 1000 correct (71.70)

Iteration 400, loss = 0.7330
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 500, loss = 0.6036
Checking accuracy on validation set
Got 737 / 1000 correct (73.70)

Iteration 600, loss = 0.7662
Checking accuracy on validation set
```

```
Got 739 / 1000 correct (73.90)

Iteration 700, loss = 0.7441
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 0, loss = 0.5060
Checking accuracy on validation set
Got 735 / 1000 correct (73.50)

Iteration 100, loss = 0.7287
Checking accuracy on validation set
Got 743 / 1000 correct (74.30)

Iteration 200, loss = 0.4544
Checking accuracy on validation set
Got 742 / 1000 correct (74.20)

Iteration 300, loss = 0.5631
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 400, loss = 0.5178
Checking accuracy on validation set
Got 758 / 1000 correct (75.80)

Iteration 500, loss = 0.5775
Checking accuracy on validation set
Got 767 / 1000 correct (76.70)

Iteration 600, loss = 0.4237
Checking accuracy on validation set
Got 769 / 1000 correct (76.90)

Iteration 700, loss = 0.6814
Checking accuracy on validation set
Got 765 / 1000 correct (76.50)

Iteration 0, loss = 0.5362
Checking accuracy on validation set
Got 753 / 1000 correct (75.30)

Iteration 100, loss = 0.3925
Checking accuracy on validation set
Got 772 / 1000 correct (77.20)

Iteration 200, loss = 0.7011
Checking accuracy on validation set
```

```
Got 777 / 1000 correct (77.70)

Iteration 300, loss = 0.4879
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)

Iteration 400, loss = 0.3324
Checking accuracy on validation set
Got 742 / 1000 correct (74.20)

Iteration 500, loss = 0.5245
Checking accuracy on validation set
Got 762 / 1000 correct (76.20)

Iteration 600, loss = 0.4666
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)

Iteration 700, loss = 0.5296
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 0, loss = 0.3602
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 100, loss = 0.1005
Checking accuracy on validation set
Got 758 / 1000 correct (75.80)

Iteration 200, loss = 0.4660
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 300, loss = 0.2827
Checking accuracy on validation set
Got 764 / 1000 correct (76.40)

Iteration 400, loss = 0.4302
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 500, loss = 0.4564
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 600, loss = 0.2638
Checking accuracy on validation set
```

```
Got 760 / 1000 correct (76.00)

Iteration 700, loss = 0.3841
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 0, loss = 0.2093
Checking accuracy on validation set
Got 751 / 1000 correct (75.10)

Iteration 100, loss = 0.3345
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 200, loss = 0.1047
Checking accuracy on validation set
Got 743 / 1000 correct (74.30)

Iteration 300, loss = 0.1679
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)

Iteration 400, loss = 0.1914
Checking accuracy on validation set
Got 745 / 1000 correct (74.50)

Iteration 500, loss = 0.2642
Checking accuracy on validation set
Got 751 / 1000 correct (75.10)

Iteration 600, loss = 0.2383
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)

Iteration 700, loss = 0.2220
Checking accuracy on validation set
Got 752 / 1000 correct (75.20)

Iteration 0, loss = 0.1667
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 100, loss = 0.2650
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 200, loss = 0.2041
Checking accuracy on validation set
```

```
Got 738 / 1000 correct (73.80)

Iteration 300, loss = 0.1229
Checking accuracy on validation set
Got 749 / 1000 correct (74.90)

Iteration 400, loss = 0.1853
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)

Iteration 500, loss = 0.2271
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 600, loss = 0.1204
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 700, loss = 0.3428
Checking accuracy on validation set
Got 749 / 1000 correct (74.90)

Iteration 0, loss = 0.0308
Checking accuracy on validation set
Got 739 / 1000 correct (73.90)

Iteration 100, loss = 0.2387
Checking accuracy on validation set
Got 753 / 1000 correct (75.30)

Iteration 200, loss = 0.1196
Checking accuracy on validation set
Got 730 / 1000 correct (73.00)

Iteration 300, loss = 0.1852
Checking accuracy on validation set
Got 725 / 1000 correct (72.50)

Iteration 400, loss = 0.1764
Checking accuracy on validation set
Got 740 / 1000 correct (74.00)

Iteration 500, loss = 0.1402
Checking accuracy on validation set
Got 739 / 1000 correct (73.90)

Iteration 600, loss = 0.2099
Checking accuracy on validation set
```

```
Got 739 / 1000 correct (73.90)

Iteration 700, loss = 0.3773
Checking accuracy on validation set
Got 742 / 1000 correct (74.20)
```

7.1 Describe what you did

In the cell below you should write an explanation of what you did, any additional features that you implemented, and/or any graphs that you made in the process of training and evaluating your network.

The graph is shown as below:

conv(32 * 5 * 5) -> ReLU -> conv(64 * 3 * 3) -> ReLU -> MaxPool(2 * 2) -> conv(64 * 5 * 5) -> ReLU -> conv(16 * 3 * 3) -> ReLU -> MaxPool(2 * 2) -> FC(1000) -> ReLU -> FC(10)

Firstly I tried the network without pooling, which only got 65% accuracy. After, adding pooling, the accuracy gets up to about 74%.

7.2 Test set – run this only once

Now that we've gotten a result we're happy with, we test our final model on the test set (which you should store in best_model). Think about how this compares to your validation set accuracy.

```
In [66]: best_model = model
         check_accuracy_part34(loader_test, best_model)

Checking accuracy on test set
Got 7394 / 10000 correct (73.94)
```