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.

Affine layer: foward

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 [3]:

```
# 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:  9.769847728806635e-10
```

Affine layer: backward

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

In [4]:

```
# 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
```

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 [5]:

```
# 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
```

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 [6]:

```
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
```

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

Answer:

1. Only the sigmoid suffers from the traditional vanishing gradient problem of gradient<<1 for extreme magnitude activation values. ReLU does not suffer from this, but the ReLU can "die" (zero gradient) if x < 0. The Leaky ReLU gives the ReLU a chance to re-activate for x < 0 and places a lower bound on the vanishing gradient possibility (since the slope of the leaky portion is also constant).

Generally speaking, inputs of very very high magnitude will trigger the vanishing gradient problem since it is at these extreme values of x where the gradient of e.g. sigmoid(x) becomes very small.

"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 [7]:

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

# 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:  6.750562121603446e-11
dw error:  8.162015570444288e-11
db error:  7.826724021458994e-12
```

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 [8]:

```
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 order of e-9
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 around e-8
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
```

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 [9]:

```
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,  16.09215096]
,
   [12.05769098,  12.74614105,  13.43459113,  14.1230412,   14.81149128, 15.49994135,  16.18839143]
,
   [12.58373087,  13.20054771,  13.81736455,  14.43418138,  15.05099822, 15.66781506,  16.2846319 ]
])
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: 1.52e-08
W2 relative error: 3.48e-10
b1 relative error: 6.55e-09
b2 relative error: 4.33e-10
Running numeric gradient check with reg =  0.7
W1 relative error: 8.18e-07
W2 relative error: 2.85e-08
b1 relative error: 1.09e-09
b2 relative error: 7.76e-10
```

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 [10]:

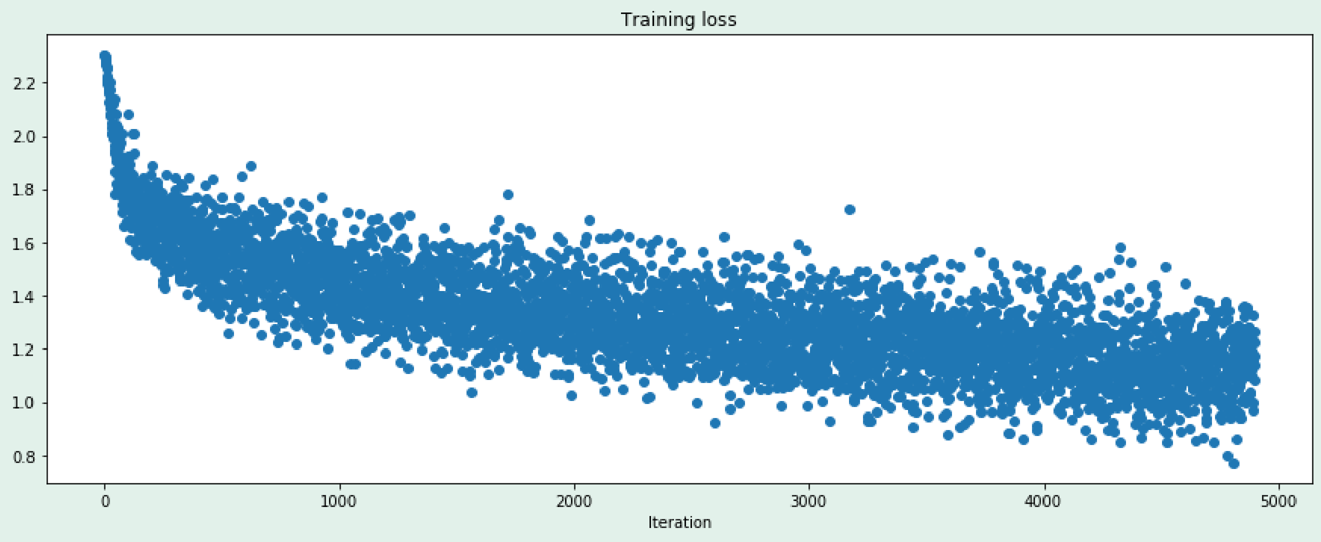
```
model = TwoLayerNet()
solver = None

##############################################################################
# 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)*****
# Initialize with CIFAR-10 and default TwoLayerNet
solver = Solver(model, data, optim_config={'learning_rate': 1e-3}, lr_decay=0.95,
                num_epochs=10, batch_size=100, print_every=100)
solver.train()
pass

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

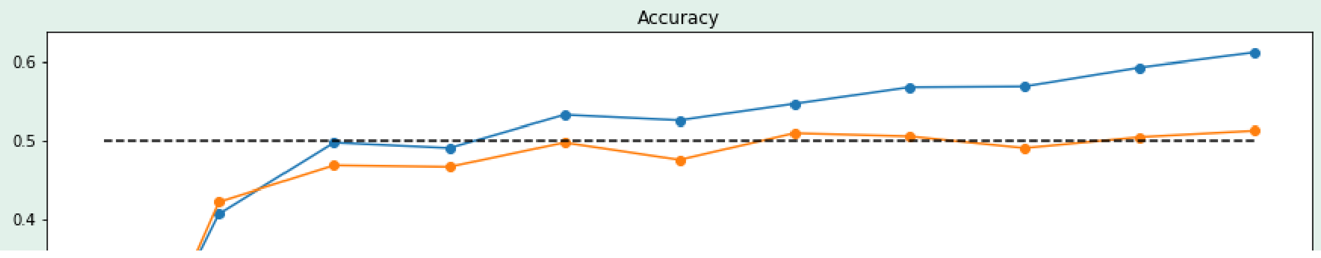
```
(Iteration 1 / 4900) loss: 2.304060
(Epoch 0 / 10) train acc: 0.116000; val_acc: 0.094000
(Iteration 101 / 4900) loss: 1.829613
(Iteration 201 / 4900) loss: 1.857390
(Iteration 301 / 4900) loss: 1.744448
(Iteration 401 / 4900) loss: 1.420187
(Epoch 1 / 10) train acc: 0.407000; val_acc: 0.422000
(Iteration 501 / 4900) loss: 1.565913
(Iteration 601 / 4900) loss: 1.700510
(Iteration 701 / 4900) loss: 1.732213
(Iteration 801 / 4900) loss: 1.688361
(Iteration 901 / 4900) loss: 1.439529
(Epoch 2 / 10) train acc: 0.497000; val_acc: 0.468000
(Iteration 1001 / 4900) loss: 1.385772
(Iteration 1101 / 4900) loss: 1.278401
(Iteration 1201 / 4900) loss: 1.641580
(Iteration 1301 / 4900) loss: 1.438847
(Iteration 1401 / 4900) loss: 1.172536
(Epoch 3 / 10) train acc: 0.490000; val_acc: 0.466000
(Iteration 1501 / 4900) loss: 1.346286
(Iteration 1601 / 4900) loss: 1.268492
(Iteration 1701 / 4900) loss: 1.318215
(Iteration 1801 / 4900) loss: 1.395750
(Iteration 1901 / 4900) loss: 1.338233
(Epoch 4 / 10) train acc: 0.532000; val_acc: 0.497000
(Iteration 2001 / 4900) loss: 1.343165
(Iteration 2101 / 4900) loss: 1.393173
(Iteration 2201 / 4900) loss: 1.276734
(Iteration 2301 / 4900) loss: 1.287951
(Iteration 2401 / 4900) loss: 1.352778
(Epoch 5 / 10) train acc: 0.525000; val_acc: 0.475000
(Iteration 2501 / 4900) loss: 1.390234
```

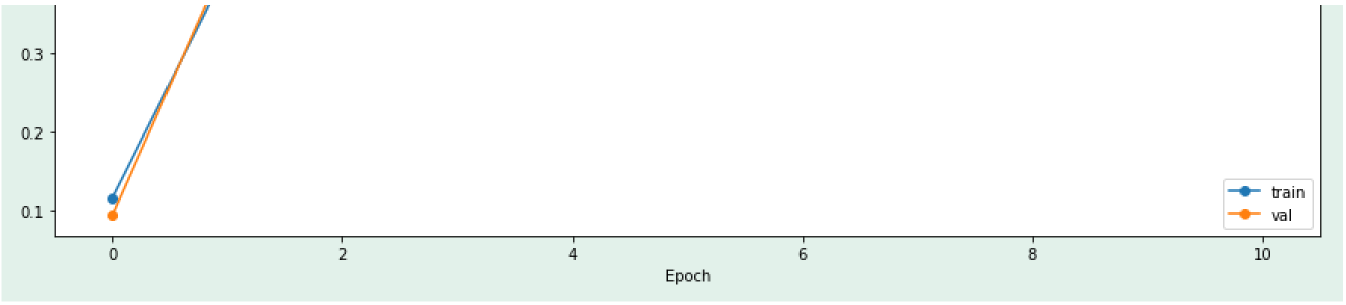
```
(Iteration 2601 / 4900) loss: 1.276361
(Iteration 2701 / 4900) loss: 1.111768
(Iteration 2801 / 4900) loss: 1.271688
(Iteration 2901 / 4900) loss: 1.272039
(Epoch 6 / 10) train acc: 0.546000; val_acc: 0.509000
(Iteration 3001 / 4900) loss: 1.304489
(Iteration 3101 / 4900) loss: 1.346667
(Iteration 3201 / 4900) loss: 1.325510
(Iteration 3301 / 4900) loss: 1.392728
(Iteration 3401 / 4900) loss: 1.402001
(Epoch 7 / 10) train acc: 0.567000; val_acc: 0.505000
(Iteration 3501 / 4900) loss: 1.319024
(Iteration 3601 / 4900) loss: 1.153287
(Iteration 3701 / 4900) loss: 1.180922
(Iteration 3801 / 4900) loss: 1.093164
(Iteration 3901 / 4900) loss: 1.135902
(Epoch 8 / 10) train acc: 0.568000; val_acc: 0.490000
(Iteration 4001 / 4900) loss: 1.191735
(Iteration 4101 / 4900) loss: 1.359396
(Iteration 4201 / 4900) loss: 1.227283
(Iteration 4301 / 4900) loss: 1.024113
(Iteration 4401 / 4900) loss: 1.327583
(Epoch 9 / 10) train acc: 0.592000; val_acc: 0.504000
(Iteration 4501 / 4900) loss: 0.963330
(Iteration 4601 / 4900) loss: 1.445619
(Iteration 4701 / 4900) loss: 1.007542
(Iteration 4801 / 4900) loss: 1.005175
(Epoch 10 / 10) train acc: 0.611000; val_acc: 0.512000
```

In [11]:

```python
# 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()
```







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.

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 [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 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])))
```

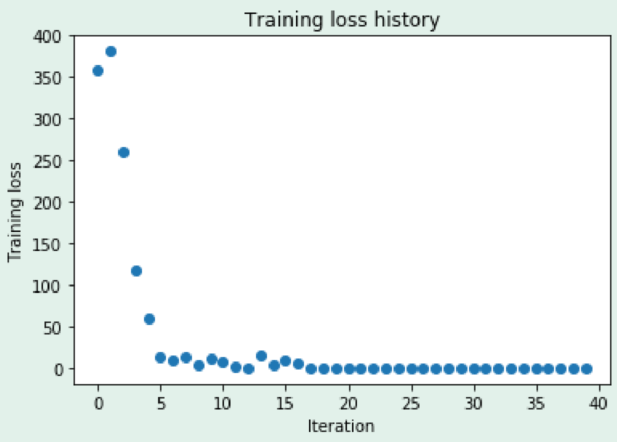
```
Running check with reg =  0
Initial loss:  2.3004790897684924
W1 relative error: 1.48e-07
W2 relative error: 2.21e-05
W3 relative error: 3.53e-07
b1 relative error: 5.38e-09
b2 relative error: 2.09e-09
b3 relative error: 5.80e-11
Running check with reg =  3.14
Initial loss:  7.052114776533016
W1 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 [13]:

```python
# 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 = 0.1   # Experiment with this!
learning_rate = 1e-3  # 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: 357.428290
(Epoch 0 / 20) train acc: 0.220000; val_acc: 0.111000
(Epoch 1 / 20) train acc: 0.380000; val_acc: 0.141000
(Epoch 2 / 20) train acc: 0.520000; val_acc: 0.138000
(Epoch 3 / 20) train acc: 0.740000; val_acc: 0.130000
(Epoch 4 / 20) train acc: 0.820000; val_acc: 0.153000
(Epoch 5 / 20) train acc: 0.860000; val_acc: 0.175000
(Iteration 11 / 40) loss: 6.726589
(Epoch 6 / 20) train acc: 0.940000; val_acc: 0.163000
(Epoch 7 / 20) train acc: 0.960000; val_acc: 0.166000
(Epoch 8 / 20) train acc: 0.960000; val_acc: 0.164000
(Epoch 9 / 20) train acc: 0.980000; val_acc: 0.162000
(Epoch 10 / 20) train acc: 0.980000; val_acc: 0.162000
(Iteration 21 / 40) loss: 0.800243
(Epoch 11 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 12 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 13 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 15 / 20) train acc: 1.000000; val_acc: 0.158000
(Iteration 31 / 40) loss: 0.000000
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.158000
```

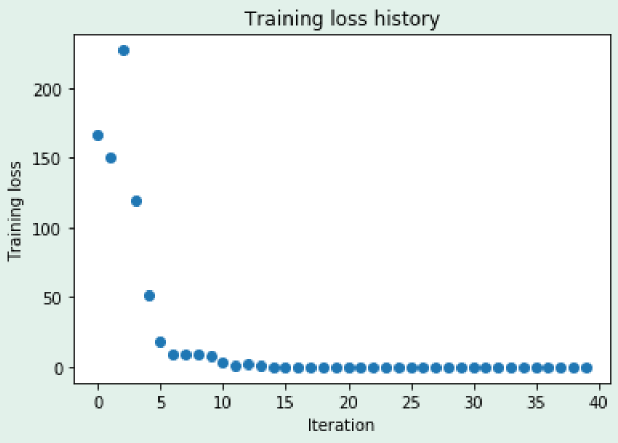


Now try to use a five-layer network with 100 units on each layer to overfit 50 training examples. Again, you will have to adjust the learning rate and weight initialization scale, but you should be able to achieve 100% training accuracy within 20 epochs.

In [14]:

```
# 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-3  # Experiment with this!
weight_scale = 1e-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: 166.501707
(Epoch 0 / 20) train acc: 0.100000; val_acc: 0.107000
(Epoch 1 / 20) train acc: 0.320000; val_acc: 0.101000
(Epoch 2 / 20) train acc: 0.160000; val_acc: 0.122000
(Epoch 3 / 20) train acc: 0.380000; val_acc: 0.106000
(Epoch 4 / 20) train acc: 0.520000; val_acc: 0.111000
(Epoch 5 / 20) train acc: 0.760000; val_acc: 0.113000
(Iteration 11 / 40) loss: 3.343141
(Epoch 6 / 20) train acc: 0.840000; val_acc: 0.122000
(Epoch 7 / 20) train acc: 0.920000; val_acc: 0.113000
(Epoch 8 / 20) train acc: 0.940000; val_acc: 0.125000
(Epoch 9 / 20) train acc: 0.960000; val_acc: 0.125000
(Epoch 10 / 20) train acc: 0.980000; val_acc: 0.121000
(Iteration 21 / 40) loss: 0.039138
(Epoch 11 / 20) train acc: 0.980000; val_acc: 0.123000
(Epoch 12 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 13 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 15 / 20) train acc: 1.000000; val_acc: 0.121000
(Iteration 31 / 40) loss: 0.000644
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.121000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.121000
```



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?

Answer:

The deeper network seemed more sensitive to the initialization scale. This makes sense because since there are more layers, there is more depth in the network to allow for the weights to "diverge" towards uneven distributions of activation outputs, so it becomes increasingly important to initialize the weights (i.e. set the correct value of the weight scale) such that this does not occur.

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.

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 [15]:

```
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 [16]:

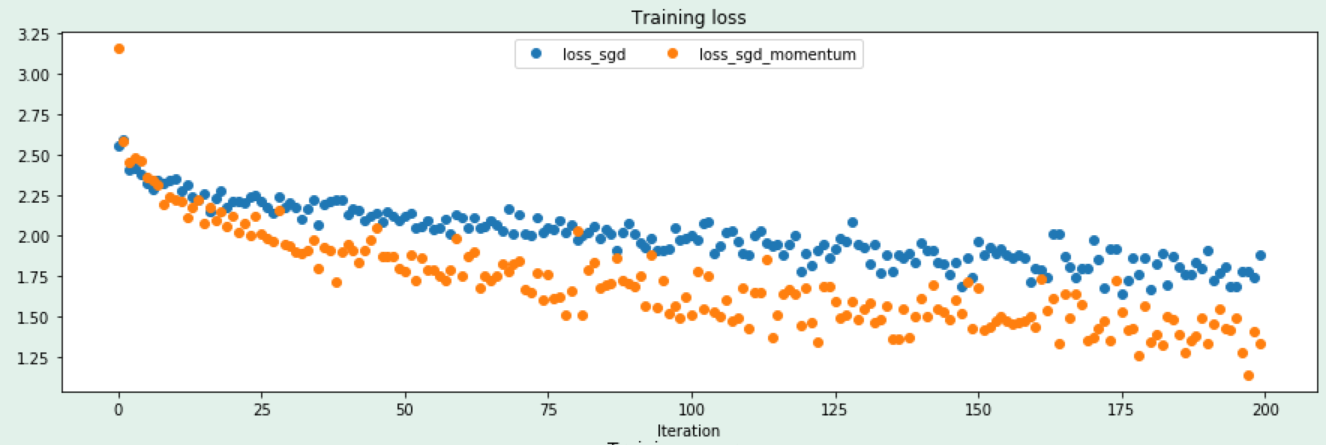
```
num_train = 4000
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
```

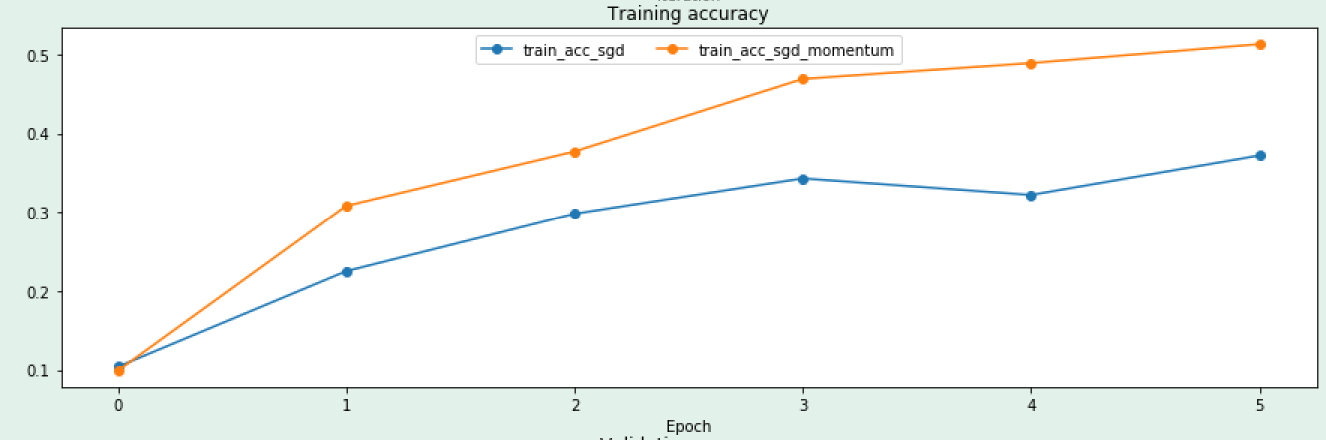
```python
solvers = {}

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()
```

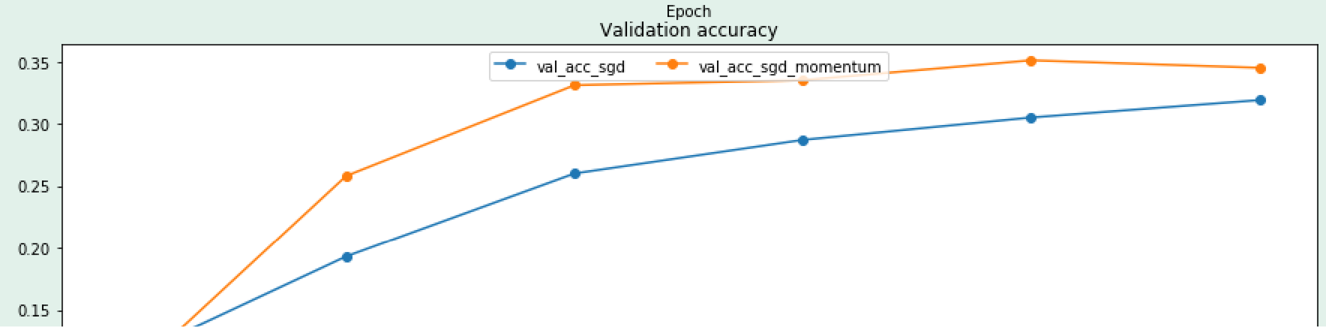
```
running with  sgd
(Iteration 1 / 200) loss: 2.559978
(Epoch 0 / 5) train acc: 0.104000; val_acc: 0.107000
(Iteration 11 / 200) loss: 2.356069
(Iteration 21 / 200) loss: 2.214091
(Iteration 31 / 200) loss: 2.205928
(Epoch 1 / 5) train acc: 0.225000; val_acc: 0.193000
(Iteration 41 / 200) loss: 2.132095
(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: 1.891516
(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: 3.153778
(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: 1.946330
(Iteration 51 / 200) loss: 1.780463
(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: 2.028390
(Iteration 91 / 200) loss: 1.685415
(Iteration 101 / 200) loss: 1.513205
(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: 1.545243
(Iteration 141 / 200) loss: 1.616405
(Iteration 151 / 200) loss: 1.676435
(Epoch 4 / 5) train acc: 0.489000; val_acc: 0.351000
(Iteration 161 / 200) loss: 1.442014
(Iteration 171 / 200) loss: 1.375687
(Iteration 181 / 200) loss: 1.344824
(Iteration 191 / 200) loss: 1.337178
(Epoch 5 / 5) train acc: 0.513000; val_acc: 0.345000
```

```
C:\Users\Anand Natu\AppData\Local\conda\conda\envs\cs231n\lib\site-
packages\matplotlib\figure.py:98: MatplotlibDeprecationWarning:
Adding an axes using the same arguments as a previous axes currently reuses the earlier instance.
In a future version, a new instance will always be created and returned.  Meanwhile, this warning
can be suppressed, and the future behavior ensured, by passing a unique label to each axes instanc
e.
  "Adding an axes using the same arguments as a previous axes "
```







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 [17]:

```
# 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 [18]:

```
# 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
```

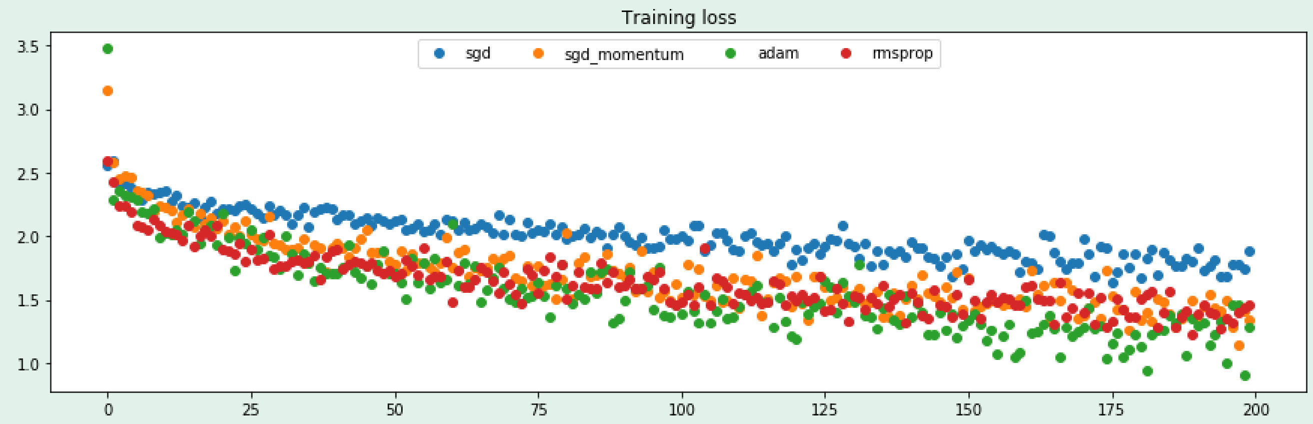
Once you have debugged your RMSProp and Adam implementations, run the following to train a pair of deep networks using these new update rules:

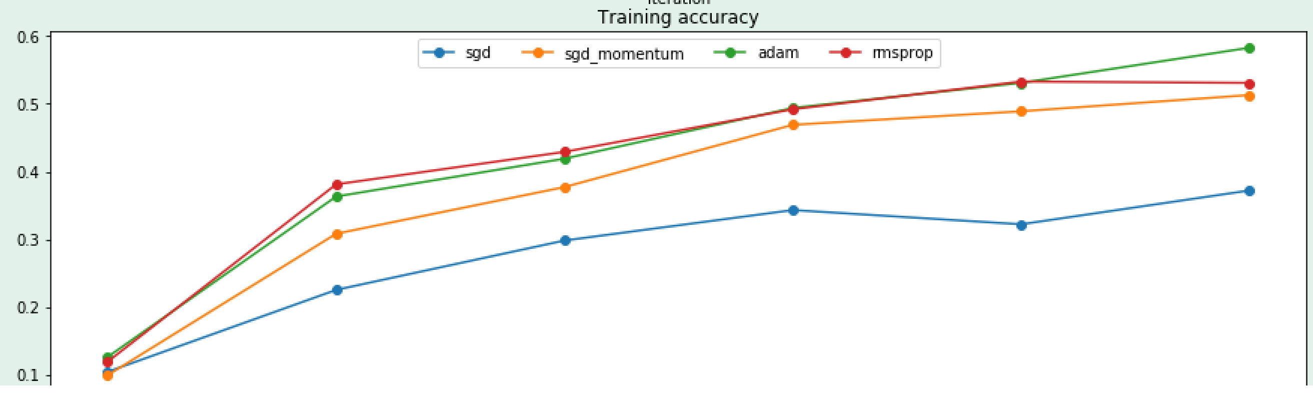
In [19]:

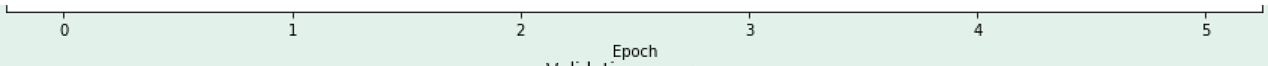
```
learning_rates = {'rmsprop': 1e-4, 'adam': 1e-3}
for update_rule in ['adam', 'rmsprop']:
  print('running with ', update_rule)
  model = FullyConnectedNet([100, 100, 100, 100, 100], weight_scale=5e-2)

  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()
```

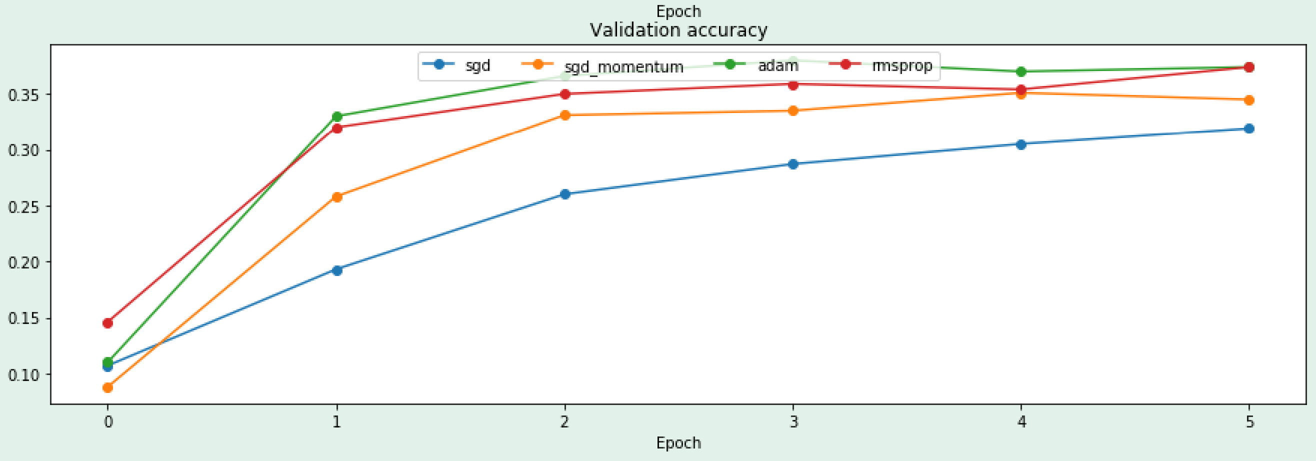
```
running with  adam
(Iteration 1 / 200) loss: 3.476928
(Epoch 0 / 5) train acc: 0.126000; val_acc: 0.110000
(Iteration 11 / 200) loss: 2.027712
(Iteration 21 / 200) loss: 2.183358
(Iteration 31 / 200) loss: 1.744257
(Epoch 1 / 5) train acc: 0.363000; val_acc: 0.330000
(Iteration 41 / 200) loss: 1.707951
(Iteration 51 / 200) loss: 1.703835
(Iteration 61 / 200) loss: 2.094758
```

```
(Iteration 71 / 200) loss: 1.505614
(Epoch 2 / 5) train acc: 0.419000; val_acc: 0.366000
(Iteration 81 / 200) loss: 1.593840
(Iteration 91 / 200) loss: 1.492122
(Iteration 101 / 200) loss: 1.393160
(Iteration 111 / 200) loss: 1.441590
(Epoch 3 / 5) train acc: 0.494000; val_acc: 0.380000
(Iteration 121 / 200) loss: 1.188173
(Iteration 131 / 200) loss: 1.484940
(Iteration 141 / 200) loss: 1.363281
(Iteration 151 / 200) loss: 1.340405
(Epoch 4 / 5) train acc: 0.531000; val_acc: 0.370000
(Iteration 161 / 200) loss: 1.488828
(Iteration 171 / 200) loss: 1.278309
(Iteration 181 / 200) loss: 1.123501
(Iteration 191 / 200) loss: 1.290712
(Epoch 5 / 5) train acc: 0.583000; val_acc: 0.374000

running with  rmsprop
(Iteration 1 / 200) loss: 2.589166
(Epoch 0 / 5) train acc: 0.119000; val_acc: 0.146000
(Iteration 11 / 200) loss: 2.032921
(Iteration 21 / 200) loss: 1.897277
(Iteration 31 / 200) loss: 1.770793
(Epoch 1 / 5) train acc: 0.381000; val_acc: 0.320000
(Iteration 41 / 200) loss: 1.895731
(Iteration 51 / 200) loss: 1.681091
(Iteration 61 / 200) loss: 1.487204
(Iteration 71 / 200) loss: 1.629973
(Epoch 2 / 5) train acc: 0.429000; val_acc: 0.350000
(Iteration 81 / 200) loss: 1.506686
(Iteration 91 / 200) loss: 1.610742
(Iteration 101 / 200) loss: 1.486124
(Iteration 111 / 200) loss: 1.559454
(Epoch 3 / 5) train acc: 0.492000; val_acc: 0.359000
(Iteration 121 / 200) loss: 1.496859
(Iteration 131 / 200) loss: 1.531552
(Iteration 141 / 200) loss: 1.550195
(Iteration 151 / 200) loss: 1.657838
(Epoch 4 / 5) train acc: 0.533000; val_acc: 0.354000
(Iteration 161 / 200) loss: 1.603105
(Iteration 171 / 200) loss: 1.405372
(Iteration 181 / 200) loss: 1.503740
(Iteration 191 / 200) loss: 1.385278
(Epoch 5 / 5) train acc: 0.531000; val_acc: 0.374000
```









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?

Answer:

Given the nature of the Adagrad update, it follows that the magnitude of updates that are applied to the weights is a function fo the magnitude of the gradients that these weights receive - weights that have high gradients and update magnitudes will accordingly become smaller. Adam still performs per-parameter normalization of the learning rate, but it does not do so with respect to the cache (i.e. sum of squared gradients) and as a result does not have this issue.

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 [4]:

```
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)*****
learning_rates = [1e-4, 1e-3, 1e-2]
weight_scales = [1e-3, 1e-2, 1e-1]

bestValAcc = -1
bestTrainAcc = -1
best_lr = -1
best_ws = -1

for lr in learning_rates:
    for ws in weight_scales:
        model = FullyConnectedNet(hidden_dims = [500,400,300,200,100]
        model = FullyConnectedNet(hidden_dims = [500,400,300,200,100],
                                 normalization = "batchnorm", dropout = 0.7,
                                 weight_scale = ws)
        optim_config = {"epsilon": 1e-8,
                       "learning_rate": lr,
                       "beta1": 0.9,
                       "beta2": 0.9}
        solver = Solver(model, data, print_every=100, num_epochs = 15, batch_size = 100,
                       update_rule = "adam", optim_config = optim_config, verbose = True)
        solver.train()

        y_train_pred = np.argmax(model.loss(data["X_train"]), axis=1)
        y_train_val = np.argmax(model.loss(data["X_val"]), axis=1)

        trainAcc = np.mean(y_train_pred == data["y_train"])
        valAcc = np.mean(y_train_val == data["y_val"])

        if valAcc > bestValAcc:
            bestValAcc = valAcc
            bestTrainAcc = trainAcc
            best_lr = lr
            best_ws = ws
            best_model = model

pass

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

```
(Iteration 1 / 7350) loss: 2.302450
(Epoch 0 / 15) train acc: 0.121000; val_acc: 0.115000
(Iteration 101 / 7350) loss: 2.091587
(Iteration 201 / 7350) loss: 1.976740
(Iteration 301 / 7350) loss: 1.870831
(Iteration 401 / 7350) loss: 1.844303
(Epoch 1 / 15) train acc: 0.362000; val_acc: 0.372000
(Iteration 501 / 7350) loss: 1.816164
(Iteration 601 / 7350) loss: 1.702539
(Iteration 701 / 7350) loss: 1.831758
(Iteration 801 / 7350) loss: 1.686345
(Iteration 901 / 7350) loss: 1.713946
(Epoch 2 / 15) train acc: 0.421000; val_acc: 0.420000
(Iteration 1001 / 7350) loss: 1.454797
(Iteration 1101 / 7350) loss: 1.854887
(Iteration 1201 / 7350) loss: 1.597242
(Iteration 1301 / 7350) loss: 1.599171
(Iteration 1401 / 7350) loss: 1.464804
(Epoch 3 / 15) train acc: 0.476000; val_acc: 0.444000
(Iteration 1501 / 7350) loss: 1.523858
(Iteration 1601 / 7350) loss: 1.997923
(Iteration 1701 / 7350) loss: 1.485150
(Iteration 1801 / 7350) loss: 1.571352
(Iteration 1901 / 7350) loss: 1.460584
(Epoch 4 / 15) train acc: 0.508000; val_acc: 0.491000
(Iteration 2001 / 7350) loss: 1.596989
(Iteration 2101 / 7350) loss: 1.432272
(Iteration 2201 / 7350) loss: 1.358945
(Iteration 2301 / 7350) loss: 1.528513
(Iteration 2401 / 7350) loss: 1.532225
(Epoch 5 / 15) train acc: 0.543000; val_acc: 0.499000
(Iteration 2501 / 7350) loss: 1.667431
(Iteration 2601 / 7350) loss: 1.524037
(Iteration 2701 / 7350) loss: 1.516205
(Iteration 2801 / 7350) loss: 1.445150
(Iteration 2901 / 7350) loss: 1.477873
(Epoch 6 / 15) train acc: 0.542000; val_acc: 0.514000
(Iteration 3001 / 7350) loss: 1.413746
(Iteration 3101 / 7350) loss: 1.433505
(Iteration 3201 / 7350) loss: 1.369776
(Iteration 3301 / 7350) loss: 1.321846
(Iteration 3401 / 7350) loss: 1.410482
(Epoch 7 / 15) train acc: 0.544000; val_acc: 0.536000
(Iteration 3501 / 7350) loss: 1.221618
(Iteration 3601 / 7350) loss: 1.350990
(Iteration 3701 / 7350) loss: 1.312467
(Iteration 3801 / 7350) loss: 1.316643
```

```
(Iteration 3901 / 7350) loss: 1.186193
(Epoch 8 / 15) train acc: 0.589000; val_acc: 0.546000
(Iteration 4001 / 7350) loss: 1.362171
(Iteration 4101 / 7350) loss: 1.233717
(Iteration 4201 / 7350) loss: 1.206955
(Iteration 4301 / 7350) loss: 1.318999
(Iteration 4401 / 7350) loss: 1.294183
(Epoch 9 / 15) train acc: 0.606000; val_acc: 0.550000
(Iteration 4501 / 7350) loss: 1.445663
(Iteration 4601 / 7350) loss: 1.264299
(Iteration 4701 / 7350) loss: 1.463524
(Iteration 4801 / 7350) loss: 1.293595
(Epoch 10 / 15) train acc: 0.584000; val_acc: 0.562000
(Iteration 4901 / 7350) loss: 1.327364
(Iteration 5001 / 7350) loss: 1.312719
(Iteration 5101 / 7350) loss: 1.462508
(Iteration 5201 / 7350) loss: 1.216430
(Iteration 5301 / 7350) loss: 1.270350
(Epoch 11 / 15) train acc: 0.589000; val_acc: 0.577000
(Iteration 5401 / 7350) loss: 1.232138
(Iteration 5501 / 7350) loss: 1.390194
(Iteration 5601 / 7350) loss: 1.465016
(Iteration 5701 / 7350) loss: 1.199706
(Iteration 5801 / 7350) loss: 1.162109
(Epoch 12 / 15) train acc: 0.605000; val_acc: 0.559000
(Iteration 5901 / 7350) loss: 1.184990
(Iteration 6001 / 7350) loss: 1.381191
(Iteration 6101 / 7350) loss: 1.255636
(Iteration 6201 / 7350) loss: 1.383913
(Iteration 6301 / 7350) loss: 1.258512
(Epoch 13 / 15) train acc: 0.638000; val_acc: 0.564000
(Iteration 6401 / 7350) loss: 1.049499
(Iteration 6501 / 7350) loss: 1.314134
(Iteration 6601 / 7350) loss: 1.014660
(Iteration 6701 / 7350) loss: 1.107914
(Iteration 6801 / 7350) loss: 1.377279
(Epoch 14 / 15) train acc: 0.633000; val_acc: 0.549000
(Iteration 6901 / 7350) loss: 1.420283
(Iteration 7001 / 7350) loss: 1.240734
(Iteration 7101 / 7350) loss: 1.146877
(Iteration 7201 / 7350) loss: 1.064239
(Iteration 7301 / 7350) loss: 1.322874
(Epoch 15 / 15) train acc: 0.649000; val_acc: 0.552000
(Iteration 1 / 7350) loss: 2.298575
(Epoch 0 / 15) train acc: 0.099000; val_acc: 0.085000
(Iteration 101 / 7350) loss: 2.154707
(Iteration 201 / 7350) loss: 2.038825
(Iteration 301 / 7350) loss: 1.876297
(Iteration 401 / 7350) loss: 1.791582
(Epoch 1 / 15) train acc: 0.420000; val_acc: 0.414000
(Iteration 501 / 7350) loss: 1.766255
(Iteration 601 / 7350) loss: 1.672735
(Iteration 701 / 7350) loss: 1.706656
(Iteration 801 / 7350) loss: 1.747770
(Iteration 901 / 7350) loss: 1.572933
(Epoch 2 / 15) train acc: 0.498000; val_acc: 0.477000
(Iteration 1001 / 7350) loss: 1.551694
(Iteration 1101 / 7350) loss: 1.704568
(Iteration 1201 / 7350) loss: 1.583272
(Iteration 1301 / 7350) loss: 1.560024
(Iteration 1401 / 7350) loss: 1.459196
(Epoch 3 / 15) train acc: 0.523000; val_acc: 0.491000
(Iteration 1501 / 7350) loss: 1.521261
(Iteration 1601 / 7350) loss: 1.471328
(Iteration 1701 / 7350) loss: 1.420854
(Iteration 1801 / 7350) loss: 1.480375
(Iteration 1901 / 7350) loss: 1.528432
(Epoch 4 / 15) train acc: 0.525000; val_acc: 0.513000
(Iteration 2001 / 7350) loss: 1.398660
(Iteration 2101 / 7350) loss: 1.339381
(Iteration 2201 / 7350) loss: 1.414695
(Iteration 2301 / 7350) loss: 1.487610
(Iteration 2401 / 7350) loss: 1.540482
(Epoch 5 / 15) train acc: 0.569000; val_acc: 0.533000
(Iteration 2501 / 7350) loss: 1.462017
(Iteration 2601 / 7350) loss: 1.444602
(Iteration 2701 / 7350) loss: 1.316462
```

```
(Iteration 2701 / 7350) loss: 1.516462
(Iteration 2801 / 7350) loss: 1.584756
(Iteration 2901 / 7350) loss: 1.411857
(Epoch 6 / 15) train acc: 0.566000; val_acc: 0.533000
(Iteration 3001 / 7350) loss: 1.324016
(Iteration 3101 / 7350) loss: 1.409869
(Iteration 3201 / 7350) loss: 1.305497
(Iteration 3301 / 7350) loss: 1.388263
(Iteration 3401 / 7350) loss: 1.190700
(Epoch 7 / 15) train acc: 0.565000; val_acc: 0.540000
(Iteration 3501 / 7350) loss: 1.300950
(Iteration 3601 / 7350) loss: 1.388345
(Iteration 3701 / 7350) loss: 1.488745
(Iteration 3801 / 7350) loss: 1.422422
(Iteration 3901 / 7350) loss: 1.532463
(Epoch 8 / 15) train acc: 0.598000; val_acc: 0.531000
(Iteration 4001 / 7350) loss: 1.394517
(Iteration 4101 / 7350) loss: 1.415899
(Iteration 4201 / 7350) loss: 1.380225
(Iteration 4301 / 7350) loss: 1.438912
(Iteration 4401 / 7350) loss: 1.215328
(Epoch 9 / 15) train acc: 0.591000; val_acc: 0.549000
(Iteration 4501 / 7350) loss: 1.405709
(Iteration 4601 / 7350) loss: 1.071149
(Iteration 4701 / 7350) loss: 1.370368
(Iteration 4801 / 7350) loss: 1.303605
(Epoch 10 / 15) train acc: 0.592000; val_acc: 0.552000
(Iteration 4901 / 7350) loss: 1.323934
(Iteration 5001 / 7350) loss: 1.367369
(Iteration 5101 / 7350) loss: 1.196964
(Iteration 5201 / 7350) loss: 1.345428
(Iteration 5301 / 7350) loss: 1.173679
(Epoch 11 / 15) train acc: 0.595000; val_acc: 0.564000
(Iteration 5401 / 7350) loss: 1.188295
(Iteration 5501 / 7350) loss: 1.063845
(Iteration 5601 / 7350) loss: 1.275543
(Iteration 5701 / 7350) loss: 1.158143
(Iteration 5801 / 7350) loss: 0.968895
(Epoch 12 / 15) train acc: 0.617000; val_acc: 0.561000
(Iteration 5901 / 7350) loss: 1.116864
(Iteration 6001 / 7350) loss: 1.269887
(Iteration 6101 / 7350) loss: 1.239188
(Iteration 6201 / 7350) loss: 1.440616
(Iteration 6301 / 7350) loss: 1.296666
(Epoch 13 / 15) train acc: 0.643000; val_acc: 0.573000
(Iteration 6401 / 7350) loss: 1.214028
(Iteration 6501 / 7350) loss: 1.236511
(Iteration 6601 / 7350) loss: 1.274744
(Iteration 6701 / 7350) loss: 1.126973
(Iteration 6801 / 7350) loss: 1.249599
(Epoch 14 / 15) train acc: 0.646000; val_acc: 0.571000
(Iteration 6901 / 7350) loss: 1.149398
(Iteration 7001 / 7350) loss: 1.052828
(Iteration 7101 / 7350) loss: 1.321026
(Iteration 7201 / 7350) loss: 1.214310
(Iteration 7301 / 7350) loss: 1.138341
(Epoch 15 / 15) train acc: 0.666000; val_acc: 0.581000
(Iteration 1 / 7350) loss: 2.680924
(Epoch 0 / 15) train acc: 0.094000; val_acc: 0.075000
(Iteration 101 / 7350) loss: 2.445977
(Iteration 201 / 7350) loss: 2.337796
(Iteration 301 / 7350) loss: 2.203130
(Iteration 401 / 7350) loss: 2.104975
(Epoch 1 / 15) train acc: 0.280000; val_acc: 0.289000
(Iteration 501 / 7350) loss: 2.240947
(Iteration 601 / 7350) loss: 2.041428
(Iteration 701 / 7350) loss: 2.059455
(Iteration 801 / 7350) loss: 1.916655
(Iteration 901 / 7350) loss: 2.027752
(Epoch 2 / 15) train acc: 0.311000; val_acc: 0.333000
(Iteration 1001 / 7350) loss: 1.918690
(Iteration 1101 / 7350) loss: 1.916358
(Iteration 1201 / 7350) loss: 1.965481
(Iteration 1301 / 7350) loss: 1.886915
(Iteration 1401 / 7350) loss: 2.021892
(Epoch 3 / 15) train acc: 0.378000; val_acc: 0.363000
(Iteration 1501 / 7350) loss: 1.965115
(Iteration 1601 / 7350) loss: 1.779522
```

```
(Iteration 1601 / 7350) loss: 1.779522
(Iteration 1701 / 7350) loss: 1.793482
(Iteration 1801 / 7350) loss: 1.798034
(Iteration 1901 / 7350) loss: 1.943152
(Epoch 4 / 15) train acc: 0.415000; val_acc: 0.385000
(Iteration 2001 / 7350) loss: 1.887237
(Iteration 2101 / 7350) loss: 1.759962
(Iteration 2201 / 7350) loss: 1.868657
(Iteration 2301 / 7350) loss: 1.763670
(Iteration 2401 / 7350) loss: 1.803117
(Epoch 5 / 15) train acc: 0.425000; val_acc: 0.423000
(Iteration 2501 / 7350) loss: 1.626448
(Iteration 2601 / 7350) loss: 1.881668
(Iteration 2701 / 7350) loss: 1.748192
(Iteration 2801 / 7350) loss: 1.692626
(Iteration 2901 / 7350) loss: 1.726317
(Epoch 6 / 15) train acc: 0.420000; val_acc: 0.423000
(Iteration 3001 / 7350) loss: 1.839387
(Iteration 3101 / 7350) loss: 1.712797
(Iteration 3201 / 7350) loss: 1.756472
(Iteration 3301 / 7350) loss: 1.617860
(Iteration 3401 / 7350) loss: 1.593882
(Epoch 7 / 15) train acc: 0.432000; val_acc: 0.445000
(Iteration 3501 / 7350) loss: 1.756572
(Iteration 3601 / 7350) loss: 1.679707
(Iteration 3701 / 7350) loss: 1.711750
(Iteration 3801 / 7350) loss: 1.764458
(Iteration 3901 / 7350) loss: 1.730353
(Epoch 8 / 15) train acc: 0.464000; val_acc: 0.460000
(Iteration 4001 / 7350) loss: 1.526279
(Iteration 4101 / 7350) loss: 1.712690
(Iteration 4201 / 7350) loss: 1.680706
(Iteration 4301 / 7350) loss: 1.577342
(Iteration 4401 / 7350) loss: 1.598123
(Epoch 9 / 15) train acc: 0.469000; val_acc: 0.461000
(Iteration 4501 / 7350) loss: 1.528262
(Iteration 4601 / 7350) loss: 1.856224
(Iteration 4701 / 7350) loss: 1.467290
(Iteration 4801 / 7350) loss: 1.715317
(Epoch 10 / 15) train acc: 0.498000; val_acc: 0.457000
(Iteration 4901 / 7350) loss: 1.528425
(Iteration 5001 / 7350) loss: 1.446937
(Iteration 5101 / 7350) loss: 1.675175
(Iteration 5201 / 7350) loss: 1.713310
(Iteration 5301 / 7350) loss: 1.676760
(Epoch 11 / 15) train acc: 0.496000; val_acc: 0.473000
(Iteration 5401 / 7350) loss: 1.361117
(Iteration 5501 / 7350) loss: 1.560665
(Iteration 5601 / 7350) loss: 1.588294
(Iteration 5701 / 7350) loss: 1.534071
(Iteration 5801 / 7350) loss: 1.609508
(Epoch 12 / 15) train acc: 0.520000; val_acc: 0.473000
(Iteration 5901 / 7350) loss: 1.475869
(Iteration 6001 / 7350) loss: 1.604550
(Iteration 6101 / 7350) loss: 1.596180
(Iteration 6201 / 7350) loss: 1.682658
(Iteration 6301 / 7350) loss: 1.523731
(Epoch 13 / 15) train acc: 0.518000; val_acc: 0.474000
(Iteration 6401 / 7350) loss: 1.411771
(Iteration 6501 / 7350) loss: 1.802254
(Iteration 6601 / 7350) loss: 1.358968
(Iteration 6701 / 7350) loss: 1.388554
(Iteration 6801 / 7350) loss: 1.364199
(Epoch 14 / 15) train acc: 0.527000; val_acc: 0.482000
(Iteration 6901 / 7350) loss: 1.483071
(Iteration 7001 / 7350) loss: 1.592281
(Iteration 7101 / 7350) loss: 1.400269
(Iteration 7201 / 7350) loss: 1.479904
(Iteration 7301 / 7350) loss: 1.595437
(Epoch 15 / 15) train acc: 0.539000; val_acc: 0.487000
(Iteration 1 / 7350) loss: 2.302724
(Epoch 0 / 15) train acc: 0.101000; val_acc: 0.118000
(Iteration 101 / 7350) loss: 1.769975
(Iteration 201 / 7350) loss: 1.774038
(Iteration 301 / 7350) loss: 1.614483
(Iteration 401 / 7350) loss: 1.544445
(Epoch 1 / 15) train acc: 0.401000; val_acc: 0.436000
(Iteration 501 / 7350) loss: 1.694740
```

```
(Iteration 501 / 7350) loss: 1.694740
(Iteration 601 / 7350) loss: 1.604502
(Iteration 701 / 7350) loss: 1.420407
(Iteration 801 / 7350) loss: 1.387191
(Iteration 901 / 7350) loss: 1.703950
(Epoch 2 / 15) train acc: 0.490000; val_acc: 0.487000
(Iteration 1001 / 7350) loss: 1.559539
(Iteration 1101 / 7350) loss: 1.415635
(Iteration 1201 / 7350) loss: 1.735920
(Iteration 1301 / 7350) loss: 1.391336
(Iteration 1401 / 7350) loss: 1.354833
(Epoch 3 / 15) train acc: 0.521000; val_acc: 0.533000
(Iteration 1501 / 7350) loss: 1.522870
(Iteration 1601 / 7350) loss: 1.372761
(Iteration 1701 / 7350) loss: 1.448510
(Iteration 1801 / 7350) loss: 1.220147
(Iteration 1901 / 7350) loss: 1.423219
(Epoch 4 / 15) train acc: 0.550000; val_acc: 0.514000
(Iteration 2001 / 7350) loss: 1.438465
(Iteration 2101 / 7350) loss: 1.813177
(Iteration 2201 / 7350) loss: 1.312544
(Iteration 2301 / 7350) loss: 1.333381
(Iteration 2401 / 7350) loss: 1.312430
(Epoch 5 / 15) train acc: 0.560000; val_acc: 0.531000
(Iteration 2501 / 7350) loss: 1.433886
(Iteration 2601 / 7350) loss: 1.364705
(Iteration 2701 / 7350) loss: 1.183011
(Iteration 2801 / 7350) loss: 1.323588
(Iteration 2901 / 7350) loss: 1.318560
(Epoch 6 / 15) train acc: 0.597000; val_acc: 0.544000
(Iteration 3001 / 7350) loss: 1.402610
(Iteration 3101 / 7350) loss: 1.280899
(Iteration 3201 / 7350) loss: 1.207828
(Iteration 3301 / 7350) loss: 1.346912
(Iteration 3401 / 7350) loss: 1.320120
(Epoch 7 / 15) train acc: 0.607000; val_acc: 0.540000
(Iteration 3501 / 7350) loss: 1.308980
(Iteration 3601 / 7350) loss: 1.249800
(Iteration 3701 / 7350) loss: 1.404480
(Iteration 3801 / 7350) loss: 1.224725
(Iteration 3901 / 7350) loss: 1.154994
(Epoch 8 / 15) train acc: 0.587000; val_acc: 0.552000
(Iteration 4001 / 7350) loss: 1.352677
(Iteration 4101 / 7350) loss: 1.320181
(Iteration 4201 / 7350) loss: 1.213659
(Iteration 4301 / 7350) loss: 1.148453
(Iteration 4401 / 7350) loss: 1.284080
(Epoch 9 / 15) train acc: 0.635000; val_acc: 0.577000
(Iteration 4501 / 7350) loss: 1.216030
(Iteration 4601 / 7350) loss: 1.354586
(Iteration 4701 / 7350) loss: 1.149403
(Iteration 4801 / 7350) loss: 1.217224
(Epoch 10 / 15) train acc: 0.651000; val_acc: 0.557000
(Iteration 4901 / 7350) loss: 1.106099

---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-4-c463053e9c99> in <module>
     25         solver = Solver(model, data, print_every=100, num_epochs = 15, batch_size = 100,
     26                         update_rule = "adam", optim_config = optim_config, verbose = True)
---> 27         solver.train()
     28 
     29         y_train_pred = np.argmax(model.loss(data["X_train"]), axis=1)

~\Desktop\CS231n-Assignments\assignment2\cs231n\solver.py in train(self)
    264 
    265         for t in range(num_iterations):
--> 266             self._step()
    267 
    268             # Maybe print training loss

~\Desktop\CS231n-Assignments\assignment2\cs231n\solver.py in _step(self)
    187             dw = grads[p]
    188             config = self.optim_configs[p]
--> 189             next_w, next_config = self.update_rule(w, dw, config)
    190             self.model.params[p] = next_w
    191             self.optim_configs[p] = next_config
```

```
~\Desktop\CS231n-Assignments\assignment2\cs231n\optim.py in adam(w, dw, config)
    161     # calculate m
    162     config["m"] = config["beta1"]*config["m"] + (1-config["beta1"])*dw
--> 163     m_t = config["m"]/(1-config["beta1"]**config["t"])
    164 
    165     # Caclulate v

KeyboardInterrupt:
```

Test your model!

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

In [21]:

```
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:  0.571
Test set accuracy:  0.574
```

In [ ]:

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.

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 [15]:

```
# 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:   [4.16333634e-19 2.55004351e-18 5.65953534e-19]
  stds:    [0.03678496 0.02922733 0.02653497]

After batch normalization (gamma= [1. 2. 3.] , beta= [11. 12. 13.] )
  means:   [11. 12. 13.]
  stds:    [0.03678496 0.05845465 0.07960491]
```

In [14]:

```
# 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]
```

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 [26]:

```
# 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)
```

```
_, cache = batchnorm_forward(x, gamma, beta, bn_param)
dx, dgamma, dbeta = batchnorm_backward(dout, cache)
#You should expect to see relative errors between 1e-13 and 1e-8
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:  1.6674604875341426e-09
dgamma error:  7.417225040694815e-13
dbeta error:  2.379446949959628e-12
```

Batch normalization: alternative backward

In class we talked about two different implementations for the sigmoid backward pass. One strategy is to write out a computation graph composed of simple operations and backprop through all intermediate values. Another strategy is to work out the derivatives on paper. For example, you can derive a very simple formula for the sigmoid function's backward pass by simplifying gradients on paper.

Surprisingly, it turns out that you can do a similar simplification for the batch normalization backward pass too!

In the forward pass, given a set of inputs $X = \begin{bmatrix} x_1 \\ x_2 \\ \ldots \\ x_N \end{bmatrix}$,

we first calculate the mean μ and variance v. With μ and v calculated, we can calculate the standard deviation σ and normalized data Y. The equations and graph illustration below describe the computation (y_i is the i-th element of the vector Y).

$$\mu = \frac{1}{N}\sum_{k=1}^{N} x_k \qquad v = \frac{1}{N}\sum_{k=1}^{N} (x_k - \mu)^2$$

$$\sigma = \sqrt{v + \epsilon} \qquad y_i = \frac{x_i - \mu}{\sigma}$$

In [28]:

```
np.random.seed(231)
N, D = 100, 500
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'}
out, cache = batchnorm_forward(x, gamma, beta, bn_param)

t1 = time.time()
dx1, dgamma1, dbeta1 = batchnorm_backward(dout, cache)
t2 = time.time()
dx2, dgamma2, dbeta2 = batchnorm_backward_alt(dout, cache)
t3 = time.time()

print('dx difference: ', rel_error(dx1, dx2))
print('dgamma difference: ', rel_error(dgamma1, dgamma2))
print('dbeta difference: ', rel_error(dbeta1, dbeta2))
print('speedup: %.2fx' % ((t2 - t1) / (t3 - t2)))
```

```
dx difference:  9.890497291190823e-13
dgamma difference:  0.0
dbeta difference:  0.0

---------------------------------------------------------------------------
ZeroDivisionError                         Traceback (most recent call last)
<ipython-input-28-77fa69d24e58> in <module>
     18 print('dgamma difference: ', rel_error(dgamma1, dgamma2))
     19 print('dbeta difference: ', rel_error(dbeta1, dbeta2))
---> 20 print('speedup: %.2fx' % ((t2 - t1) / (t3 - t2)))
```

```
ZeroDivisionError: float division by zero
```

Fully Connected Nets with Batch Normalization

Now that you have a working implementation for batch normalization, go back to your `FullyConnectedNet` in the file `cs231n/classifiers/fc_net.py`. Modify your implementation to add batch normalization.

Concretely, when the `normalization` flag is set to `"batchnorm"` in the constructor, you should insert a batch normalization layer before each ReLU nonlinearity. The outputs from the last layer of the network should not be normalized. Once you are done, run the following to gradient-check your implementation.

HINT: You might find it useful to define an additional helper layer similar to those in the file `cs231n/layer_utils.py`. If you decide to do so, do it in the file `cs231n/classifiers/fc_net.py`.

In [41]:

```
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,))

# You should expect losses between 1e-4~1e-10 for W,
# losses between 1e-08~1e-10 for b,
# and losses between 1e-08~1e-09 for beta and gammas.
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,
                            normalization='batchnorm')

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

  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])))
  if reg == 0: print()
```

```
Running check with reg =  0
Initial loss:  2.2611955101340957
W1 relative error: 1.10e-04
W2 relative error: 2.76e-06
W3 relative error: 3.92e-10
b1 relative error: 2.22e-08
b2 relative error: 2.22e-08
b3 relative error: 1.01e-10
beta1 relative error: 7.85e-09
beta2 relative error: 1.17e-09
gamma1 relative error: 6.96e-09
gamma2 relative error: 1.96e-09

Running check with reg =  3.14
Initial loss:  6.996533220108303
W1 relative error: 1.98e-06
W2 relative error: 2.28e-06
W3 relative error: 1.11e-08
b1 relative error: 2.78e-09
b2 relative error: 0.00e+00
b3 relative error: 2.23e-10
beta1 relative error: 6.65e-09
beta2 relative error: 3.48e-09
gamma1 relative error: 5.94e-09
gamma2 relative error: 4.14e-09
```

Batchnorm for deep networks

Run the following to train a six-layer network on a subset of 1000 training examples both with and without batch normalization.

In [42]:

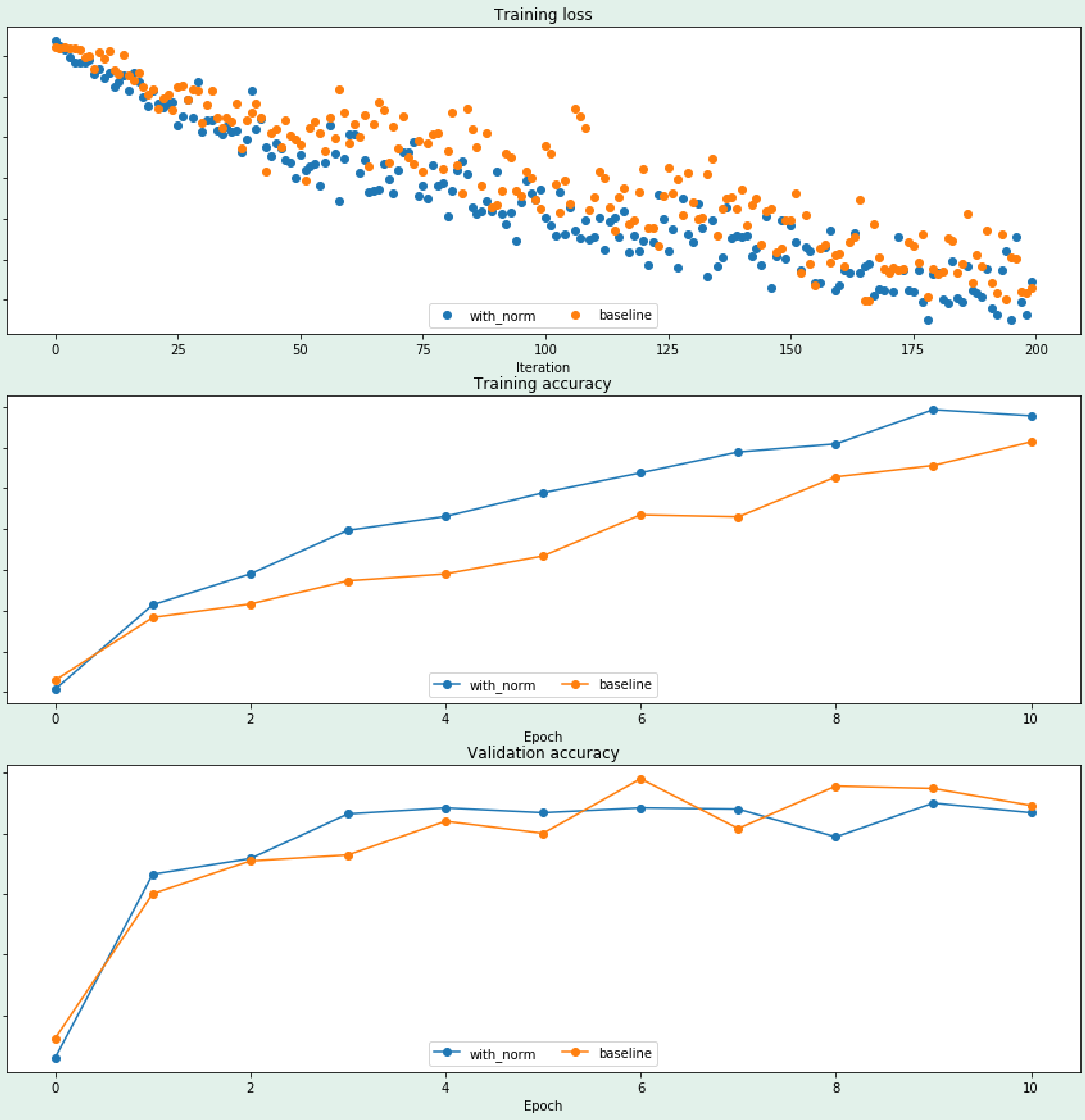
```
np.random.seed(231)
```

```
# Try training a very deep net with batchnorm
hidden_dims = [100, 100, 100, 100, 100]

num_train = 1000
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 = 2e-2
bn_model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale, normalization='batchnorm')
model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale, normalization=None)

print('Solver with batch norm:')
bn_solver = Solver(bn_model, small_data,
                num_epochs=10, batch_size=50,
                update_rule='adam',
                optim_config={
                  'learning_rate': 1e-3,
                },
                verbose=True,print_every=20)
bn_solver.train()

print('\nSolver without batch norm:')
solver = Solver(model, small_data,
                num_epochs=10, batch_size=50,
                update_rule='adam',
                optim_config={
                  'learning_rate': 1e-3,
                },
                verbose=True, print_every=20)
solver.train()
```

```
Solver with batch norm:
(Iteration 1 / 200) loss: 2.340975
(Epoch 0 / 10) train acc: 0.107000; val_acc: 0.115000
(Epoch 1 / 10) train acc: 0.314000; val_acc: 0.266000
(Iteration 21 / 200) loss: 2.039365
(Epoch 2 / 10) train acc: 0.390000; val_acc: 0.279000
(Iteration 41 / 200) loss: 2.036710
(Epoch 3 / 10) train acc: 0.497000; val_acc: 0.316000
(Iteration 61 / 200) loss: 1.769536
(Epoch 4 / 10) train acc: 0.531000; val_acc: 0.321000
(Iteration 81 / 200) loss: 1.265761
(Epoch 5 / 10) train acc: 0.589000; val_acc: 0.317000
(Iteration 101 / 200) loss: 1.256780
(Epoch 6 / 10) train acc: 0.638000; val_acc: 0.321000
(Iteration 121 / 200) loss: 1.115818
(Epoch 7 / 10) train acc: 0.689000; val_acc: 0.320000
(Iteration 141 / 200) loss: 1.138578
(Epoch 8 / 10) train acc: 0.709000; val_acc: 0.297000
(Iteration 161 / 200) loss: 0.837159
(Epoch 9 / 10) train acc: 0.793000; val_acc: 0.325000
(Iteration 181 / 200) loss: 0.921417
(Epoch 10 / 10) train acc: 0.778000; val_acc: 0.317000

Solver without batch norm:
(Iteration 1 / 200) loss: 2.302332
(Epoch 0 / 10) train acc: 0.129000; val_acc: 0.131000
(Epoch 1 / 10) train acc: 0.283000; val_acc: 0.250000
(Iteration 21 / 200) loss: 2.041970
(Epoch 2 / 10) train acc: 0.316000; val_acc: 0.277000
(Iteration 41 / 200) loss: 1.900473
(Epoch 3 / 10) train acc: 0.373000; val_acc: 0.282000
(Iteration 61 / 200) loss: 1.713156
(Epoch 4 / 10) train acc: 0.390000; val_acc: 0.310000
(Iteration 81 / 200) loss: 1.662209
(Epoch 5 / 10) train acc: 0.434000; val_acc: 0.300000
(Iteration 101 / 200) loss: 1.696059
(Epoch 6 / 10) train acc: 0.535000; val_acc: 0.345000
(Iteration 121 / 200) loss: 1.557987
(Epoch 7 / 10) train acc: 0.530000; val_acc: 0.304000
(Iteration 141 / 200) loss: 1.432189
(Epoch 8 / 10) train acc: 0.628000; val_acc: 0.339000
(Iteration 161 / 200) loss: 1.033931
```

```
(Epoch 9 / 10) train acc: 0.656000; val_acc: 0.337000
(Iteration 181 / 200) loss: 0.908564
(Epoch 10 / 10) train acc: 0.714000; val_acc: 0.323000
```

Run the following to visualize the results from two networks trained above. You should find that using batch normalization helps the network to converge much faster.

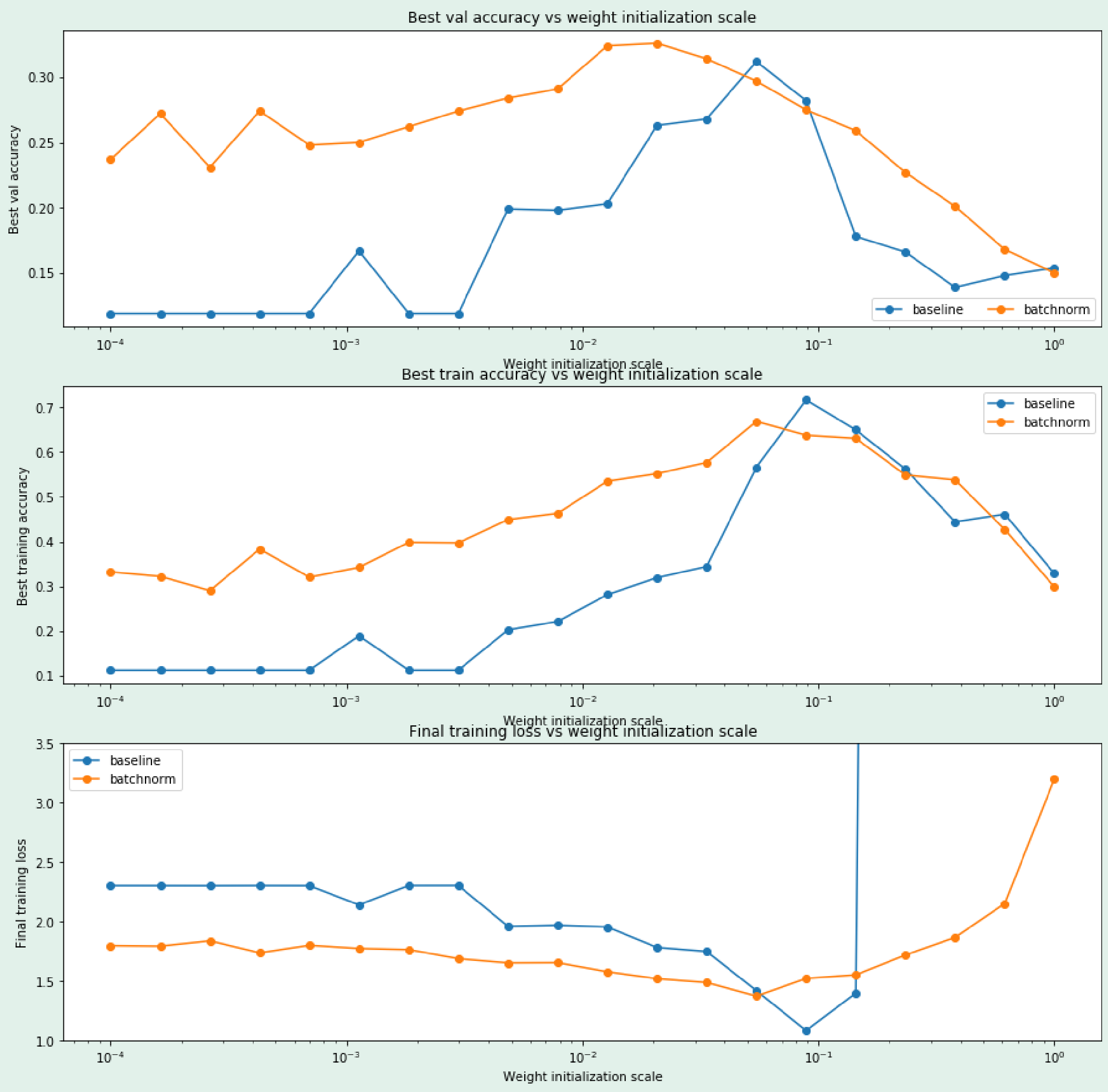


Batch normalization and initialization

We will now run a small experiment to study the interaction of batch normalization and weight initialization.

The first cell will train 8-layer networks both with and without batch normalization using different scales for weight initialization. The second layer will plot training accuracy, validation set accuracy, and training loss as a function of the weight initialization scale.

```
Running weight scale 1 / 20
Running weight scale 2 / 20
Running weight scale 3 / 20
Running weight scale 4 / 20
Running weight scale 5 / 20
Running weight scale 6 / 20
Running weight scale 7 / 20
Running weight scale 8 / 20
Running weight scale 9 / 20
Running weight scale 10 / 20
Running weight scale 11 / 20
Running weight scale 12 / 20
Running weight scale 13 / 20
Running weight scale 14 / 20
Running weight scale 15 / 20
Running weight scale 16 / 20
Running weight scale 17 / 20
Running weight scale 18 / 20
Running weight scale 19 / 20
Running weight scale 20 / 20
```



Inline Question 1:

Describe the results of this experiment. How does the scale of weight initialization affect models with/without batch normalization differently, and why?

Answer:

Generally, visual inspection of the above plots indicates that weight initialization has a much more severe effect on training results without batch normalization, while the trends are much smoother / more "buffered" when batch normalization is applied. This makes sense because batchnorm is introducing learnable parameters that adjust the distribution of the layer outputs such that they are optimally distributed with respect to the activation function (i.e. so as to avoid saturation). Therefore, batchnorm essentially makes the network less sensitive to weight initialization since the distributions of the activations can be learned to accommodate for any given choice of initialization scale, a remedy that is unavailable in the baseline scenario.

Batch normalization and batch size

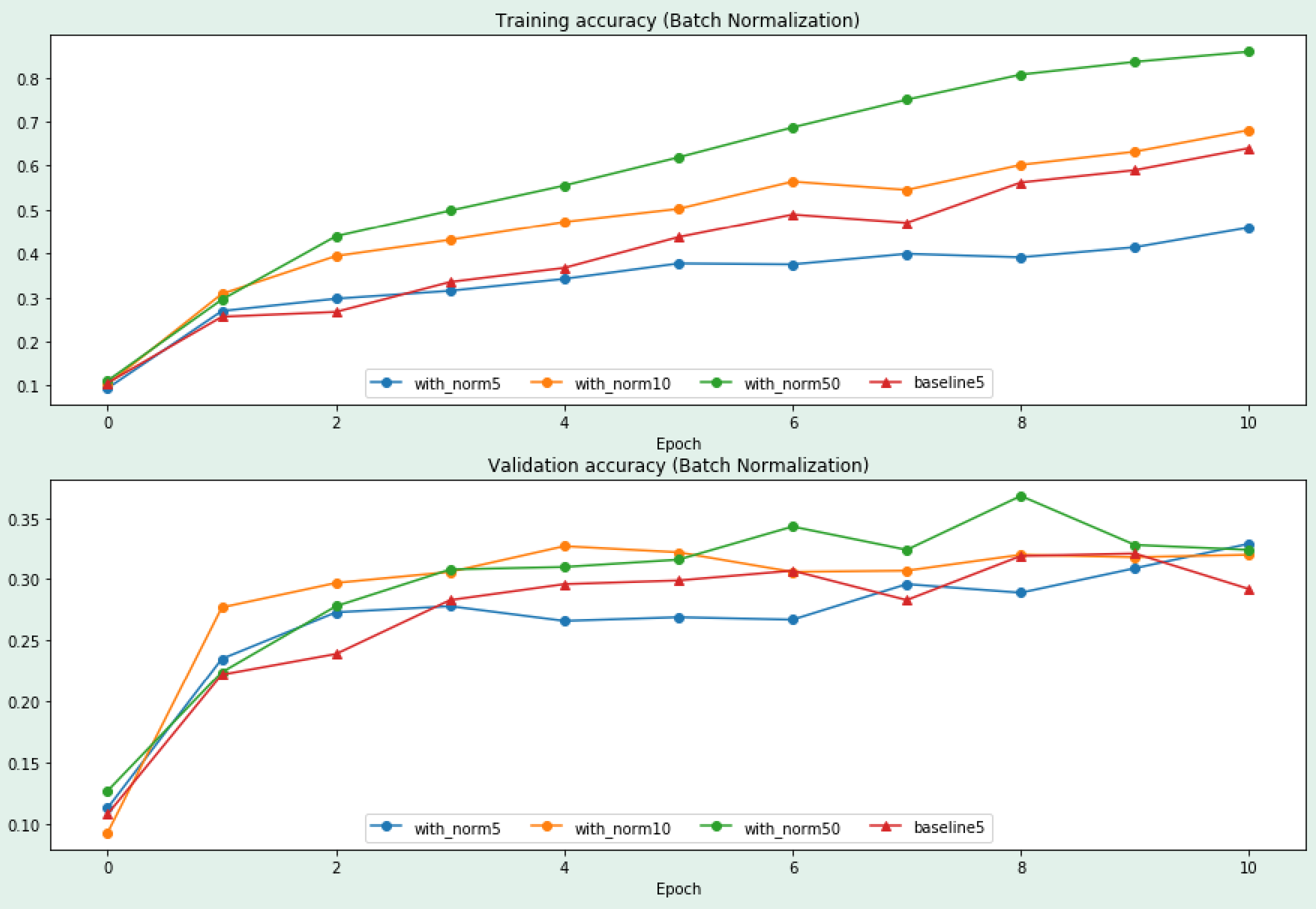
We will now run a small experiment to study the interaction of batch normalization and batch size.

The first cell will train 6-layer networks both with and without batch normalization using different batch sizes. The second layer will plot training accuracy and validation set accuracy over time.

```
No normalization: batch size =  5
Normalization: batch size =  5
Normalization: batch size =  10
Normalization: batch size =  50
```

In [47]:

```
plt.subplot(2, 1, 1)
plot_training_history('Training accuracy (Batch Normalization)','Epoch', solver_bsize,
bn_solvers_bsize, \
                      lambda x: x.train_acc_history, bl_marker='-^', bn_marker='-o', labels=batch_s
izes)
plt.subplot(2, 1, 2)
plot_training_history('Validation accuracy (Batch Normalization)','Epoch', solver_bsize,
bn_solvers_bsize, \
                      lambda x: x.val_acc_history, bl_marker='-^', bn_marker='-o', labels=batch_siz
es)

plt.gcf().set_size_inches(15, 10)
plt.show()
```



Inline Question 2:

Describe the results of this experiment. What does this imply about the relationship between batch normalization and batch size? Why is this relationship observed?

Answer:

The above results indicate that while batch size has a positive effect on training accuracy, it has virtually no effect on the validation accuracy. This is because batch normalization is primarily intended to safeguard against activation saturation. In the training case, increasing the batch size means the activation distributions are more closely tuned during training, which improves accuracy. However, as long as the batch size is big enough for the normalization to be accurate, marginal increases in the batch size have no incremental effect on model generality, which is why the validation set performance does not change.

Layer Normalization

Batch normalization has proved to be effective in making networks easier to train, but the dependency on batch size makes it less useful in complex networks which have a cap on the input batch size due to hardware limitations.

Several alternatives to batch normalization have been proposed to mitigate this problem; one such technique is Layer Normalization [2]. Instead of normalizing over the batch, we normalize over the features. In other words, when using Layer Normalization, each feature vector corresponding to a single datapoint is normalized based on the sum of all terms within that feature vector.

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

Inline Question 3:

Which of these data preprocessing steps is analogous to batch normalization, and which is analogous to layer normalization?

1. Scaling each image in the dataset, so that the RGB channels for each row of pixels within an image sums up to 1.
2. Scaling each image in the dataset, so that the RGB channels for all pixels within an image sums up to 1.
3. Subtracting the mean image of the dataset from each image in the dataset.
4. Setting all RGB values to either 0 or 1 depending on a given threshold.

Answer:

Option 3 is analogous to batch normalization since it applies a universal transform across the image, and that transform is informed by the mean over a set of examples.

Option 2 corresponds to layer normalization, because it applies a transform to the feature vector of each data point that is informed by mean over the values of all of terms within the feature vector (i.e. all pixels within the image, as compared to e.g. Option 1 where normalization occurs only over a subset of the terms in the feature vector)

Layer Normalization: Implementation

Now you'll implement layer normalization. This step should be relatively straightforward, as conceptually the implementation is almost identical to that of batch normalization. One significant difference though is that for layer normalization, we do not keep track of the moving moments, and the testing phase is identical to the training phase, where the mean and variance are directly calculated per datapoint.

Here's what you need to do:

- In `cs231n/layers.py`, implement the forward pass for layer normalization in the function `layernorm_backward`.

Run the cell below to check your results.

- In `cs231n/layers.py`, implement the backward pass for layer normalization in the function `layernorm_backward`.

Run the second cell below to check your results.

- Modify `cs231n/classifiers/fc_net.py` to add layer normalization to the `FullyConnectedNet`. When the `normalization` flag is set to `"layernorm"` in the constructor, you should insert a layer normalization layer before each ReLU nonlinearity.

Run the third cell below to run the batch size experiment on layer normalization.

In [68]:

```
# Check the training-time forward pass by checking means and variances
# of features both before and after layer normalization
# Simulate the forward pass for a two-layer network
np.random.seed(231)
N, D1, D2, D3 =4, 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 layer normalization:')
print_mean_std(a,axis=1)

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

gamma = np.asarray([3.0,3.0,3.0])
beta = np.asarray([5.0,5.0,5.0])
# Now means should be close to beta and stds close to gamma
print('After layer normalization (gamma=', gamma, ', beta=', beta, ')')
a_norm, _ = layernorm_forward(a, gamma, beta, {'mode': 'train'})
print_mean_std(a_norm,axis=1)
```

```
Before layer normalization:
  means:   [-59.06673243 -47.60782686 -43.31137368 -26.40991744]
  stds:    [10.07429373 28.39478981 35.28360729  4.01831507]

After layer normalization (gamma=1, beta=0)
  means:   [-4.81096644e-16  0.00000000e+00  7.40148683e-17 -5.92118946e-16]
  stds:    [0.99999995 0.99999999 1.         0.99999969]

After layer normalization (gamma= [3. 3. 3.] , beta= [5. 5. 5.] )
  means:   [5. 5. 5. 5.]
  stds:    [2.99999985 2.99999998 2.99999999 2.99999907]
```

In [80]:

```
# 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)

ln_param = {}
fx = lambda x: layernorm_forward(x, gamma, beta, ln_param)[0]
fg = lambda a: layernorm_forward(x, a, beta, ln_param)[0]
fb = lambda b: layernorm_forward(x, gamma, b, ln_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)

_, cache = layernorm_forward(x, gamma, beta, ln_param)
dx, dgamma, dbeta = layernorm_backward(dout, cache)

#You should expect to see relative errors between 1e-12 and 1e-8
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:  2.107279147162234e-09
dgamma error:  4.519489546032799e-12
dbeta error:  2.5842537629899423e-12
```

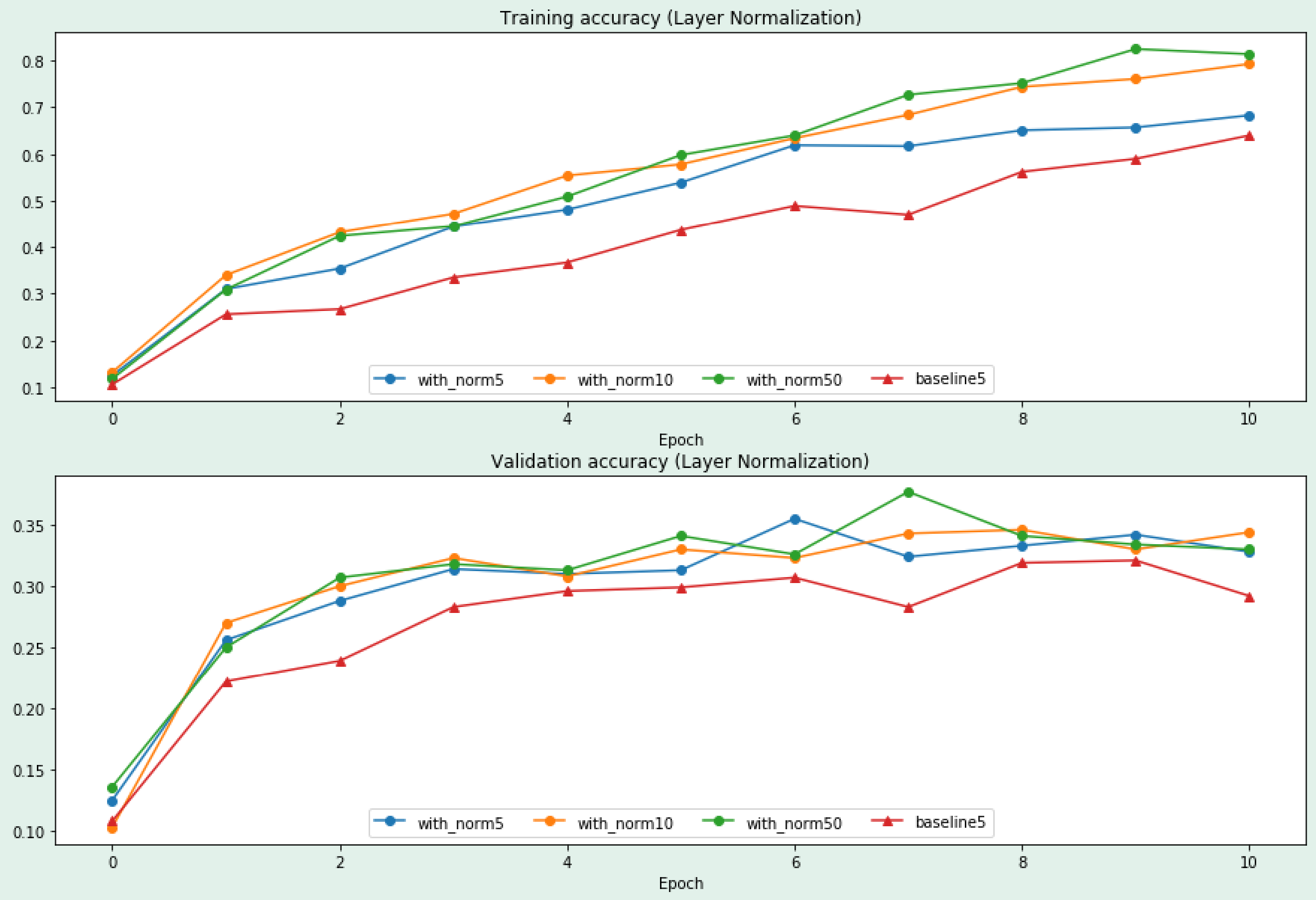
Layer Normalization and batch size

We will now run the previous batch size experiment with layer normalization instead of batch normalization. Compared to the previous experiment, you should see a markedly smaller influence of batch size on the training history!

In [82]:

```
ln_solvers_bsize, solver_bsize, batch_sizes = run_batchsize_experiments('layernorm')

plt.subplot(2, 1, 1)
plot_training_history('Training accuracy (Layer Normalization)','Epoch', solver_bsize,
ln_solvers_bsize, \
                      lambda x: x.train_acc_history, bl_marker='-^', bn_marker='-o', labels=batch_s
zes)
plt.subplot(2, 1, 2)
plot_training_history('Validation accuracy (Layer Normalization)','Epoch', solver_bsize,
ln_solvers_bsize, \
                      lambda x: x.val_acc_history, bl_marker='-^', bn_marker='-o', labels=batch_siz
s)

plt.gcf().set_size_inches(15, 10)
plt.show()
```

```
No normalization: batch size =  5
Normalization: batch size =  5
Normalization: batch size =  10
Normalization: batch size =  50
```



Inline Question 4:

When is layer normalization likely to not work well, and why?

1. Using it in a very deep network
2. Having a very small dimension of features
3. Having a high regularization term

Answer:

Option 2. Since layer normalization performs its normalization step with respect to a particular feature vector, having low-dimensional features means the effective "sample size" against which the data is being normalized is smaller, which in turn compromises the statistical robustness of the normalization being applied.

```
In [ ]:
```

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

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 [8]:

```
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:  2.5035147792443206
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:  3.991167063504464
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:  6.9914683385116
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
```

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 [7]:

```
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], x, dout)

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

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

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?

Answer:

The values must be divided by p to correct the expected value of the output. Dropout changes the expected output value from x to px + (1-p)*0=px. Therefore, to rescale back to x we have to divide out by p. This is more easily done during training time, so that the test-time run of the model can be left untouched rather than having to scale up the output at test-time by a factor of p to recover the train-time expected value of px in the case where we do not perform this division.

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 [9]:

```
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
```

```
W1 relative error: [illegible]
W2 relative error: 1.84e-08
W3 relative error: 5.35e-08
b1 relative error: 2.58e-08
b2 relative error: 2.99e-09
b3 relative error: 1.13e-10
```

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 [10]:

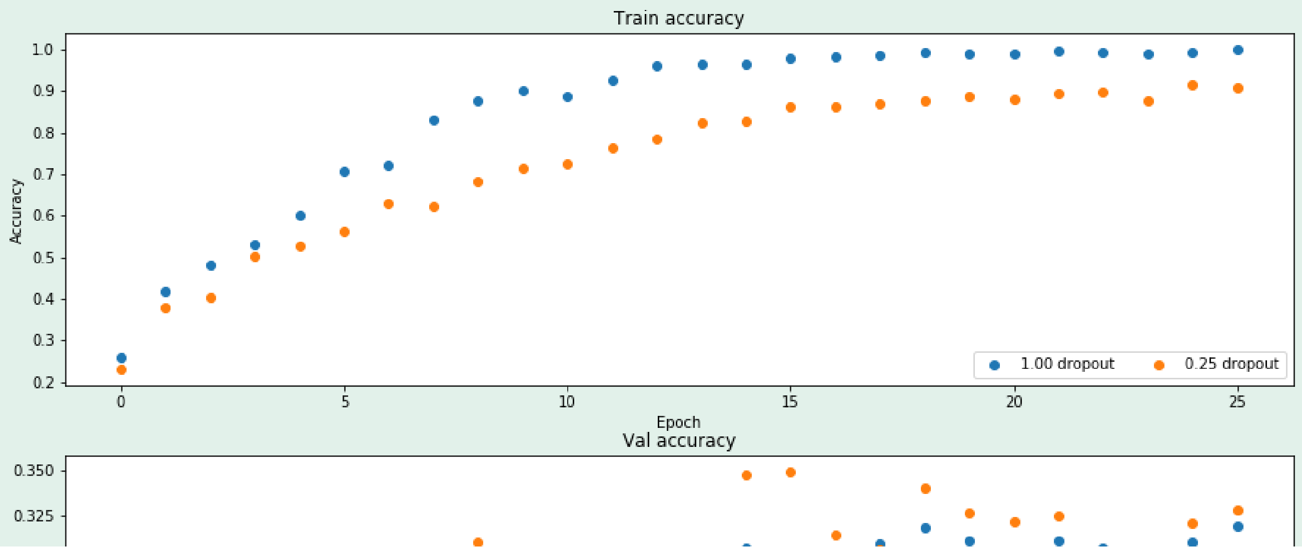
```
# Train two identical nets, one with dropout and one without
np.random.seed(231)
num_train = 500
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

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()
```

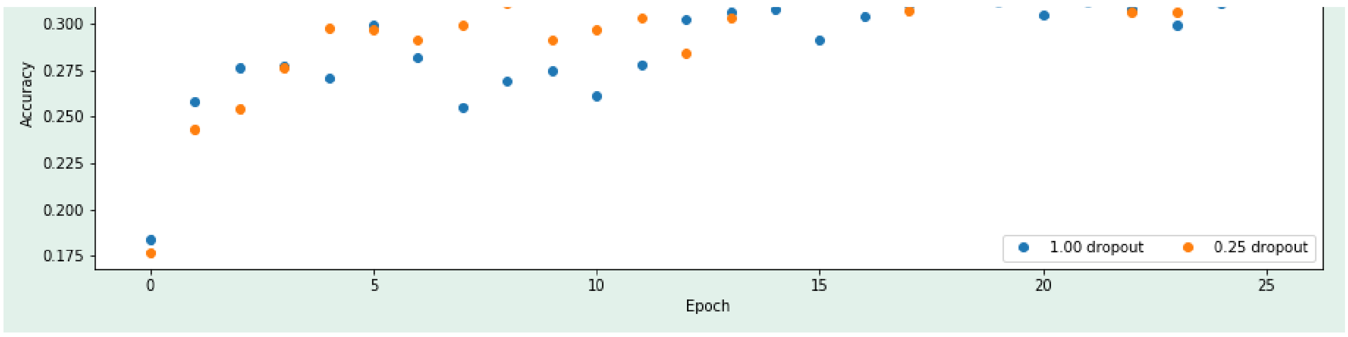
```
1
(Iteration 1 / 125) loss: 7.856644
(Epoch 0 / 25) train acc: 0.260000; val_acc: 0.184000
(Epoch 1 / 25) train acc: 0.416000; val_acc: 0.258000
(Epoch 2 / 25) train acc: 0.482000; val_acc: 0.276000
(Epoch 3 / 25) train acc: 0.532000; val_acc: 0.277000
(Epoch 4 / 25) train acc: 0.600000; val_acc: 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: 0.308000
(Epoch 15 / 25) train acc: 0.978000; val_acc: 0.291000
(Epoch 16 / 25) train acc: 0.982000; val_acc: 0.304000
(Epoch 17 / 25) train acc: 0.986000; val_acc: 0.310000
(Epoch 18 / 25) train acc: 0.994000; val_acc: 0.319000
(Epoch 19 / 25) train acc: 0.990000; val_acc: 0.312000
(Epoch 20 / 25) train acc: 0.990000; val_acc: 0.305000
(Iteration 101 / 125) loss: 0.020621
(Epoch 21 / 25) train acc: 0.998000; val_acc: 0.312000
(Epoch 22 / 25) train acc: 0.992000; val_acc: 0.308000
(Epoch 23 / 25) train acc: 0.990000; val_acc: 0.299000
(Epoch 24 / 25) train acc: 0.992000; val_acc: 0.311000
(Epoch 25 / 25) train acc: 1.000000; val_acc: 0.320000

0.25
(Iteration 1 / 125) loss: 17.318479
(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: 0.628000; val_acc: 0.291000
(Epoch 7 / 25) train acc: 0.622000; val_acc: 0.299000
(Epoch 8 / 25) train acc: 0.684000; val_acc: 0.311000
(Epoch 9 / 25) train acc: 0.714000; val_acc: 0.291000
(Epoch 10 / 25) train acc: 0.724000; val_acc: 0.297000
(Epoch 11 / 25) train acc: 0.762000; val_acc: 0.303000
(Epoch 12 / 25) train acc: 0.786000; val_acc: 0.284000
(Epoch 13 / 25) train acc: 0.824000; val_acc: 0.303000
(Epoch 14 / 25) train acc: 0.826000; val_acc: 0.347000
(Epoch 15 / 25) train acc: 0.862000; val_acc: 0.349000
(Epoch 16 / 25) train acc: 0.862000; val_acc: 0.315000
(Epoch 17 / 25) train acc: 0.870000; val_acc: 0.307000
(Epoch 18 / 25) train acc: 0.876000; val_acc: 0.340000
(Epoch 19 / 25) train acc: 0.886000; val_acc: 0.327000
(Epoch 20 / 25) train acc: 0.880000; val_acc: 0.322000
(Iteration 101 / 125) loss: 3.870114
(Epoch 21 / 25) train acc: 0.894000; val_acc: 0.325000
(Epoch 22 / 25) train acc: 0.898000; val_acc: 0.306000
(Epoch 23 / 25) train acc: 0.878000; val_acc: 0.306000
(Epoch 24 / 25) train acc: 0.914000; val_acc: 0.321000
(Epoch 25 / 25) train acc: 0.910000; val_acc: 0.328000
```

In [11]:

```python
# 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()
```





Inline Question 2:

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

Answer:

The results suggest that dropout is effective as a regularizer - from the training accuracy curve we see that implementing dropout reduces the extent to which the model overfits to the training data. We also observe a slight improvement in validation accuracy from using dropout, but the difference is very minor. Generally, we also observe that dropout becomes more effective throughout the course of training.

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)?

Answer:

If the size of the hidden layers decreases, we will want to reduce the extent of dropout (i.e. increase the dropout parameter) to counteract the decrease in size, such that the number of active nodes in each layer remains roughly constant after the dimensions of the hidden layers change.

```
In [ ]:
```

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.

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:

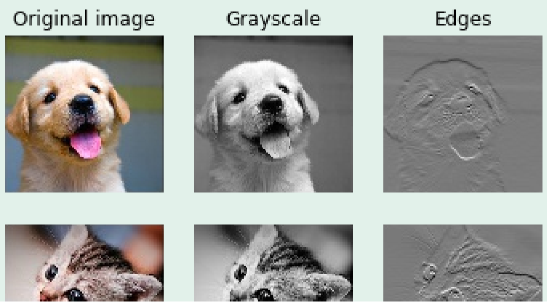
In [3]:

```
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
```

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.



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_param)[0], x, dou
t)
dw_num = eval_numerical_gradient_array(lambda w: conv_forward_naive(x, w, b, conv_param)[0], w, dou
t)
db_num = eval_numerical_gradient_array(lambda b: conv_forward_naive(x, w, b, conv_param)[0], b, dou
t)

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:  1.1597815076211182e-08
dw error:  2.2471264748452487e-10
db error:  3.37264006649648e-11
```

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
```

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)[0], x, dout)

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
```

Fast layers

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

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

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

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

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

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

In [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('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: 3.546488s
Fast: 0.019926s
Speedup: 177.982315x
Difference:  4.926407851494105e-11

Testing conv_backward_fast:
Naive: 4.741319s
Fast: 0.013335s
Speedup: 355.561094x
dx difference:  1.383704034070129e-11
dw difference:  4.4985195578905695e-13
db difference:  0.0
```

In [9]:

```
# 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: 0.325163s
fast: 0.002993s
speedup: 108.654557x
difference:  0.0

Testing pool_backward_fast:
Naive: 0.733065s
fast: 0.009947s
speedup: 73.700209x
dx difference:  0.0
```

Convolutional "sandwich" layers

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 [10]:

```
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_param, pool_p
aram)[0], x, dout)
dw_num = eval_numerical_gradient_array(lambda w: conv_relu_pool_forward(x, w, b, conv_param, pool_p
aram)[0], w, dout)
db_num = eval_numerical_gradient_array(lambda b: conv_relu_pool_forward(x, w, b, conv_param, pool_p
aram)[0], b, dout)

# 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:  6.514336569263308e-09
dw error:  1.490843753539445e-08
db error:  2.037390356217257e-09
```

In [11]:

```
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_param)[0], x, dout
)
dw_num = eval_numerical_gradient_array(lambda w: conv_relu_forward(x, w, b, conv_param)[0], w, dout
)
db_num = eval_numerical_gradient_array(lambda b: conv_relu_forward(x, w, b, conv_param)[0], b, dout
)

# 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:  3.5600610115232832e-09
dw error:  2.2497700915729298e-10
db error:  1.3087619975802167e-10
```

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:

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 [12]:

```python
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):  2.508255638232932
```

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 [13]:

```python
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=False, h=1e-6)
    e = rel_error(param_grad_num, grads[param_name])
    print('%s max relative error: %e' % (param_name, rel_error(param_grad_num, grads[param_name])))
```

```
W1 max relative error: 1.380104e-04
W2 max relative error: 1.822723e-02
W3 max relative error: 3.064049e-04
b1 max relative error: 3.477652e-05
b2 max relative error: 2.516375e-03
b3 max relative error: 7.945660e-10
```

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 [14]:

```python
np.random.seed(231)

num_train = 100
```

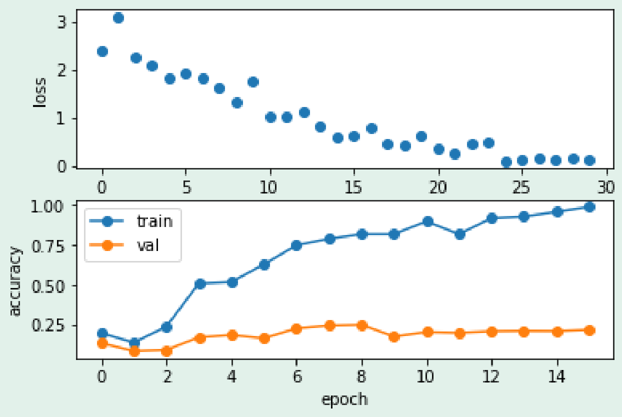
```
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}

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
```

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

In [15]:

```
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()
```



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 [16]:

```
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
```

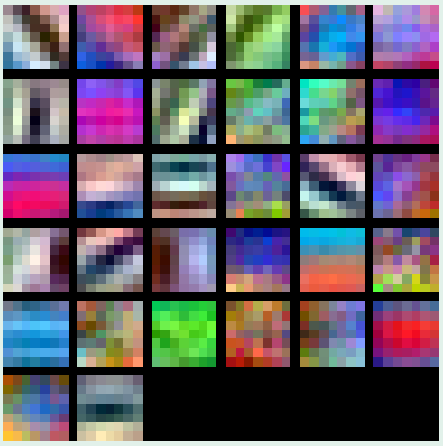
```
(Iteration 721 / 980) loss: 1.644564
(Iteration 741 / 980) loss: 1.708919
(Iteration 761 / 980) loss: 1.494252
(Iteration 781 / 980) loss: 1.901751
(Iteration 801 / 980) loss: 1.898991
(Iteration 821 / 980) loss: 1.489988
(Iteration 841 / 980) loss: 1.377615
(Iteration 861 / 980) loss: 1.763751
(Iteration 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
```

Visualize Filters

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

In [17]:

```python
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()
```



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.]

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 [18]:

```
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  7.49400542e-17 -7.21644966e-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 [19]:

```
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]
```

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 [20]:

```
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:  3.4238386124286293e-07
dgamma error:  7.096223120960538e-12
dbeta error:  3.275380797385891e-12
```

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.

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 [33]:

```
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  2.58126853e-16 -3.62672855e-16]
  Stds:  [0.99999963 0.99999948 0.99999973 0.99999968]
```

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 [31]:

```
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:  6.34590431845254e-08
dgamma error:  1.0546047434202244e-11
dbeta error:  3.810857316122484e-12
```

In [ ]:

```

```

In [ ]:

```

```

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).

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.

```
using device: cpu
```

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.

```
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]])
```

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

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.

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)*****
    _, _, h1, w1 = conv_w1.shape
    _, _, h2, w2 = conv_w2.shape

    conv1 = F.conv2d(input=x, weight=conv_w1, bias=conv_b1, padding = (h1//2, w1//2))
    act1 = F.relu(conv1)
    conv2 = F.conv2d(input=act1, weight=conv_w2, bias=conv_b2, padding = (h2//2,w2//2))
    act2 = flatten(F.relu(conv2))
    scores = act2.mm(fc_w) + fc_b
    pass

    # *****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).

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

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

Out[8]:

```
tensor([[-0.9725,  1.0698,  0.1174, -0.0421,  0.8836],
        [-2.2840, -1.3963, -0.5550, -0.1723, -0.0827],
        [-0.7593, -0.5770, -0.6039,  0.3059,  1.4289]], requires_grad=True)
```

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.

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.

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 [12]:

```
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 = 3.6670
Checking accuracy on the val set
Got 119 / 1000 correct (11.90%)

Iteration 100, loss = 2.3699
Checking accuracy on the val set
Got 306 / 1000 correct (30.60%)

Iteration 200, loss = 2.2307
Checking accuracy on the val set
Got 339 / 1000 correct (33.90%)

Iteration 300, loss = 2.2600
Checking accuracy on the val set
Got 410 / 1000 correct (41.00%)

Iteration 400, loss = 1.9158
Checking accuracy on the val set
Got 425 / 1000 correct (42.50%)

Iteration 500, loss = 1.9248
Checking accuracy on the val set
Got 438 / 1000 correct (43.80%)

Iteration 600, loss = 1.7285
Checking accuracy on the val set
```

```
Got 457 / 1000 correct (45.70%)

Iteration 700, loss = 1.7659
Checking accuracy on the val set
Got 448 / 1000 correct (44.80%)
```

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 [14]:

```python
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)*****
numClasses = 10
conv_w1 = random_weight((channel_1,3,5,5))
conv_b1=zero_weight(channel_1)

conv_w2 = random_weight((channel_2, channel_1,3,3))
conv_b2 = zero_weight(channel_2)

fc_w = random_weight((32*32*channel_2, numClasses))
fc_b = zero_weight(numClasses)
pass

# *****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 = 3.2205
Checking accuracy on the val set
Got 115 / 1000 correct (11.50%)

Iteration 100, loss = 2.1180
Checking accuracy on the val set
Got 344 / 1000 correct (34.40%)

Iteration 200, loss = 1.7351
Checking accuracy on the val set
Got 406 / 1000 correct (40.60%)

Iteration 300, loss = 1.5200
```

```
Checking accuracy on the val set
Got 430 / 1000 correct (43.00%)

Iteration 400, loss = 1.5180
Checking accuracy on the val set
Got 465 / 1000 correct (46.50%)

Iteration 500, loss = 1.6128
Checking accuracy on the val set
Got 478 / 1000 correct (47.80%)

Iteration 600, loss = 1.6658
Checking accuracy on the val set
Got 469 / 1000 correct (46.90%)

Iteration 700, loss = 1.5169
Checking accuracy on the val set
Got 497 / 1000 correct (49.70%)
```

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.

Module API: Two-Layer Network

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

In [15]:

```
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 dimension 50
    model = TwoLayerFC(input_size, 42, 10)
    scores = model(x)
    print(scores.size())  # you should see [64, 10]
test_TwoLayerFC()
```

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

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 [18]:

```
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, kernel_size=5, padding=2, stride=1)
        self.conv2 = nn.Conv2d(channel_1, channel_2, kernel_size=3, padding=1, stride=1)
        self.fcLayer = nn.Linear(32*32*channel_2, num_classes)

        nn.init.kaiming_normal_(self.conv1.weight)
        nn.init.constant_(self.conv1.bias, 0)
        nn.init.kaiming_normal_(self.conv2.weight)
        nn.init.constant_(self.conv2.bias, 0)
        nn.init.kaiming_normal_(self.fcLayer.weight)
        nn.init.constant_(self.fcLayer.bias, 0)
        pass

        # *****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)*****
        out1 = self.conv1(x)
        act1 = F.relu(out1)
        out2 = self.conv2(act1)
        act2 = F.relu(out2)
        scores = self.fcLayer(flatten(act2))
        pass

        # *****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, 32, 32]
    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])
```

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 [19]:

```
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))
```

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 [20]:

```
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()
```

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 [21]:

```
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 = 3.7428
Checking accuracy on validation set
Got 102 / 1000 correct (10.20)

Iteration 100, loss = 2.4448
Checking accuracy on validation set
Got 341 / 1000 correct (34.10)

Iteration 200, loss = 1.9244
Checking accuracy on validation set
Got 357 / 1000 correct (35.70)

Iteration 300, loss = 1.7471
Checking accuracy on validation set
Got 447 / 1000 correct (44.70)

Iteration 400, loss = 1.8054
Checking accuracy on validation set
Got 422 / 1000 correct (42.20)

Iteration 500, loss = 1.2979
Checking accuracy on validation set
Got 458 / 1000 correct (45.80)

Iteration 600, loss = 1.5525
Checking accuracy on validation set
Got 431 / 1000 correct (43.10)

Iteration 700, loss = 1.7129
Checking accuracy on validation set
Got 453 / 1000 correct (45.30)
```

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 [22]:

```
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(in_channel=3, channel_1=channel_1, channel_2=channel_2, num_classes = 10)
optimizer = optim.SGD(model.parameters(), lr=learning_rate)
pass

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

train_part34(model, optimizer)
```

```
Iteration 0, loss = 3.3002
Checking accuracy on validation set
Got 128 / 1000 correct (12.80)

Iteration 100, loss = 1.8379
Checking accuracy on validation set
Got 377 / 1000 correct (37.70)

Iteration 200, loss = 1.8600
Checking accuracy on validation set
Got 422 / 1000 correct (42.20)

Iteration 300, loss = 1.6565
Checking accuracy on validation set
Got 425 / 1000 correct (42.50)

Iteration 400, loss = 1.5057
Checking accuracy on validation set
Got 450 / 1000 correct (45.00)

Iteration 500, loss = 1.4421
Checking accuracy on validation set
Got 457 / 1000 correct (45.70)

Iteration 600, loss = 1.5413
Checking accuracy on validation set
Got 465 / 1000 correct (46.50)

Iteration 700, loss = 1.6297
Checking accuracy on validation set
Got 491 / 1000 correct (49.10)
```

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.

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 [23]:

```
# 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 = 2.3805
Checking accuracy on validation set
Got 157 / 1000 correct (15.70)

Iteration 100, loss = 1.8450
Checking accuracy on validation set
Got 366 / 1000 correct (36.60)

Iteration 200, loss = 1.7033
Checking accuracy on validation set
Got 397 / 1000 correct (39.70)

Iteration 300, loss = 1.9300
Checking accuracy on validation set
Got 404 / 1000 correct (40.40)

Iteration 400, loss = 1.6917
Checking accuracy on validation set
Got 403 / 1000 correct (40.30)

Iteration 500, loss = 1.7084
Checking accuracy on validation set
Got 415 / 1000 correct (41.50)

Iteration 600, loss = 1.7756
Checking accuracy on validation set
Got 450 / 1000 correct (45.00)

Iteration 700, loss = 1.4627
Checking accuracy on validation set
Got 456 / 1000 correct (45.60)
```

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 [26]:

```
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,stride=1), nn.ReLU(),
                      nn.Conv2d(channel_1,channel_2,3,padding=1,stride=1), nn.ReLU(),
                     Flatten(), nn.Linear(32*32*channel_2,10))
optimizer = optim.SGD(model.parameters(), lr=learning_rate,
                     momentum=0.9, nesterov=True)
pass

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

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.2832
Checking accuracy on validation set
Got 131 / 1000 correct (13.10)

Iteration 100, loss = 1.5665
Checking accuracy on validation set
Got 441 / 1000 correct (44.10)

Iteration 200, loss = 1.4066
Checking accuracy on validation set
Got 471 / 1000 correct (47.10)

Iteration 300, loss = 1.3989
Checking accuracy on validation set
Got 511 / 1000 correct (51.10)

Iteration 400, loss = 1.3234
Checking accuracy on validation set
Got 536 / 1000 correct (53.60)

Iteration 500, loss = 1.2593
Checking accuracy on validation set
Got 574 / 1000 correct (57.40)

Iteration 600, loss = 1.2449
Checking accuracy on validation set
Got 574 / 1000 correct (57.40)

Iteration 700, loss = 1.2295
Checking accuracy on validation set
Got 588 / 1000 correct (58.80)
```

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

Things you might try:

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.

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.

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

Have fun and happy training!

In [ ]:

```
################################################################################
# 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)*****

pass

# *****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)
```

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.

TODO: Describe what you did

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 [ ]:

```
best_model = model
check_accuracy_part34(loader_test, best_model)
```

What's this TensorFlow 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, TensorFlow (or PyTorch, if you choose to work with that notebook).

Part I: Preparation

First, we load the CIFAR-10 dataset. This might take a few minutes to download the first time you run it, but after that the files should be cached on disk and loading should be faster.

In previous parts of the assignment we used CS231N-specific code to download and read the CIFAR-10 dataset; however the `tf.keras.datasets` package in TensorFlow provides prebuilt utility functions for loading many common datasets.

For the purposes of this assignment we will still write our own code to preprocess the data and iterate through it in minibatches. The `tf.data` package in TensorFlow provides tools for automating this process, but working with this package adds extra complication and is beyond the scope of this notebook. However using `tf.data` can be much more efficient than the simple approach used in this notebook, so you should consider using it for your project.

In [ ]:

```
# We can iterate through a dataset like this:
for t, (x, y) in enumerate(train_dset):
    print(t, x.shape, y.shape)
    if t > 5: break
```

You can optionally **use GPU by setting the flag to True below**. It's not neccessary to use a GPU for this assignment; if you are working on Google Cloud then we recommend that you do not use a GPU, as it will be significantly more expensive.

Barebones TensorFlow: Define a Two-Layer Network

We will now implement our first neural network with TensorFlow: a fully-connected ReLU network with two hidden layers and no biases on the CIFAR10 dataset. For now we will use only low-level TensorFlow operators to define the network; later we will see how to use the higher-level abstractions provided by `tf.keras` to simplify the process.

We will define the forward pass of the network in the function `two_layer_fc` ; this will accept TensorFlow Tensors for the inputs and weights of the network, and return a TensorFlow Tensor for the scores.

After defining the network architecture in the `two_layer_fc` function, we will test the implementation by checking the shape of the output.

It's important that you read and understand this implementation.

Barebones TensorFlow: 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. 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.

HINT: For convolutions: https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/nn/conv2d; be careful with padding!

HINT: For biases: https://www.tensorflow.org/performance/xla/broadcasting

In [ ]:

```
def three_layer_convnet(x, params):
    """
    A three-layer convolutional network with the architecture described above.

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

    pass

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

After defing the forward pass of the three-layer ConvNet above, run the following cell to test your implementation. Like the two-layer network, we run the graph on a batch of zeros just to make sure the function doesn't crash, and produces outputs of the correct shape.

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

Barebones TensorFlow: Training Step

We now define the `training_step` function performs a single training step. This will take three basic steps:

1. Compute the loss
2. Compute the gradient of the loss with respect to all network weights
3. Make a weight update step using (stochastic) gradient descent.

We need to use a few new TensorFlow functions to do all of this:

- For computing the cross-entropy loss we'll use `tf.nn.sparse_softmax_cross_entropy_with_logits`: https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/nn/sparse_softmax_cross_entropy_with_logits
- For averaging the loss across a minibatch of data we'll use `tf.reduce_mean`: https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/reduce_mean
- For computing gradients of the loss with respect to the weights we'll use `tf.GradientTape` (useful for Eager execution): https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/GradientTape
- We'll mutate the weight values stored in a TensorFlow Tensor using `tf.assign_sub` ("sub" is for subtraction): https://www.tensorflow.org/api_docs/python/tf/assign_sub

Barebones TensorFlow: Initialization

We'll use the following utility method to initialize the weight matrices for our models using Kaiming's normalization method.

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

In [ ]:

```
def create_matrix_with_kaiming_normal(shape):
    if len(shape) == 2:
        fan_in, fan_out = shape[0], shape[1]
    elif len(shape) == 4:
        fan_in, fan_out = np.prod(shape[:3]), shape[3]
    return tf.keras.backend.random_normal(shape) * np.sqrt(2.0 / fan_in)
```

Barebones TensorFlow: Train a Two-Layer Network

We are finally ready to use all of the pieces defined above to train a two-layer fully-connected network on CIFAR-10.

We just need to define a function to initialize the weights of the model, and call `train_part2`.

Defining the weights of the network introduces another important piece of TensorFlow API: `tf.Variable`. A TensorFlow Variable is a Tensor whose value is stored in the graph and persists across runs of the computational graph; however unlike constants defined with `tf.zeros` or `tf.random_normal`, the values of a Variable can be mutated as the graph runs; these mutations will persist across graph runs. Learnable parameters of the network are usually stored in Variables.

You don't need to tune any hyperparameters, but you should achieve validation accuracies above 40% after one epoch of training.

In [ ]:

```
def two_layer_fc_init():
    """
    Initialize the weights of a two-layer network, for use with the
    two_layer_network function defined above.
    You can use the `create_matrix_with_kaiming_normal` helper!

    Inputs: None

    Returns: A list of:
    - w1: TensorFlow tf.Variable giving the weights for the first layer
    - w2: TensorFlow tf.Variable giving the weights for the second layer
    """
    hidden_layer_size = 4000
    w1 = tf.Variable(create_matrix_with_kaiming_normal((3 * 32 * 32, 4000)))
    w2 = tf.Variable(create_matrix_with_kaiming_normal((4000, 10)))
    return [w1, w2]

learning_rate = 1e-2
train_part2(two_layer_fc, two_layer_fc_init, learning_rate)
```

Barebones TensorFlow: Train a three-layer ConvNet

We will now use TensorFlow to train a three-layer ConvNet on CIFAR-10.

You need to implement the `three_layer_convnet_init` function. Recall that the architecture of the network is:

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

You don't need to do any hyperparameter tuning, but you should see validation accuracies above 43% after one epoch of training.

In [ ]:

```
def three_layer_convnet_init():
    """
    Initialize the weights of a Three-Layer ConvNet, for use with the
    three_layer_convnet function defined above.
    You can use the `create_matrix_with_kaiming_normal` helper!

    Inputs: None
    Returns a list containing:
    - conv_w1: TensorFlow tf.Variable giving weights for the first conv layer
    - conv_b1: TensorFlow tf.Variable giving biases for the first conv layer
    - conv_w2: TensorFlow tf.Variable giving weights for the second conv layer
    - conv_b2: TensorFlow tf.Variable giving biases for the second conv layer
    - fc_w: TensorFlow tf.Variable giving weights for the fully-connected layer
    - fc_b: TensorFlow tf.Variable giving biases for the fully-connected layer
    """
    params = None
    ############################################################################
    # TODO: Initialize the parameters of the three-layer network.              #
    ############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    pass

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

learning_rate = 3e-3
train_part2(three_layer_convnet, three_layer_convnet_init, learning_rate)
```

Keras Model Subclassing API: Three-Layer ConvNet

Now it's your turn to implement a three-layer ConvNet using the `tf.keras.Model` API. Your model should have the same architecture used in Part II:

1. Convolutional layer with 5 x 5 kernels, with zero-padding of 2
2. ReLU nonlinearity
3. Convolutional layer with 3 x 3 kernels, with zero-padding of 1
4. ReLU nonlinearity
5. Fully-connected layer to give class scores
6. Softmax nonlinearity

You should initialize the weights of your network using the same initialization method as was used in the two-layer network above.

Hint: Refer to the documentation for `tf.keras.layers.Conv2D` and `tf.keras.layers.Dense`:

https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/Conv2D

https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/Dense

In [ ]:

```
class ThreeLayerConvNet(tf.keras.Model):
    def __init__(self, channel_1, channel_2, num_classes):
        super(ThreeLayerConvNet, self).__init__()
        ########################################################################
        # TODO: Implement the __init__ method for a three-layer ConvNet. You   #
        # should instantiate layer objects to be used in the forward pass.     #
        ########################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

        pass

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

    def call(self, x, training=False):
        scores = None
        ########################################################################
        # TODO: Implement the forward pass for a three-layer ConvNet. You      #
        # should use the layer objects defined in the __init__ method.         #
        ########################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

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

Once you complete the implementation of the `ThreeLayerConvNet` above you can run the following to ensure that your implementation does not crash and produces outputs of the expected shape.

In [ ]:

```
def test_ThreeLayerConvNet():
    channel_1, channel_2, num_classes = 12, 8, 10
    model = ThreeLayerConvNet(channel_1, channel_2, num_classes)
    with tf.device(device):
        x = tf.zeros((64, 3, 32, 32))
        scores = model(x)
        print(scores.shape)

test_ThreeLayerConvNet()
```

Keras Model Subclassing API: Eager Training

While keras models have a builtin training loop (using the `model.fit`), sometimes you need more customization. Here's an example, of a training loop implemented with eager execution.

In particular, notice `tf.GradientTape`. Automatic differentiation is used in the backend for implementing backpropagation in frameworks like TensorFlow. During eager execution, `tf.GradientTape` is used to trace operations for computing gradients later. A particular `tf.GradientTape` can only compute one gradient; subsequent calls to tape will throw a runtime error.

TensorFlow 2.0 ships with easy-to-use built-in metrics under `tf.keras.metrics` module. Each metric is an object, and we can use `update_state()` to add observations and `reset_state()` to clear all observations. We can get the current result of a metric by calling `result()` on the metric object.

Keras Model Subclassing API: Train a Two-Layer Network

We can now use the tools defined above to train a two-layer network on CIFAR-10. We define the `model_init_fn` and `optimizer_init_fn` that construct the model and optimizer respectively when called. Here we want to train the model using stochastic gradient descent with no momentum, so we construct a `tf.keras.optimizers.SGD` function; you can read about it here.

You don't need to tune any hyperparameters here, but you should achieve validation accuracies above 40% after one epoch of training.

In [ ]:

```
hidden_size, num_classes = 4000, 10
learning_rate = 1e-2

def model_init_fn():
    return TwoLayerFC(hidden_size, num_classes)

def optimizer_init_fn():
    return tf.keras.optimizers.SGD(learning_rate=learning_rate)

train_part34(model_init_fn, optimizer_init_fn)
```

Keras Model Subclassing API: Train a Three-Layer ConvNet

Here you should use the tools we've defined above to train a three-layer ConvNet on CIFAR-10. Your ConvNet should use 32 filters in the first convolutional layer and 16 filters in the second layer.

To train the model you should use gradient descent with Nesterov momentum 0.9.

HINT: https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/optimizers/SGD

You don't need to perform any hyperparameter tuning, but you should achieve validation accuracies above 50% after training for one epoch

epoch.

In [ ]:

```
learning_rate = 3e-3
channel_1, channel_2, num_classes = 32, 16, 10

def model_init_fn():
    model = None
    ############################################################################
    # TODO: Complete the implementation of model_fn.                           #
    ############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    pass

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

def optimizer_init_fn():
    optimizer = None
    ############################################################################
    # TODO: Complete the implementation of model_fn.                           #
    ############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    pass

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

train_part34(model_init_fn, optimizer_init_fn)
```

Part IV: Keras Sequential API

In Part III we introduced the `tf.keras.Model` API, which allows you to define models with any number of learnable layers and with arbitrary connectivity between layers.

However for many models you don't need such flexibility - a lot of models can be expressed as a sequential stack of layers, with the output of each layer fed to the next layer as input. If your model fits this pattern, then there is an even easier way to define your model: using `tf.keras.Sequential`. You don't need to write any custom classes; you simply call the `tf.keras.Sequential` constructor with a list containing a sequence of layer objects.

One complication with `tf.keras.Sequential` is that you must define the shape of the input to the model by passing a value to the `input_shape` of the first layer in your model.

Keras Sequential API: Two-Layer Network

In this subsection, we will rewrite the two-layer fully-connected network using `tf.keras.Sequential`, and train it using the training loop defined above.

You don't need to perform any hyperparameter tuning here, but you should see validation accuracies above 40% after training for one epoch.

In [ ]:

```
learning_rate = 1e-2

def model_init_fn():
    input_shape = (32, 32, 3)
    hidden_layer_size, num_classes = 4000, 10
    initializer = tf.initializers.VarianceScaling(scale=2.0)
    layers = [
        tf.keras.layers.Flatten(input_shape=input_shape),
        tf.keras.layers.Dense(hidden_layer_size, activation='relu',
                              kernel_initializer=initializer),
        tf.keras.layers.Dense(num_classes, activation='softmax',
        tf.keras.layers.Dense(num_classes, activation='softmax',
                              kernel_initializer=initializer),
    ]
    model = tf.keras.Sequential(layers)
    return model

def optimizer_init_fn():
    return tf.keras.optimizers.SGD(learning_rate=learning_rate)

train_part34(model_init_fn, optimizer_init_fn)
```

Abstracting Away the Training Loop

In the previous examples, we used a customised training loop to train models (e.g. `train_part34`). Writing your own training loop is only required if you need more flexibility and control during training your model. Alternately, you can also use built-in APIs like `tf.keras.Model.fit()` and `tf.keras.Model.evaluate` to train and evaluate a model. Also remember to configure your model for training by calling `tf.keras.Model.compile.

You don't need to perform any hyperparameter tuning here, but you should see validation and test accuracies above 42% after training for one epoch.

In [ ]:

```
model = model_init_fn()
model.compile(optimizer=tf.keras.optimizers.SGD(learning_rate=learning_rate),
              loss='sparse_categorical_crossentropy',
              metrics=[tf.keras.metrics.sparse_categorical_accuracy])
model.fit(X_train, y_train, batch_size=64, epochs=1, validation_data=(X_val, y_val))
model.evaluate(X_test, y_test)
```

Keras Sequential API: Three-Layer ConvNet

Here you should use `tf.keras.Sequential` to reimplement the same three-layer ConvNet architecture used in Part II and Part III. As a reminder, your model should have the following architecture:

1. Convolutional layer with 32 5x5 kernels, using zero padding of 2
2. ReLU nonlinearity
3. Convolutional layer with 16 3x3 kernels, using zero padding of 1
4. ReLU nonlinearity
5. Fully-connected layer giving class scores
6. Softmax nonlinearity

You should initialize the weights of the model using a `tf.initializers.VarianceScaling` as above.

You should train the model using Nesterov momentum 0.9.

You don't need to perform any hyperparameter search, but you should achieve accuracy above 45% after training for one epoch.

In [ ]:

```
def model_init_fn():
    model = None
    ############################################################################
    # TODO: Construct a three-layer ConvNet using tf.keras.Sequential.         #
    ############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    pass

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

learning_rate = 5e-4
def optimizer_init_fn():
    optimizer = None
    ############################################################################
    # TODO: Complete the implementation of model_fn.                           #
    ############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    pass

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

train_part34(model_init_fn, optimizer_init_fn)
```

We will also train this model with the built-in training loop APIs provided by TensorFlow.

In [ ]:

```
model = model_init_fn()
model.compile(optimizer='sgd',
              loss='sparse_categorical_crossentropy',
              metrics=[tf.keras.metrics.sparse_categorical_accuracy])
model.fit(X_train, y_train, batch_size=64, epochs=1, validation_data=(X_val, y_val))
model.evaluate(X_test, y_test)
```

Part IV: Functional API

Demonstration with a Two-Layer Network

In the previous section, we saw how we can use `tf.keras.Sequential` to stack layers to quickly build simple models. But this comes at the cost of losing flexibility.

Often we will have to write complex models that have non-sequential data flows: a layer can have **multiple inputs and/or outputs**, such as stacking the output of 2 previous layers together to feed as input to a third! (Some examples are residual connections and dense blocks.)

In such cases, we can use Keras functional API to write models with complex topologies such as:

1. Multi-input models
2. Multi-output models
3. Models with shared layers (the same layer called several times)
4. Models with non-sequential data flows (e.g. residual connections)

Writing a model with Functional API requires us to create a `tf.keras.Model` instance and explicitly write input tensors and output tensors for this model.

Keras Functional API: Train a Two-Layer Network

You can now train this two-layer network constructed using the functional API.

You don't need to perform any hyperparameter tuning here, but you should see validation accuracies above 40% after training for one epoch.

In [ ]:

```
input_shape = (32, 32, 3)
hidden_size, num_classes = 4000, 10
learning_rate = 1e-2

def model_init_fn():
    return two_layer_fc_functional(input_shape, hidden_size, num_classes)

def optimizer_init_fn():
    return tf.keras.optimizers.SGD(learning_rate=learning_rate)

train_part34(model_init_fn, optimizer_init_fn)
```

Part V: CIFAR-10 open-ended challenge

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

You should experiment with architectures, hyperparameters, loss functions, regularization, or anything else you can think of to train a

You should experiment with architectures, hyperparameters, loss functions, regularization, or anything else you can think of to train a model that achieves **at least 70%** accuracy on the **validation** set within 10 epochs. You can use the built-in train function, the `train_part34` function from above, or implement your own training loop.

Describe what you did at the end of the notebook.

Some things you can try:

- **Filter size**: Above we used 5x5 and 3x3; is this optimal?
- **Number of filters**: Above we used 16 and 32 filters. Would more or fewer do better?
- **Pooling**: We didn't use any pooling above. Would this improve the model?
- **Normalization**: Would your model be improved with batch normalization, layer normalization, group normalization, or some other normalization strategy?
- **Network architecture**: The ConvNet above has only three layers of trainable parameters. Would a deeper model do better?
- **Global average pooling**: Instead of flattening after the final convolutional layer, would global average pooling do better? This strategy is used for example in Google's Inception network and in Residual Networks.
- **Regularization**: Would some kind of regularization improve performance? Maybe weight decay or dropout?

NOTE: Batch Normalization / Dropout

If you are using Batch Normalization and Dropout, remember to pass `is_training=True` if you use the `train_part34()` function. BatchNorm and Dropout layers have different behaviors at training and inference time. `training` is a specific keyword argument reserved for this purpose in any `tf.keras.Model`'s `call()` function. Read more about this here :
https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/BatchNormalization#methods
https://www.tensorflow.org/versions/r2.0/api_docs/python/tf/keras/layers/Dropout#methods

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.

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

Have fun and happy training!

In [ ]:

```
class CustomConvNet(tf.keras.Model):
    def __init__(self):
        super(CustomConvNet, self).__init__()
        ############################################################################
        # TODO: Construct a model that performs well on CIFAR-10                   #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

        pass

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

    def call(self, input_tensor, training=False):
        ############################################################################
        # TODO: Construct a model that performs well on CIFAR-10                   #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

        pass

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

        return x

device = '/device:GPU:0'   # Change this to a CPU/GPU as you wish!
# device = '/cpu:0'        # Change this to a CPU/GPU as you wish!
print_every = 700
num_epochs = 10

model = CustomConvNet()

def model_init_fn():
    return CustomConvNet()

def optimizer_init_fn():
    learning_rate = 1e-3
    return tf.keras.optimizers.Adam(learning_rate)

train_part34(model_init_fn, optimizer_init_fn, num_epochs=num_epochs, is_training=True)
```

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.

TODO: Tell us what you did

1 layers.py

```python
from builtins import range
import numpy as np


def affine_forward(x, w, b):
    """
    Computes the forward pass for an affine (fully-connected) layer.

    The input x has shape (N, d_1, ..., d_k) and contains a minibatch of N
    examples, where each example x[i] has shape (d_1, ..., d_k). We will
    reshape each input into a vector of dimension D = d_1 * ... * d_k, and
    then transform it to an output vector of dimension M.

    Inputs:
    - x: A numpy array containing input data, of shape (N, d_1, ..., d_k)
    - w: A numpy array of weights, of shape (D, M)
    - b: A numpy array of biases, of shape (M,)

    Returns a tuple of:
    - out: output, of shape (N, M)
    - cache: (x, w, b)
    """
    out = None
    ###########################################################################
    # TODO: Implement the affine forward pass. Store the result in out. You   #
    # will need to reshape the input into rows.                               #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    # Flatten the images so that we have a Nsamples x d 2D matrix
    resh = x.reshape(x.shape[0], -1)
    out = np.dot(resh, w) + b
    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                             END OF YOUR CODE                            #
    ###########################################################################
    cache = (x, w, b)
    return out, cache


def affine_backward(dout, cache):
    """
    Computes the backward pass for an affine layer.

    Inputs:
    - dout: Upstream derivative, of shape (N, M)
    - cache: Tuple of:
      - x: Input data, of shape (N, d_1, ... d_k)
      - w: Weights, of shape (D, M)
      - b: Biases, of shape (M,)

    Returns a tuple of:
    - dx: Gradient with respect to x, of shape (N, d1, ..., d_k)
    - dw: Gradient with respect to w, of shape (D, M)
    - db: Gradient with respect to b, of shape (M,)
    """
    x, w, b = cache
    dx, dw, db = None, None, None
    ###########################################################################
    # TODO: Implement the affine backward pass.                               #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    # dx
    # Dimensions: dout = (N,M), w^T=(M,D) result = NxD
    dx = np.dot(dout, w.T)
    # Reshape back to original x dims
    dx = dx.reshape(x.shape)
    # dw
    # x dot dout (NxM) (MxN)
    resh = x.reshape(x.shape[0], -1)
    dw = np.dot(resh.T, dout)
    # db - column-major sum across dout
    db = np.sum(dout, axis = 0)

    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                             END OF YOUR CODE                            #
    ###########################################################################
    return dx, dw, db


def relu_forward(x):
    """
    Computes the forward pass for a layer of rectified linear units (ReLUs).

    Input:
    - x: Inputs, of any shape

    Returns a tuple of:
    - out: Output, of the same shape as x
    - cache: x
    """
    out = None
    ###########################################################################
    # TODO: Implement the ReLU forward pass.                                  #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    out = np.maximum(x, 0)
    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                             END OF YOUR CODE                            #
    ###########################################################################
    cache = x
    return out, cache


def relu_backward(dout, cache):
    """
    Computes the backward pass for a layer of rectified linear units (ReLUs).

    Input:
    - dout: Upstream derivatives, of any shape
    - cache: Input x, of same shape as dout

    Returns:
    - dx: Gradient with respect to x
    """
    dx, x = None, cache
    ###########################################################################
    # TODO: Implement the ReLU backward pass.                                 #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

    # Apply mask to input x to see which are activated by ReLU
    xMask = 1*(x > 0)
    # Multiply by upstream dout for derivatives
    dx = dout*xMask
    pass

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


def batchnorm_forward(x, gamma, beta, bn_param):
    """
    Forward pass for batch normalization.

    During training the sample mean and (uncorrected) sample variance are
    computed from minibatch statistics and used to normalize the incoming data.
    During training we also keep an exponentially decaying running mean of the
    mean and variance of each feature, and these averages are used to normalize
    data at test-time.

    At each timestep we update the running averages for mean and variance using
    an exponential decay based on the momentum parameter:

    running_mean = momentum * running_mean + (1 - momentum) * sample_mean
    running_var = momentum * running_var + (1 - momentum) * sample_var

    Note that the batch normalization paper suggests a different test-time
    behavior: they compute sample mean and variance for each feature using a
    large number of training images rather than using a running average. For
    this implementation we have chosen to use running averages instead since
    they do not require an additional estimation step; the torch7
    implementation of batch normalization also uses running averages.

    Input:
    - x: Data of shape (N, D)
    - gamma: Scale parameter of shape (D,)
    - beta: Shift paremeter of shape (D,)
    - bn_param: Dictionary with the following keys:
      - mode: 'train' or 'test'; required
      - eps: Constant for numeric stability
      - momentum: Constant for running mean / variance.
      - running_mean: Array of shape (D,) giving running mean of features
      - running_var Array of shape (D,) giving running variance of features

    Returns a tuple of:
    - out: of shape (N, D)
    - cache: A tuple of values needed in the backward pass
    """
    mode = bn_param['mode']
    eps = bn_param.get('eps', 1e-5)
    momentum = bn_param.get('momentum', 0.9)

    N, D = x.shape
    running_mean = bn_param.get('running_mean', np.zeros(D, dtype=x.dtype))
    running_var = bn_param.get('running_var', np.zeros(D, dtype=x.dtype))

    out, cache = None, None
    if mode == 'train':
        #######################################################################
        # TODO: Implement the training-time forward pass for batch norm.      #
        # Use minibatch statistics to compute the mean and variance, use      #
        # these statistics to normalize the incoming data, and scale and      #
        # shift the normalized data using gamma and beta.                     #
        #                                                                     #
        # You should store the output in the variable out. Any intermediates  #
        # that you need for the backward pass should be stored in the cache   #
        # variable.                                                           #
        #                                                                     #
        # You should also use your computed sample mean and variance together #
        # with the momentum variable to update the running mean and running   #
        # variance, storing your result in the running_mean and running_var   #
        # variables.                                                          #
        #                                                                     #
        # Note that though you should be keeping track of the running         #
        # variance, you should normalize the data based on the standard       #
        # deviation (square root of variance) instead!                        #
        # Referencing the original paper (https://arxiv.org/abs/1502.03167)   #
        # might prove to be helpful.                                          #
        #######################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        # Calculate standard normal variable Z
        mean = np.mean(x, axis=0)
        var = np.var(x, axis=0)
        varDenom = 1./np.sqrt(var+eps)

        xdev = x - mean
        xhat = xdev*varDenom

        # Scale and shift
        out = gamma*xhat + beta

        # Update running mean and variance
        running_mean = momentum*running_mean + (1-momentum)*mean
        running_var = momentum*running_var + (1-momentum)*var

        cache = (xhat, xdev, var, varDenom, gamma, eps)
        pass

        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        #######################################################################
        #                          END OF YOUR CODE                           #
        #######################################################################
    elif mode == 'test':
        #######################################################################
        # TODO: Implement the test-time forward pass for batch normalization. #
        # Use the running mean and variance to normalize the incoming data,   #
        # then scale and shift the normalized data using gamma and beta.      #
        # Store the result in the out variable.                               #
        #######################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

        Z = (x-running_mean)/np.sqrt(running_var+eps)
        out = gamma*Z + beta
        pass

        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        #######################################################################
        #                          END OF YOUR CODE                           #
        #######################################################################
    else:
        raise ValueError('Invalid forward batchnorm mode "%s"' % mode)

    # Store the updated running means back into bn_param
    bn_param['running_mean'] = running_mean
    bn_param['running_var'] = running_var

    return out, cache


def batchnorm_backward(dout, cache):
    """
    Backward pass for batch normalization.

    For this implementation, you should write out a computation graph for
    batch normalization on paper and propagate gradients backward through
    intermediate nodes.

    Inputs:
    - dout: Upstream derivatives, of shape (N, D)
    - cache: Variable of intermediates from batchnorm_forward.

    Returns a tuple of:
    - dx: Gradient with respect to inputs x, of shape (N, D)
    - dgamma: Gradient with respect to scale parameter gamma, of shape (D,)
    - dbeta: Gradient with respect to shift parameter beta, of shape (D,)
    """
    dx, dgamma, dbeta = None, None, None
    ###########################################################################
    # TODO: Implement the backward pass for batch normalization. Store the    #
    # results in the dx, dgamma, and dbeta variables.                         #
    # Referencing the original paper (https://arxiv.org/abs/1502.03167)       #
    # might prove to be helpful.                                              #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    N,D = dout.shape

    # Pull intermediates from the cache
    xhat, xdev, var, varDenom, gamma, eps = cache

    # First, dbeta and dgamma w.r.t output
    # Addition gate for beta: mult by 1
    dbeta = np.sum(dout, axis=0)
    # Mult gate for gamma: Multiply by other variable
    # Don't sum for dxhat since dims are NxD
    dgamma = np.sum(dout*xhat, axis=0)
    dxhat = dout*gamma

    # Mult gate for Z calc ((x-mu)*(1/var)) i.e. xdev*varDenom
    # Don't sum dxdev since it's NxD
    dxdev = dxhat*varDenom
    dvarDenom = np.sum(dxhat*xdev, axis=0)

    # Reciprocal gate for variance, grad is -1/u^2 * du
    dsqVar = (-1./np.sqrt(var+eps)**2)*dvarDenom

    # Square root gate for var + eps, grad is 1/2sqrt(u) * du
    dvar = (0.5*1./np.sqrt(var+eps))*dsqVar

    # Sigma gate for mean calculation
    dsigma = (1./N)*np.ones((N,D))*dvar

    # Square gate for variance calculation. Grad is 2u*du
    dxdev2 = 2*xdev*dsigma

    # Subtraction gate for mean-centering (x - mu)
    # has two outputs - one to go into variance, one to go into normalization calc
    # First, backprop gradient from both the output branches (i.e. both xdevs resulting from this
    subtraction)
    dx1 = dxdev + dxdev2
    # Then take dmean of subtraction gate
    dmean = -1.*np.sum(dx1, axis=0)

    # Sigma gate for other xdev
    dsigma2 = (1./N)*np.ones((N,D))*dmean

    # Add together
    dx = dx1 + dsigma2


    pass

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

    return dx, dgamma, dbeta


def batchnorm_backward_alt(dout, cache):
    """
    Alternative backward pass for batch normalization.

    For this implementation you should work out the derivatives for the batch
    normalizaton backward pass on paper and simplify as much as possible. You
    should be able to derive a simple expression for the backward pass.
    See the jupyter notebook for more hints.

    Note: This implementation should expect to receive the same cache variable
    as batchnorm_backward, but might not use all of the values in the cache.

    Inputs / outputs: Same as batchnorm_backward
    """
    dx, dgamma, dbeta = None, None, None
    ###########################################################################
    # TODO: Implement the backward pass for batch normalization. Store the    #
    # results in the dx, dgamma, and dbeta variables.                         #
    #                                                                         #
    # After computing the gradient with respect to the centered inputs, you   #
    # should be able to compute gradients with respect to the inputs in a     #
    # single statement; our implementation fits on a single 80-character line.#
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    N,D = dout.shape
    xhat, xdev, var, varDenom, gamma, eps = cache

    dxhat = dout*gamma

    dx = (1./N)*varDenom*(N*dxhat - np.sum(dxhat, axis=0) - xhat*np.sum(dxhat*xhat, axis=0))
    dbeta = np.sum(dout,axis=0)
    dgamma = np.sum(xhat*dout,axis=0)

    pass

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

    return dx, dgamma, dbeta


def layernorm_forward(x, gamma, beta, ln_param):
    """
    Forward pass for layer normalization.

    During both training and test-time, the incoming data is normalized per data-point,
    before being scaled by gamma and beta parameters identical to that of batch normalization.

    Note that in contrast to batch normalization, the behavior during train and test-time for
    layer normalization are identical, and we do not need to keep track of running averages
    of any sort.

    Input:
    - x: Data of shape (N, D)
    - gamma: Scale parameter of shape (D,)
    - beta: Shift paremeter of shape (D,)
    - ln_param: Dictionary with the following keys:
        - eps: Constant for numeric stability

    Returns a tuple of:
    - out: of shape (N, D)
    - cache: A tuple of values needed in the backward pass
    """
    out, cache = None, None
    eps = ln_param.get('eps', 1e-5)
    ###########################################################################
    # TODO: Implement the training-time forward pass for layer norm.          #
    # Normalize the incoming data, and scale and  shift the normalized data   #
    #  using gamma and beta.                                                  #
    # HINT: this can be done by slightly modifying your training-time         #
    # implementation of  batch normalization, and inserting a line or two of  #
    # well-placed code. In particular, can you think of any matrix            #
    # transformations you could perform, that would enable you to copy over   #
    # the batch norm code and leave it almost unchanged?                      #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    # Compute mean and variance
    mean = np.mean(x, axis=1)
    var = np.var(x, axis=1)

    # Compute Z
    x = x.T
    xdev = x - mean
    varDenom = 1./np.sqrt(var+eps)
    xhat = xdev*varDenom
    xhat = xhat.T
    out = gamma*xhat + beta

    cache = (xhat, xdev, var, varDenom, gamma, eps)
    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                              END OF YOUR CODE                           #
    ###########################################################################
    return out, cache


def layernorm_backward(dout, cache):
    """
    Backward pass for layer normalization.

    For this implementation, you can heavily rely on the work you've done already
    for batch normalization.

    Inputs:
    - dout: Upstream derivatives, of shape (N, D)
    - cache: Variable of intermediates from layernorm_forward.

    Returns a tuple of:
```

```
    - dx: Gradient with respect to inputs x, of shape (N, D)
    - dgamma: Gradient with respect to scale parameter gamma, of shape (D,)
    - dbeta: Gradient with respect to shift parameter beta, of shape (D,)
    """
    dx, dgamma, dbeta = None, None, None
    ###########################################################################
    # TODO: Implement the backward pass for layer norm.                       #
    #                                                                         #
    # HINT: this can be done by slightly modifying your training-time         #
    # implementation of batch normalization. The hints to the forward pass    #
    # still apply!                                                            #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    xhat, xdev, var, varDenom, gamma, eps = cache


    # dbeta and gamma @ output
    dbeta = np.sum(dout, axis=0)
    dgamma = np.sum(xhat*dout, axis=0)
    dxhat = dout*gamma

    xhat = xhat.T
    dxhat = dxhat.T
    N,D = xhat.shape
    dx = (1./N)*varDenom*(N*dxhat - np.sum(dxhat, axis=0) - xhat*np.sum(dxhat*xhat, axis=0))
    dx = dx.T
    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                             END OF YOUR CODE                            #
    ###########################################################################
    return dx, dgamma, dbeta


def dropout_forward(x, dropout_param):
    """
    Performs the forward pass for (inverted) dropout.

    Inputs:
    - x: Input data, of any shape
    - dropout_param: A dictionary with the following keys:
      - p: Dropout parameter. We keep each neuron output with probability p.
      - mode: 'test' or 'train'. If the mode is train, then perform dropout;
        if the mode is test, then just return the input.
      - seed: Seed for the random number generator. Passing seed makes this
        function deterministic, which is needed for gradient checking but not
        in real networks.

    Outputs:
    - out: Array of the same shape as x.
    - cache: tuple (dropout_param, mask). In training mode, mask is the dropout
      mask that was used to multiply the input; in test mode, mask is None.

    NOTE: Please implement **inverted** dropout, not the vanilla version of dropout.
    See http://cs231n.github.io/neural-networks-2/#reg for more details.

    NOTE 2: Keep in mind that p is the probability of **keep** a neuron
    output; this might be contrary to some sources, where it is referred to
    as the probability of dropping a neuron output.
    """
    p, mode = dropout_param['p'], dropout_param['mode']
    if 'seed' in dropout_param:
        np.random.seed(dropout_param['seed'])

    mask = None
    out = None

    if mode == 'train':
        #######################################################################
        # TODO: Implement training phase forward pass for inverted dropout.   #
        # Store the dropout mask in the mask variable.                        #
        #######################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        dims = x.shape

        mask = (np.random.rand(*dims) < p)
        # Normalize
        mask = mask / p
        out = x*mask
        pass

        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ###########################################################################
        #                            END OF YOUR CODE                             #
        ###########################################################################
    elif mode == 'test':
        ###########################################################################
        # TODO: Implement the test phase forward pass for inverted dropout.      #
        ###########################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        # Do not apply dropout for testing
        out = x
        pass

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

    cache = (dropout_param, mask)
    out = out.astype(x.dtype, copy=False)

    return out, cache


def dropout_backward(dout, cache):
    """
    Perform the backward pass for (inverted) dropout.

    Inputs:
    - dout: Upstream derivatives, of any shape
    - cache: (dropout_param, mask) from dropout_forward.
    """
    dropout_param, mask = cache
    mode = dropout_param['mode']

    dx = None
    if mode == 'train':
        ###########################################################################
        # TODO: Implement training phase backward pass for inverted dropout      #
        ###########################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        dx = dout*mask
        pass

        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        ###########################################################################
        #                            END OF YOUR CODE                             #
        ###########################################################################
    elif mode == 'test':
        dx = dout
    return dx


def conv_forward_naive(x, w, b, conv_param):
    """
    A naive implementation of the forward pass for a convolutional layer.

    The input consists of N data points, each with C channels, height H and
    width W. We convolve each input with F different filters, where each filter
    spans all C channels and has height HH and width WW.

    Input:
    - x: Input data of shape (N, C, H, W)
    - w: Filter weights of shape (F, C, HH, WW)
    - b: Biases, of shape (F,)
    - conv_param: A dictionary with the following keys:
      - 'stride': The number of pixels between adjacent receptive fields in the
        horizontal and vertical directions.
      - 'pad': The number of pixels that will be used to zero-pad the input.

    During padding, 'pad' zeros should be placed symmetrically (i.e equally on both sides)
    along the height and width axes of the input. Be careful not to modfiy the original
    input x directly.

    Returns a tuple of:
    - out: Output data, of shape (N, F, H', W') where H' and W' are given by
      H' = 1 + (H + 2 * pad - HH) / stride
      W' = 1 + (W + 2 * pad - WW) / stride
    - cache: (x, w, b, conv_param)
    """
    out = None
    ###########################################################################
    # TODO: Implement the convolutional forward pass.                         #
    # Hint: you can use the function np.pad for padding.                      #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    # Unpack sizes
    N, C, H, W = x.shape
    F, C, HH, WW = w.shape

    # Unpack parameters
    pad = conv_param["pad"]
    stride = conv_param["stride"]

    # Compute output vol
    Hprime = np.int((H + 2*pad - HH)/stride) + 1
    Wprime = np.int((W + 2*pad - WW)/stride) + 1

    # Apply padding to image (only on the planar dimension)
    pads = ((0,0), (0,0), (pad,pad), (pad,pad))
    xPad = np.pad(x, pads, mode="constant")

    # Initialize out
    out = np.zeros((N, F, Hprime, Wprime))

    # Slide the filter masks across the image
    # Go through each point
    for point in range(N):
        # SLide along height
        for py in range(Hprime):
            # Start of window jumps by the stride
            h_i = py*stride
            # End is start + height of filter mask
            h_f = h_i + HH
            for px in range(Wprime):
                # Analogoous for width
                w_i = px*stride
                w_f = w_i + WW
                # Pull the mask region for that point using the h and w windows
                mask_region = xPad[point,:,w_i:w_f,h_i:h_f]
                # Iterate through the filters and apply weights
                for f in range(F):
                    # Pull weights for the f-th filter
                    filtWeights = w[f,:,:,:]
                    # Calculate result + bias, store in out
                    out[point, f, px, py] = np.sum(filtWeights*mask_region) + b[f]

    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                             END OF YOUR CODE                            #
    ###########################################################################
    cache = (x, w, b, conv_param)
    return out, cache


def conv_backward_naive(dout, cache):
    """
    A naive implementation of the backward pass for a convolutional layer.

    Inputs:
    - dout: Upstream derivatives.
    - cache: A tuple of (x, w, b, conv_param) as in conv_forward_naive

    Returns a tuple of:
    - dx: Gradient with respect to x
    - dw: Gradient with respect to w
    - db: Gradient with respect to b
    """
    dx, dw, db = None, None, None
    ###########################################################################
    # TODO: Implement the convolutional backward pass.                        #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    # Unpack the cache
    x, w, b, conv_param = cache

    pad = conv_param["pad"]
    stride = conv_param["stride"]

    N, C, H, W = x.shape
    F, C, HH, WW, = w.shape

    # Get output sizes from upstream
    _, _, Hprime, Wprime = dout.shape

    # Apply padding
    pads = ((0,0), (0,0), (pad, pad), (pad, pad))
    xPad = np.pad(x, pads, mode="constant")
    dxPad = np.zeros(xPad.shape)

    dx = np.zeros(x.shape)
    dw = np.zeros(w.shape)
    db = np.sum(dout, axis=(0,2,3))

    for point in range(N):
        for py in range(Hprime):
            h_i = py*stride
            h_f = h_i + HH
            for px in range(Wprime):
                w_i = px*stride
                w_f = w_i + WW
                mask_region = xPad[point,:,h_i:h_f,w_i:w_f]
                for f in range(F):
                    # Propagate the gradients
                    dw[f] = dw[f] + mask_region*dout[point, f, py, px]
                    dxPad[point, :, h_i:h_f, w_i:w_f] = dxPad[point, :, h_i:h_f, w_i:w_f] + w[f]*dout[
    point, f, py, px]

    # Undo the padding for the final dx
    dx = dxPad[:, :, pad:-pad, pad:-pad]


    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                             END OF YOUR CODE                            #
    ###########################################################################
    return dx, dw, db


def max_pool_forward_naive(x, pool_param):
    """
    A naive implementation of the forward pass for a max-pooling layer.

    Inputs:
    - x: Input data, of shape (N, C, H, W)
    - pool_param: dictionary with the following keys:
      - 'pool_height': The height of each pooling region
      - 'pool_width': The width of each pooling region
      - 'stride': The distance between adjacent pooling regions

    No padding is necessary here. Output size is given by

    Returns a tuple of:
    - out: Output data, of shape (N, C, H', W') where H' and W' are given by
      H' = 1 + (H - pool_height) / stride
      W' = 1 + (W - pool_width) / stride
    - cache: (x, pool_param)
    """
    out = None
    ###########################################################################
    # TODO: Implement the max-pooling forward pass                            #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    hPool = pool_param["pool_height"]
    wPool = pool_param["pool_width"]
    stride = pool_param["stride"]
    N, C, H, W = x.shape

    Hprime = 1 + np.int((H-hPool)/stride)
    Wprime = 1 + np.int((W-wPool)/stride)

    out = np.zeros((N, C, Hprime, Wprime))

    for point in range(N):
        for chan in range(C):
            for py in range(Hprime):
                h_i = py*stride
                h_f = h_i + hPool
                for px in range(Wprime):
                    w_i = px*stride
                    w_f = w_i + wPool
                    # Form the region and pool over it by taking the max
                    poolRegion = x[point, chan, h_i:h_f, w_i:w_f]
                    out[point, chan, py, px] = np.max(poolRegion)


    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                             END OF YOUR CODE                            #
    ###########################################################################
    cache = (x, pool_param)
    return out, cache


def max_pool_backward_naive(dout, cache):
    """
    A naive implementation of the backward pass for a max-pooling layer.

    Inputs:
    - dout: Upstream derivatives
    - cache: A tuple of (x, pool_param) as in the forward pass.

    Returns:
    - dx: Gradient with respect to x
    """
    dx = None
    ###########################################################################
    # TODO: Implement the max-pooling backward pass                           #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    x, pool_param = cache
    hPool = pool_param["pool_height"]
    wPool = pool_param["pool_width"]
    stride = pool_param["stride"]
    N,C,H,W = x.shape

    _, _, Hprime, Wprime = dout.shape

    dx = np.zeros(x.shape)

    for point in range(N):
        for chan in range(C):
            for py in range(Hprime):
                h_i = py*stride
                h_f = h_i + hPool
                for px in range(Wprime):
                    w_i = px*stride
                    w_f = w_i + wPool
                    # Apply the max-pool mask and propagate upwards by dout multiplication
                    poolRegion = x[point, chan, h_i:h_f, w_i:w_f]
                    mask = (poolRegion == np.max(poolRegion))
                    dx[point, chan, h_i:h_f, w_i:w_f] = dout[point, chan, py, px]*mask

    pass

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


def spatial_batchnorm_forward(x, gamma, beta, bn_param):
    """
    Computes the forward pass for spatial batch normalization.

    Inputs:
    - x: Input data of shape (N, C, H, W)
    - gamma: Scale parameter, of shape (C,)
    - beta: Shift parameter, of shape (C,)
    - bn_param: Dictionary with the following keys:
      - mode: 'train' or 'test'; required
      - eps: Constant for numeric stability
      - momentum: Constant for running mean / variance. momentum=0 means that
        old information is discarded completely at every time step, while
        momentum=1 means that new information is never incorporated. The
        default of momentum=0.9 should work well in most situations.
      - running_mean: Array of shape (D,) giving running mean of features
      - running_var Array of shape (D,) giving running variance of features

    Returns a tuple of:
    - out: Output data, of shape (N, C, H, W)
    - cache: Values needed for the backward pass
    """
    out, cache = None, None

    ###########################################################################
    # TODO: Implement the forward pass for spatial batch normalization.       #
    #                                                                         #
    # HINT: You can implement spatial batch normalization by calling the      #
    # vanilla version of batch normalization you implemented above.           #
    # Your implementation should be very short; ours is less than five lines. #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    N, C, H, W = x.shape
    # Transform x for batch normalization
    # First change dims to (N,W,H,C) then flatten by channel
    x = x.transpose((0, 3, 2, 1))
    x = x.reshape(N*H*W, C)
    out, cache = batchnorm_forward(x,gamma,beta,bn_param)
    out = out.reshape(N,W,H,C)
    out = out.transpose((0,3,2,1))
    pass

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

    return out, cache


def spatial_batchnorm_backward(dout, cache):
    """
    Computes the backward pass for spatial batch normalization.

    Inputs:
    - dout: Upstream derivatives, of shape (N, C, H, W)
    - cache: Values from the forward pass

    Returns a tuple of:
    - dx: Gradient with respect to inputs, of shape (N, C, H, W)
    - dgamma: Gradient with respect to scale parameter, of shape (C,)
    - dbeta: Gradient with respect to shift parameter, of shape (C,)
    """
    dx, dgamma, dbeta = None, None, None

```

```python
    ###########################################################################
    # TODO: Implement the backward pass for spatial batch normalization.      #
    #                                                                         #
    # HINT: You can implement spatial batch normalization by calling the      #
    # vanilla version of batch normalization you implemented above.           #
    # Your implementation should be very short; ours is less than five lines. #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    N, C, H, W = dout.shape

    dout = dout.transpose((0,3,2,1))
    dout = dout.reshape(N*H*W,C)
    dx, dgamma, dbeta = batchnorm_backward(dout, cache)
    dx = dx.reshape(N,W,H,C)
    dx = dx.transpose((0,3,2,1))

    pass

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

    return dx, dgamma, dbeta


def spatial_groupnorm_forward(x, gamma, beta, G, gn_param):
    """
    Computes the forward pass for spatial group normalization.
    In contrast to layer normalization, group normalization splits each entry
    in the data into G contiguous pieces, which it then normalizes independently.
    Per feature shifting and scaling are then applied to the data, in a manner identical to that of batch
    normalization and layer normalization.

    Inputs:
    - x: Input data of shape (N, C, H, W)
    - gamma: Scale parameter, of shape (C,)
    - beta: Shift parameter, of shape (C,)
    - G: Integer mumber of groups to split into, should be a divisor of C
    - gn_param: Dictionary with the following keys:
      - eps: Constant for numeric stability

    Returns a tuple of:
    - out: Output data, of shape (N, C, H, W)
    - cache: Values needed for the backward pass
    """
    out, cache = None, None
    eps = gn_param.get('eps',1e-5)
    ###########################################################################
    # TODO: Implement the forward pass for spatial group normalization.       #
    # This will be extremely similar to the layer norm implementation.        #
    # In particular, think about how you could transform the matrix so that   #
    # the bulk of the code is similar to both train-time batch normalization  #
    # and layer normalization!                                                #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    N,C,H,W = x.shape
    # Reshape so that layernorm code can be used
    newDims = (N*G, (C//G)*W*H)
    x = x.reshape(newDims)
    # Perform normalization using layernorm function
    out, cache = layernorm_forward(x=x,gamma=1,beta=0,ln_param=gn_param)
    out = out.reshape(N,C,H,W)
    out = gamma*out + beta

    # Update cache values
    xhat, xdev, var, varDenom, _, eps = cache
    cache = (xhat, xdev, var, varDenom, gamma, beta, eps, G)
    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                             END OF YOUR CODE                            #
    ###########################################################################
    return out, cache

```

```python

def spatial_groupnorm_backward(dout, cache):
    """
    Computes the backward pass for spatial group normalization.

    Inputs:
    - dout: Upstream derivatives, of shape (N, C, H, W)
    - cache: Values from the forward pass

    Returns a tuple of:
    - dx: Gradient with respect to inputs, of shape (N, C, H, W)
    - dgamma: Gradient with respect to scale parameter, of shape (C,)
    - dbeta: Gradient with respect to shift parameter, of shape (C,)
    """
    dx, dgamma, dbeta = None, None, None

    ###########################################################################
    # TODO: Implement the backward pass for spatial group normalization.      #
    # This will be extremely similar to the layer norm implementation.        #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    xhat, xdev, var, varDenom, gamma, beta, eps, G = cache

    N,C,H,W = dout.shape

    xhat = xhat.reshape(dout.shape)
    dxhat = dout*gamma

    dgamma = np.sum(dout*xhat, axis = (0,2,3), keepdims = True)
    dbeta = np.sum(dout, axis = (0,2,3), keepdims = True)

    newDims = (N*G, (C//G)*W*H)

    xhat = xhat.reshape(newDims).T
    dxhat = dxhat.reshape(newDims).T

    newN = dxhat.shape[0]
    dx = (1./newN)*varDenom*(newN*dxhat - np.sum(dxhat, axis=0) - xhat*np.sum(dxhat*xhat, axis=0))

    dx = dx.T.reshape(N,C,H,W)

    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                             END OF YOUR CODE                            #
    ###########################################################################
    return dx, dgamma, dbeta


def svm_loss(x, y):
    """
    Computes the loss and gradient using for multiclass SVM classification.

    Inputs:
    - x: Input data, of shape (N, C) where x[i, j] is the score for the jth
      class for the ith input.
    - y: Vector of labels, of shape (N,) where y[i] is the label for x[i] and
      0 <= y[i] < C

    Returns a tuple of:
    - loss: Scalar giving the loss
    - dx: Gradient of the loss with respect to x
    """
    N = x.shape[0]
    correct_class_scores = x[np.arange(N), y]
    margins = np.maximum(0, x - correct_class_scores[:, np.newaxis] + 1.0)
    margins[np.arange(N), y] = 0
    loss = np.sum(margins) / N
    num_pos = np.sum(margins > 0, axis=1)
    dx = np.zeros_like(x)
    dx[margins > 0] = 1
    dx[np.arange(N), y] -= num_pos
    dx /= N
    return loss, dx

```

```python

def softmax_loss(x, y):
    """
    Computes the loss and gradient for softmax classification.

    Inputs:
    - x: Input data, of shape (N, C) where x[i, j] is the score for the jth
      class for the ith input.
    - y: Vector of labels, of shape (N,) where y[i] is the label for x[i] and
      0 <= y[i] < C

    Returns a tuple of:
    - loss: Scalar giving the loss
    - dx: Gradient of the loss with respect to x
    """
    shifted_logits = x - np.max(x, axis=1, keepdims=True)
    Z = np.sum(np.exp(shifted_logits), axis=1, keepdims=True)
    log_probs = shifted_logits - np.log(Z)
    probs = np.exp(log_probs)
    N = x.shape[0]
    loss = -np.sum(log_probs[np.arange(N), y]) / N
    dx = probs.copy()
    dx[np.arange(N), y] -= 1
    dx /= N
    return loss, dx
```

2 fc_net.py

```python
from builtins import range
from builtins import object
import numpy as np

from cs231n.layers import *
from cs231n.layer_utils import *


class TwoLayerNet(object):
    """
    A two-layer fully-connected neural network with ReLU nonlinearity and
    softmax loss that uses a modular layer design. We assume an input dimension
    of D, a hidden dimension of H, and perform classification over C classes.

    The architecure should be affine - relu - affine - softmax.

    Note that this class does not implement gradient descent; instead, it
    will interact with a separate Solver object that is responsible for running
    optimization.

    The learnable parameters of the model are stored in the dictionary
    self.params that maps parameter names to numpy arrays.
    """

    def __init__(self, input_dim=3*32*32, hidden_dim=100, num_classes=10,
                 weight_scale=1e-3, reg=0.0):
        """
        Initialize a new network.

        Inputs:
        - input_dim: An integer giving the size of the input
        - hidden_dim: An integer giving the size of the hidden layer
        - num_classes: An integer giving the number of classes to classify
        - weight_scale: Scalar giving the standard deviation for random
          initialization of the weights.
        - reg: Scalar giving L2 regularization strength.
        """
        self.params = {}
        self.reg = reg

        ############################################################################
        # TODO: Initialize the weights and biases of the two-layer net. Weights    #
        # should be initialized from a Gaussian centered at 0.0 with               #
        # standard deviation equal to weight_scale, and biases should be           #
        # initialized to zero. All weights and biases should be stored in the      #
        # dictionary self.params, with first layer weights                         #
        # and biases using the keys 'W1' and 'b1' and second layer                 #
        # weights and biases using the keys 'W2' and 'b2'.                         #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        W1 = weight_scale*np.random.randn(input_dim, hidden_dim)
        W2 = weight_scale*np.random.randn(hidden_dim, num_classes)
        self.params["W1"] = W1
        self.params["W2"] = W2

        b1 = np.zeros(hidden_dim)
        b2 = np.zeros(num_classes)
        self.params["b1"] = b1
        self.params["b2"] = b2
        pass

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


    def loss(self, X, y=None):
        """
        Compute loss and gradient for a minibatch of data.

        Inputs:
        - X: Array of input data of shape (N, d_1, ..., d_k)
        - y: Array of labels, of shape (N,). y[i] gives the label for X[i].

        Returns:
        If y is None, then run a test-time forward pass of the model and return:
        - scores: Array of shape (N, C) giving classification scores, where
          scores[i, c] is the classification score for X[i] and class c.

        If y is not None, then run a training-time forward and backward pass and
        return a tuple of:
        - loss: Scalar value giving the loss
        - grads: Dictionary with the same keys as self.params, mapping parameter
          names to gradients of the loss with respect to those parameters.
        """
        scores = None
        ############################################################################
        # TODO: Implement the forward pass for the two-layer net, computing the    #
        # class scores for X and storing them in the scores variable.              #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        out1, cache1 = affine_relu_forward(X, self.params["W1"], self.params["b1"])
        scores, cache2 = affine_forward(out1, self.params["W2"], self.params["b2"])
        pass

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

        # If y is None then we are in test mode so just return scores
        if y is None:
            return scores

        loss, grads = 0, {}
        ############################################################################
        # TODO: Implement the backward pass for the two-layer net. Store the loss  #
        # in the loss variable and gradients in the grads dictionary. Compute data #
        # loss using softmax, and make sure that grads[k] holds the gradients for  #
        # self.params[k]. Don't forget to add L2 regularization!                   #
        #                                                                          #
        # NOTE: To ensure that your implementation matches ours and you pass the   #
        # automated tests, make sure that your L2 regularization includes a factor #
        # of 0.5 to simplify the expression for the gradient.                      #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        # Evaluate loss
        loss, dx = softmax_loss(scores, y)

        # Augment with regularization
        regLoss = 0.
        regLoss = regLoss + np.sum(np.square(self.params["W1"])) + np.sum(np.square(self.params["W2"]))
        loss = loss + 0.5*regLoss*self.reg

        # Compute gradients for the backwards pass
        dx2, dw2, db2 = affine_backward(dx, cache2)
        dx1, dw1, db1 = affine_relu_backward(dx2, cache1)

        grads["W1"] = dw1 + (self.reg*self.params["W1"])
        grads["W2"] = dw2 + (self.reg*self.params["W2"])

        grads["b1"] = db1
        grads["b2"] = db2

        pass

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

        return loss, grads


class FullyConnectedNet(object):
    """
    A fully-connected neural network with an arbitrary number of hidden layers,
    ReLU nonlinearities, and a softmax loss function. This will also implement
    dropout and batch/layer normalization as options. For a network with L layers,
    the architecture will be

    {affine - [batch/layer norm] - relu - [dropout]} x (L - 1) - affine - softmax

    where batch/layer normalization and dropout are optional, and the {...} block is
    repeated L - 1 times.

    Similar to the TwoLayerNet above, learnable parameters are stored in the
    self.params dictionary and will be learned using the Solver class.
    """

    def __init__(self, hidden_dims, input_dim=3*32*32, num_classes=10,
                 dropout=1, normalization=None, reg=0.0,
                 weight_scale=1e-2, dtype=np.float32, seed=None):
        """
        Initialize a new FullyConnectedNet.

        Inputs:
        - hidden_dims: A list of integers giving the size of each hidden layer.
        - input_dim: An integer giving the size of the input.
        - num_classes: An integer giving the number of classes to classify.
        - dropout: Scalar between 0 and 1 giving dropout strength. If dropout=1 then
          the network should not use dropout at all.
        - normalization: What type of normalization the network should use. Valid values
          are "batchnorm", "layernorm", or None for no normalization (the default).
        - reg: Scalar giving L2 regularization strength.
        - weight_scale: Scalar giving the standard deviation for random
          initialization of the weights.
        - dtype: A numpy datatype object; all computations will be performed using
          this datatype. float32 is faster but less accurate, so you should use
          float64 for numeric gradient checking.
        - seed: If not None, then pass this random seed to the dropout layers. This
          will make the dropout layers deteriminstic so we can gradient check the
          model.
        """
        self.normalization = normalization
        self.use_dropout = dropout != 1
        self.reg = reg
        self.num_layers = 1 + len(hidden_dims)
        self.dtype = dtype
        self.params = {}

        ############################################################################
        # TODO: Initialize the parameters of the network, storing all values in    #
        # the self.params dictionary. Store weights and biases for the first layer #
        # in W1 and b1; for the second layer use W2 and b2, etc. Weights should be #
        # initialized from a normal distribution centered at 0 with standard       #
        # deviation equal to weight_scale. Biases should be initialized to zero.   #
        #                                                                          #
        # When using batch normalization, store scale and shift parameters for the #
        # first layer in gamma1 and beta1; for the second layer use gamma2 and     #
        # beta2, etc. Scale parameters should be initialized to ones and shift     #
        # parameters should be initialized to zeros.                               #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        for i in range(self.num_layers):
            Wkey = "W" + str(i+1)
            bkey = "b" + str(i+1)

            isOutputLayer = (i == self.num_layers - 1)
            isFirstHidden = (i == 0)
            # Output, dimensions are number of classes and the last hidden dimension
            if isOutputLayer:
                self.params[Wkey] = weight_scale*np.random.randn(hidden_dims[len(hidden_dims)-1],
    num_classes)
                self.params[bkey] = np.zeros(num_classes)
            else:
                # First hidden layer, dimensions dictated by input size and first hidden dimension
                if i == 0:
                    self.params[Wkey] = weight_scale*np.random.randn(input_dim, hidden_dims[0])
                    self.params[bkey] = np.zeros(hidden_dims[0])
                # All other sandwich layers
                else:
                    self.params[Wkey] = weight_scale*np.random.randn(hidden_dims[i-1], hidden_dims[i])
                    self.params[bkey] = np.zeros(hidden_dims[i])
                if self.normalization == "batchnorm" or self.normalization == "layernorm":
                        gammaKey = 'gamma' + str(i+1)
                        betaKey = 'beta' + str(i+1)
                        self.params[gammaKey] = np.ones(hidden_dims[i])
                        self.params[betaKey] = np.zeros(hidden_dims[i])



        pass

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

        # When using dropout we need to pass a dropout_param dictionary to each
        # dropout layer so that the layer knows the dropout probability and the mode
        # (train / test). You can pass the same dropout_param to each dropout layer.
        self.dropout_param = {}
        if self.use_dropout:
            self.dropout_param = {'mode': 'train', 'p': dropout}
            if seed is not None:
                self.dropout_param['seed'] = seed

        # With batch normalization we need to keep track of running means and
        # variances, so we need to pass a special bn_param object to each batch
        # normalization layer. You should pass self.bn_params[0] to the forward pass
        # of the first batch normalization layer, self.bn_params[1] to the forward
        # pass of the second batch normalization layer, etc.
        self.bn_params = []
        if self.normalization=='batchnorm':
            self.bn_params = [{'mode': 'train'} for i in range(self.num_layers - 1)]
        if self.normalization=='layernorm':
            self.bn_params = [{} for i in range(self.num_layers - 1)]

        # Cast all parameters to the correct datatype
        for k, v in self.params.items():
            self.params[k] = v.astype(dtype)


    def loss(self, X, y=None):
        """
        Compute loss and gradient for the fully-connected net.

        Input / output: Same as TwoLayerNet above.
        """
        X = X.astype(self.dtype)
        mode = 'test' if y is None else 'train'

        # Set train/test mode for batchnorm params and dropout param since they
        # behave differently during training and testing.
        if self.use_dropout:
            self.dropout_param['mode'] = mode
        if self.normalization=='batchnorm':
            for bn_param in self.bn_params:
                bn_param['mode'] = mode
        scores = None
        ############################################################################
        # TODO: Implement the forward pass for the fully-connected net, computing  #
        # the class scores for X and storing them in the scores variable.          #
        #                                                                          #
        # When using dropout, you'll need to pass self.dropout_param to each       #
        # dropout forward pass.                                                    #
        #                                                                          #
        # When using batch normalization, you'll need to pass self.bn_params[0] to #
        # the forward pass for the first batch normalization layer, pass           #
        # self.bn_params[1] to the forward pass for the second batch normalization #
        # layer, etc.                                                              #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        cacheDict = {}

        # Deal with last layer separately
        for i in range(self.num_layers-1):
            Wkey = "W" + str(i+1)
            bkey = "b" + str(i+1)

            if (i == 0):
                out = X

            # Determine normalization
            if self.normalization == "batchnorm":
                gammaKey = "gamma" + str(i+1)
                betaKey = "beta" + str(i+1)
                fcOut, fcCache = affine_forward(out, self.params[Wkey], self.params[bkey])
                bOut, bCache = batchnorm_forward(fcOut, self.params[gammaKey], self.params[betaKey], self.
    bn_params[i])
                rOut, rCache = relu_forward(bOut)
                out = rOut
                cacheDict[i+1] = (fcCache, bCache, rCache)
            elif self.normalization == "layernorm":
                gammaKey = "gamma" + str(i+1)
                betaKey = "beta" + str(i+1)
                fcOut, fcCache = affine_forward(out, self.params[Wkey], self.params[bkey])
                lOut, lCache = layernorm_forward(fcOut, self.params[gammaKey], self.params[betaKey], self.
    bn_params[i])
                rOut, rCache = relu_forward(lOut)
                out = rOut
                cacheDict[i+1] = (fcCache, lCache, rCache)
            else:
                out, cache = affine_relu_forward(out, self.params[Wkey], self.params[bkey])
                cacheDict[i+1] = cache

            if self.use_dropout:
                dropKey = 'dropout' + str(i+1)
                out, cacheDict[dropKey] = dropout_forward(out, self.dropout_param)

        # Last layer
        Wkey = "W" + str(self.num_layers)
        bkey = "b" + str(self.num_layers)
        scores, cacheDict[self.num_layers] = affine_forward(out, self.params[Wkey], self.params[bkey])




        pass

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

        # If test mode return early
        if mode == 'test':
            return scores

        loss, grads = 0.0, {}
        ############################################################################
        # TODO: Implement the backward pass for the fully-connected net. Store the #
        # loss in the loss variable and gradients in the grads dictionary. Compute #
        # data loss using softmax, and make sure that grads[k] holds the gradients #
        # for self.params[k]. Don't forget to add L2 regularization!               #
        #                                                                          #
        # When using batch/layer normalization, you don't need to regularize the scale   #
        # and shift parameters.                                                    #
        #                                                                          #
        # NOTE: To ensure that your implementation matches ours and you pass the   #
        # automated tests, make sure that your L2 regularization includes a factor #
        # of 0.5 to simplify the expression for the gradient.                      #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        loss, dx = softmax_loss(scores,y)

        # Iterate backwards through the layers since we're doing the
        # backwards pass
        for i in range(self.num_layers, 0, -1):
            Wkey = "W" + str(i)
            bkey = "b" + str(i)
            loss = loss + 0.5*self.reg*np.sum(np.square(self.params[Wkey]))


            isLastHidden = (i == self.num_layers)
            if isLastHidden:
                dx, dw, db = affine_backward(dx, cacheDict[i])
                grads[Wkey] = dw
                grads[bkey] = db
            # All other layers
            else:
                # Update dx if dropout is enabled
                if self.use_dropout:
                    dKey = "dropout" + str(i)
                    dx = dropout_backward(dx, cacheDict[dKey])

                # Construct backward pass as relu to normalizer (batch or layer) to affine backwards
                if self.normalization == "batchnorm":
                    gammaKey = "gamma" + str(i)
                    betaKey = "beta" + str(i)

                    fcCache, bCache, rCache = cacheDict[i]
                    dbOut = relu_backward(dx, rCache)

                    dfcOut, grads[gammaKey], grads[betaKey] = batchnorm_backward(dbOut, bCache)
                    dx, dw, db = affine_backward(dfcOut, fcCache)
                    grads[Wkey] = dw
                    grads[bkey] = db

                elif self.normalization == "layernorm":
                    gammaKey = "gamma" + str(i)
                    betaKey = "beta" + str(i)

                    fcCache, lCache, rCache = cacheDict[i]
                    dlOut = relu_backward(dx, rCache)

                    dfcOut, grads[gammaKey], grads[betaKey] = layernorm_backward(dlOut, lCache)
                    dx, dw, db = affine_backward(dfcOut, fcCache)
                    grads[Wkey] = dw
                    grads[bkey] = db
                # No normalization
                else:
                    dx, dw, db = affine_relu_backward(dx, cacheDict[i])
                    grads[Wkey] = dw
                    grads[bkey] = db


            grads[Wkey] += self.reg * self.params[Wkey]

        pass

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

        return loss, grads
```

3 optim.py

```
import numpy as np

"""
This file implements various first-order update rules that are commonly used
for training neural networks. Each update rule accepts current weights and the
gradient of the loss with respect to those weights and produces the next set of
weights. Each update rule has the same interface:

def update(w, dw, config=None):

Inputs:
  - w: A numpy array giving the current weights.
  - dw: A numpy array of the same shape as w giving the gradient of the
    loss with respect to w.
  - config: A dictionary containing hyperparameter values such as learning
    rate, momentum, etc. If the update rule requires caching values over many
    iterations, then config will also hold these cached values.

Returns:
  - next_w: The next point after the update.
  - config: The config dictionary to be passed to the next iteration of the
    update rule.

NOTE: For most update rules, the default learning rate will probably not
perform well; however the default values of the other hyperparameters should
work well for a variety of different problems.

For efficiency, update rules may perform in-place updates, mutating w and
setting next_w equal to w.
"""


def sgd(w, dw, config=None):
    """
    Performs vanilla stochastic gradient descent.

    config format:
    - learning_rate: Scalar learning rate.
    """
    if config is None: config = {}
    config.setdefault('learning_rate', 1e-2)

    w -= config['learning_rate'] * dw
    return w, config


def sgd_momentum(w, dw, config=None):
    """
    Performs stochastic gradient descent with momentum.

    config format:
    - learning_rate: Scalar learning rate.
    - momentum: Scalar between 0 and 1 giving the momentum value.
      Setting momentum = 0 reduces to sgd.
    - velocity: A numpy array of the same shape as w and dw used to store a
      moving average of the gradients.
    """
    if config is None: config = {}
    config.setdefault('learning_rate', 1e-2)
    config.setdefault('momentum', 0.9)
    v = config.get('velocity', np.zeros_like(w))

    next_w = None
    ###########################################################################
    # TODO: Implement the momentum update formula. Store the updated value in #
    # the next_w variable. You should also use and update the velocity v.     #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    # Update the velocity parameter using the current momentum and gradient
    v = v*config["momentum"] - dw*config["learning_rate"]
    # Compute the new weights
    next_w = v + w
    pass

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ###########################################################################
    #                             END OF YOUR CODE                            #
    ###########################################################################
    config['velocity'] = v

    return next_w, config



def rmsprop(w, dw, config=None):
    """
    Uses the RMSProp update rule, which uses a moving average of squared
    gradient values to set adaptive per-parameter learning rates.

    config format:
    - learning_rate: Scalar learning rate.
    - decay_rate: Scalar between 0 and 1 giving the decay rate for the squared
      gradient cache.
    - epsilon: Small scalar used for smoothing to avoid dividing by zero.
    - cache: Moving average of second moments of gradients.
    """
    if config is None: config = {}
    config.setdefault('learning_rate', 1e-2)
    config.setdefault('decay_rate', 0.99)
    config.setdefault('epsilon', 1e-8)
    config.setdefault('cache', np.zeros_like(w))

    next_w = None
    ###########################################################################
    # TODO: Implement the RMSprop update formula, storing the next value of w #
    # in the next_w variable. Don't forget to update cache value stored in    #
    # config['cache'].                                                        #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    # Update cache values
    config["cache"] = config["decay_rate"]*config["cache"] + (1-config["decay_rate"])*(dw**2)
    # Calculate next w
    denom = np.sqrt(config["cache"]) + config["epsilon"]
    next_w = w - config["learning_rate"]*dw / denom
    pass

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

    return next_w, config


def adam(w, dw, config=None):
    """
    Uses the Adam update rule, which incorporates moving averages of both the
    gradient and its square and a bias correction term.

    config format:
    - learning_rate: Scalar learning rate.
    - beta1: Decay rate for moving average of first moment of gradient.
    - beta2: Decay rate for moving average of second moment of gradient.
    - epsilon: Small scalar used for smoothing to avoid dividing by zero.
    - m: Moving average of gradient.
    - v: Moving average of squared gradient.
    - t: Iteration number.
    """
    if config is None: config = {}
    config.setdefault('learning_rate', 1e-3)
    config.setdefault('beta1', 0.9)
    config.setdefault('beta2', 0.999)
    config.setdefault('epsilon', 1e-8)
    config.setdefault('m', np.zeros_like(w))
    config.setdefault('v', np.zeros_like(w))
    config.setdefault('t', 0)

    next_w = None
    ###########################################################################
    # TODO: Implement the Adam update formula, storing the next value of w in #
    # the next_w variable. Don't forget to update the m, v, and t variables   #
    # stored in config.                                                       #
    #                                                                         #
    # NOTE: In order to match the reference output, please modify t _before_  #
    # using it in any calculations.                                           #
    ###########################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    # Update the t in config
     config["t"] = config["t"] + 1

    # calculate m
     config["m"] = config["beta1"]*config["m"] + (1-config["beta1"])*dw
    m_t = config["m"]/(1-config["beta1"]**config["t"])

    # Caclulate v
     config["v"] = config["beta2"]*config["v"] + (1-config["beta2"])*(dw**2)
    v_t = config["v"]/(1-config["beta2"]**config["t"])

    # Calculate new weights
    next_w = w - config["learning_rate"]*m_t/(np.sqrt(v_t)+config["epsilon"])
     pass

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

     return next_w, config
```

4 cnn.py

```
from builtins import object
import numpy as np

from cs231n.layers import *
from cs231n.fast_layers import *
from cs231n.layer_utils import *


class ThreeLayerConvNet(object):
    """
    A three-layer convolutional network with the following architecture:

    conv - relu - 2x2 max pool - affine - relu - affine - softmax

    The network operates on minibatches of data that have shape (N, C, H, W)
    consisting of N images, each with height H and width W and with C input
    channels.
    """

    def __init__(self, input_dim=(3, 32, 32), num_filters=32, filter_size=7,
                 hidden_dim=100, num_classes=10, weight_scale=1e-3, reg=0.0,
                 dtype=np.float32):
        """
        Initialize a new network.

        Inputs:
        - input_dim: Tuple (C, H, W) giving size of input data
        - num_filters: Number of filters to use in the convolutional layer
        - filter_size: Width/height of filters to use in the convolutional layer
        - hidden_dim: Number of units to use in the fully-connected hidden layer
        - num_classes: Number of scores to produce from the final affine layer.
        - weight_scale: Scalar giving standard deviation for random initialization
          of weights.
        - reg: Scalar giving L2 regularization strength
        - dtype: numpy datatype to use for computation.
        """
        self.params = {}
        self.reg = reg
        self.dtype = dtype

        ############################################################################
        # TODO: Initialize weights and biases for the three-layer convolutional    #
        # network. Weights should be initialized from a Gaussian centered at 0.0   #
        # with standard deviation equal to weight_scale; biases should be          #
        # initialized to zero. All weights and biases should be stored in the      #
        #  dictionary self.params. Store weights and biases for the convolutional  #
        # layer using the keys 'W1' and 'b1'; use keys 'W2' and 'b2' for the       #
        # weights and biases of the hidden affine layer, and keys 'W3' and 'b3'    #
        # for the weights and biases of the output affine layer.                   #
        #                                                                          #
        # IMPORTANT: For this assignment, you can assume that the padding          #
        # and stride of the first convolutional layer are chosen so that          #
        # **the width and height of the input are preserved**. Take a look at      #
        # the start of the loss() function to see how that happens.               #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        C, H, W = input_dim
        # Input conv layer
        self.params["W1"] = weight_scale*np.random.randn(num_filters, C, filter_size, filter_size)
        self.params["b1"] = np.zeros(num_filters)
        # Pooling / affine layer
        dim2 = num_filters*int(H/2)*int(W/2)
        self.params["W2"] = weight_scale*np.random.randn(dim2, hidden_dim)
        self.params["b2"] = np.zeros(hidden_dim)
        # Affine / softmax output layer
        self.params["W3"] = weight_scale*np.random.randn(hidden_dim, num_classes)
        self.params["b3"] = np.zeros(num_classes)

        pass

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

        for k, v in self.params.items():
            self.params[k] = v.astype(dtype)


    def loss(self, X, y=None):
        """
        Evaluate loss and gradient for the three-layer convolutional network.

        Input / output: Same API as TwoLayerNet in fc_net.py.
        """
        W1, b1 = self.params['W1'], self.params['b1']
        W2, b2 = self.params['W2'], self.params['b2']
        W3, b3 = self.params['W3'], self.params['b3']

        # pass conv_param to the forward pass for the convolutional layer
        # Padding and stride chosen to preserve the input spatial size
        filter_size = W1.shape[2]
        conv_param = {'stride': 1, 'pad': (filter_size - 1) // 2}

        # pass pool_param to the forward pass for the max-pooling layer
        pool_param = {'pool_height': 2, 'pool_width': 2, 'stride': 2}

        scores = None
        ############################################################################
        # TODO: Implement the forward pass for the three-layer convolutional net,  #
        # computing the class scores for X and storing them in the scores          #
        # variable.                                                                #
        #                                                                          #
        # Remember you can use the functions defined in cs231n/fast_layers.py and  #
        # cs231n/layer_utils.py in your implementation (already imported).         #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        # conv - relu - 2x2 max pool - affine - relu - affine - softmax
        out1, cache1 = conv_relu_pool_forward(X,W1,b1,conv_param,pool_param)
        out2, cache2 = affine_relu_forward(out1, W2, b2)
        scores, cache3 = affine_forward(out2, W3, b3)
        pass

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

        if y is None:
            return scores

        loss, grads = 0, {}
        ############################################################################
        # TODO: Implement the backward pass for the three-layer convolutional net, #
        # storing the loss and gradients in the loss and grads variables. Compute  #
        # data loss using softmax, and make sure that grads[k] holds the gradients #
        # for self.params[k]. Don't forget to add L2 regularization!               #
        #                                                                          #
        # NOTE: To ensure that your implementation matches ours and you pass the   #
        # automated tests, make sure that your L2 regularization includes a factor #
        # of 0.5 to simplify the expression for the gradient.                      #
        ############################################################################
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        # conv - relu - 2x2 max pool - affine - relu - affine - softmax
        # Softmax
        loss, dout = softmax_loss(scores, y)
        loss = loss + 0.5*self.reg*(np.sum(W1**2)+np.sum(W2**2)+np.sum(W3**2))
        # Affine
        dx3, dw3, db3 = affine_backward(dout, cache3)
        # Affine-relu
        dx2, dw2, db2 = affine_relu_backward(dx3, cache2)
        # Conv/relu/pool
        dx1, dw1, db1 = conv_relu_pool_backward(dx2, cache1)

        dw1 = dw1 + self.reg*W1
        dw2 = dw2 + self.reg*W2
        dw3 = dw3 + self.reg*W3
        grads["W1"] = dw1
        grads["b1"] = db1
        grads["W2"] = dw2
        grads["b2"] = db2
        grads["W3"] = dw3
        grads["b3"] = db3
        pass

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

        return loss, grads
```