Fully-Connected Neural Nets

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

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

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

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

  return out, cache
```

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

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

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

  return dx, dw
```

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

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

In [3]:
```
# As usual, a bit of setup
from __future__ import print_function
import time
import numpy as np
import matplotlib.pyplot as plt
from cs682.classifiers.fc_net import *
from cs682.data_utils import get_CIFAR10_data
from cs682.gradient_check import eval_numerical_gradient, eval_numerical
_gradient_array
from cs682.solver import Solver

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-i
n-ipython
%load_ext autoreload
%autoreload 2

def rel_error(x, y):
  """ returns relative error """
  return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y
))))
```

In [4]:
```
# Load the (preprocessed) CIFAR10 data.

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

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

Affine layer: foward

Open the file `cs682/layers.py` and implement the `affine_forward` function.

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

In [36]:
```
# 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_sh
ape)
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 [37]:
```
# 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 [38]:
```
# 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,  0.13636
364,],
                        [ 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 [5]:
```
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:

Sigmoid and ReLU\ Sigmoid has close to zero gradient for very large positive as well as negative values. ReLU has zero gradient for all values<0.

"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 `cs682/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 [40]:
```
from cs682.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 `cs682/layers.py`.

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

In [41]:
```
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, ver
bose=False)
loss, dx = softmax_loss(x, y)

# Test softmax_loss function. Loss should be close to 2.3 and dx error s
hould 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 `cs682/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 [42]:

```
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_sca
le=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 los
s'

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

# 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=Fa
lse)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[n
ame])))
```

```
Testing initialization ...
Testing test-time forward pass ...
Testing training loss (no regularization)
Running numeric gradient check with reg =  0.0
W1 relative error: 1.22e-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: 3.12e-07
W2 relative error: 7.98e-08
b1 relative error: 1.56e-08
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.

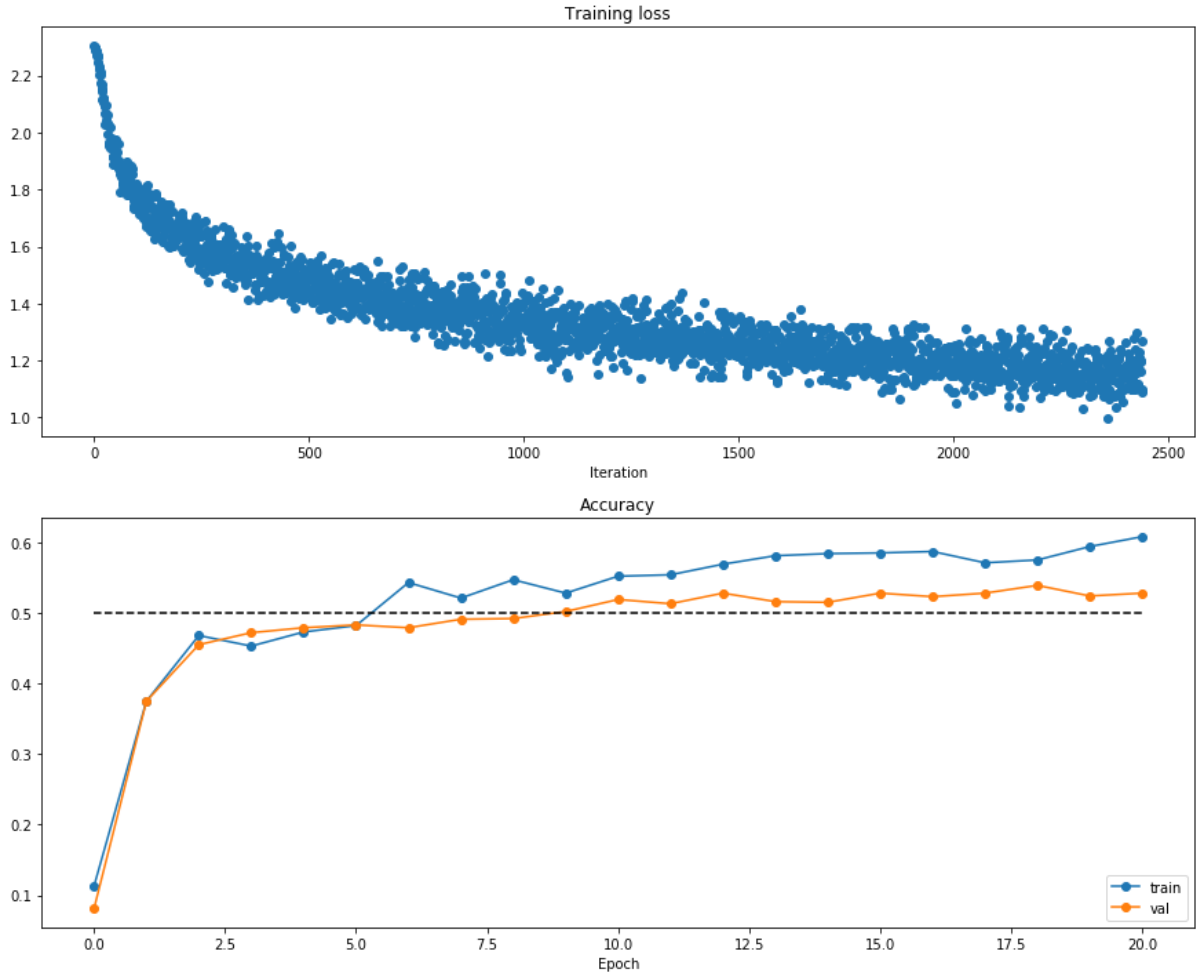
Open the file `cs682/solver.py` and read through it to familiarize yourself with the API. After doing so, use a `Solver` instance to train a `TwoLayerNet` that achieves at least `50%` accuracy on the validation set.

In [43]:

```
model = TwoLayerNet()
solver = None

################################################################################
######
# TODO: Use a Solver instance to train a TwoLayerNet that achieves at le
ast  #
# 50% accuracy on the validation set.
#
################################################################################
######
data = {'X_train':data['X_train'], 'y_train':data['y_train'], 'X_val':da
ta['X_val'], 'y_val':data['y_val']}

solver = Solver(model, data,
                update_rule = 'sgd',
                optim_config = {'learning_rate':1e-3},
                lr_decay = 0.95,
                num_epochs = 20,
                batch_size = 400,
                print_every = 100)

best_params = solver.train()
################################################################################
######
#                              END OF YOUR CODE
#
################################################################################
######
```

```
(Iteration 1 / 2440) loss: 2.304953
(Epoch 0 / 20) train acc: 0.113000; val_acc: 0.081000
(Iteration 101 / 2440) loss: 1.769195
(Epoch 1 / 20) train acc: 0.375000; val_acc: 0.375000
(Iteration 201 / 2440) loss: 1.669165
(Epoch 2 / 20) train acc: 0.468000; val_acc: 0.455000
(Iteration 301 / 2440) loss: 1.670013
(Epoch 3 / 20) train acc: 0.453000; val_acc: 0.472000
(Iteration 401 / 2440) loss: 1.558850
(Epoch 4 / 20) train acc: 0.473000; val_acc: 0.479000
(Iteration 501 / 2440) loss: 1.489412
(Iteration 601 / 2440) loss: 1.365843
(Epoch 5 / 20) train acc: 0.482000; val_acc: 0.483000
(Iteration 701 / 2440) loss: 1.411090
(Epoch 6 / 20) train acc: 0.543000; val_acc: 0.479000
(Iteration 801 / 2440) loss: 1.260651
(Epoch 7 / 20) train acc: 0.521000; val_acc: 0.491000
(Iteration 901 / 2440) loss: 1.318146
(Epoch 8 / 20) train acc: 0.547000; val_acc: 0.492000
(Iteration 1001 / 2440) loss: 1.344013
(Epoch 9 / 20) train acc: 0.528000; val_acc: 0.502000
(Iteration 1101 / 2440) loss: 1.342403
(Iteration 1201 / 2440) loss: 1.257451
(Epoch 10 / 20) train acc: 0.552000; val_acc: 0.519000
(Iteration 1301 / 2440) loss: 1.314607
(Epoch 11 / 20) train acc: 0.554000; val_acc: 0.513000
(Iteration 1401 / 2440) loss: 1.260950
(Epoch 12 / 20) train acc: 0.569000; val_acc: 0.528000
(Iteration 1501 / 2440) loss: 1.294013
(Epoch 13 / 20) train acc: 0.581000; val_acc: 0.516000
(Iteration 1601 / 2440) loss: 1.206977
(Iteration 1701 / 2440) loss: 1.250007
(Epoch 14 / 20) train acc: 0.584000; val_acc: 0.515000
(Iteration 1801 / 2440) loss: 1.285593
(Epoch 15 / 20) train acc: 0.585000; val_acc: 0.528000
(Iteration 1901 / 2440) loss: 1.309243
(Epoch 16 / 20) train acc: 0.587000; val_acc: 0.523000
(Iteration 2001 / 2440) loss: 1.150673
(Epoch 17 / 20) train acc: 0.571000; val_acc: 0.528000
(Iteration 2101 / 2440) loss: 1.183055
(Epoch 18 / 20) train acc: 0.575000; val_acc: 0.539000
(Iteration 2201 / 2440) loss: 1.144189
(Iteration 2301 / 2440) loss: 1.186106
(Epoch 19 / 20) train acc: 0.594000; val_acc: 0.524000
(Iteration 2401 / 2440) loss: 1.162940
(Epoch 20 / 20) train acc: 0.608000; val_acc: 0.528000
```

In [44]:
```
# 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 `cs682/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 [45]:
```
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=Fa
lse, h=1e-5)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[n
ame])))
```

```
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: 3.90e-09
W2 relative error: 6.87e-08
W3 relative error: 2.13e-08
b1 relative error: 1.48e-08
b2 relative error: 1.72e-09
b3 relative error: 1.57e-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 initialization scale to overfit and achieve 100% training accuracy within 20 epochs.

In [46]:

```
# 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'],
}

# for trial in range(20):
#     weight_scale = 10**np.random.uniform(-10, 2)
#     learning_rate = 10**np.random.uniform(-10, 2)
#     print(weight_scale, learning_rate)
# Result of random search : weight_scale=0.0620063159371343 learning_rat
e=0.0007450699140127562
weight_scale = 0.06
learning_rate = 0.0007
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()
```

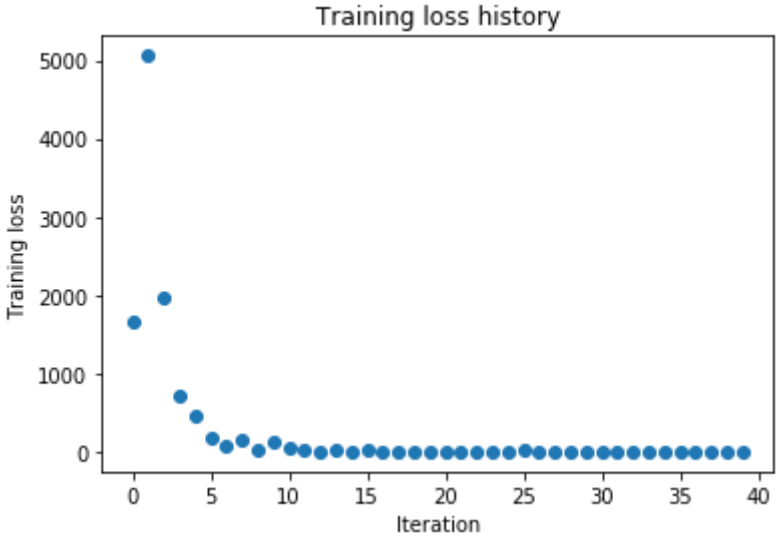
```
(Iteration 1 / 40) loss: 77.236010
(Epoch 0 / 20) train acc: 0.120000; val_acc: 0.121000
(Epoch 1 / 20) train acc: 0.240000; val_acc: 0.140000
(Epoch 2 / 20) train acc: 0.460000; val_acc: 0.139000
(Epoch 3 / 20) train acc: 0.680000; val_acc: 0.157000
(Epoch 4 / 20) train acc: 0.740000; val_acc: 0.170000
(Epoch 5 / 20) train acc: 0.900000; val_acc: 0.184000
(Iteration 11 / 40) loss: 0.012121
(Epoch 6 / 20) train acc: 0.880000; val_acc: 0.184000
(Epoch 7 / 20) train acc: 0.920000; val_acc: 0.181000
(Epoch 8 / 20) train acc: 0.960000; val_acc: 0.176000
(Epoch 9 / 20) train acc: 0.960000; val_acc: 0.178000
(Epoch 10 / 20) train acc: 0.920000; val_acc: 0.167000
(Iteration 21 / 40) loss: 2.035583
(Epoch 11 / 20) train acc: 0.960000; val_acc: 0.171000
(Epoch 12 / 20) train acc: 1.000000; val_acc: 0.166000
(Epoch 13 / 20) train acc: 1.000000; val_acc: 0.165000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.165000
(Epoch 15 / 20) train acc: 1.000000; val_acc: 0.165000
(Iteration 31 / 40) loss: 0.000103
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.165000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.166000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.166000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.166000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.166000
```

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, but you should be able to achieve 100% training accuracy within 20 epochs.

In [7]:

```
# 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'],
}

# for trial in range(20):
#     weight_scale = 10**np.random.uniform(-5, 2)
#     learning_rate = 10**np.random.uniform(-5, 2)
#     print("weight_scale, learning_rate)
# Result of random search: 0.17227070584921386 0.0004595364038438687 5
learning_rate = 0.0004
weight_scale = 0.17
model = FullyConnectedNet([100, 100, 100, 100],
                weight_scale=weight_scale, dtype=np.float64)
solver = Solver(model, small_data,
                print_every=1000, 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: 1660.237200
(Epoch 0 / 20) train acc: 0.120000; val_acc: 0.105000
(Epoch 1 / 20) train acc: 0.140000; val_acc: 0.115000
(Epoch 2 / 20) train acc: 0.340000; val_acc: 0.105000
(Epoch 3 / 20) train acc: 0.520000; val_acc: 0.130000
(Epoch 4 / 20) train acc: 0.740000; val_acc: 0.146000
(Epoch 5 / 20) train acc: 0.820000; val_acc: 0.156000
(Epoch 6 / 20) train acc: 0.860000; val_acc: 0.147000
(Epoch 7 / 20) train acc: 0.900000; val_acc: 0.152000
(Epoch 8 / 20) train acc: 0.960000; val_acc: 0.152000
(Epoch 9 / 20) train acc: 0.960000; val_acc: 0.151000
(Epoch 10 / 20) train acc: 0.980000; val_acc: 0.145000
(Epoch 11 / 20) train acc: 0.980000; val_acc: 0.145000
(Epoch 12 / 20) train acc: 0.980000; val_acc: 0.145000
(Epoch 13 / 20) train acc: 0.940000; val_acc: 0.155000
(Epoch 14 / 20) train acc: 0.960000; val_acc: 0.150000
(Epoch 15 / 20) train acc: 0.960000; val_acc: 0.141000
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.142000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.142000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.142000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.142000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.142000
```



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 five layer net was more difficult to overfit and it was also much more sensitive to the initialization scale. Having a network with more layers makes it susceptible to gradients becoming to large (exploding gradients) or too small (vanishing gradients) which running backpropogation. This increases the difficulty as the network does not learn anything when this happens. With a deeper network, the impact of the initial values of the weights gets compounded and hence, the deeper network becomes more sensitive to the initial weight values.

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 https://compsci682-fa19.github.io/notes/neural-networks-3/#sgd (https://compsci682-fa19.github.io/notes/neural-networks-3/#sgd) for more information.

Open the file `cs682/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 [48]:
```
from cs682.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
```

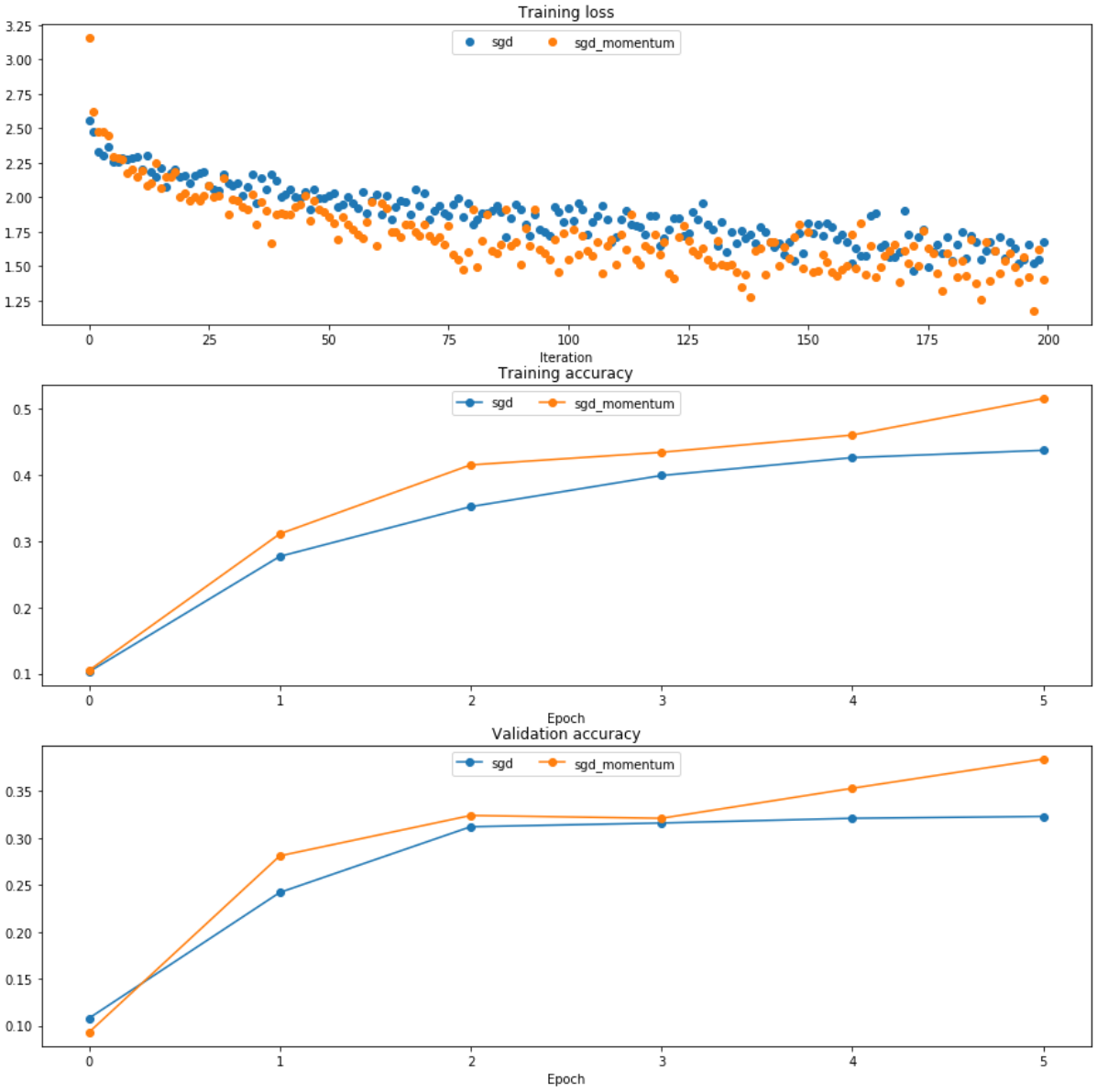
Once you have done so, run the following to train a six-layer network with both SGD and SGD+momentum. You should see the SGD+momentum update rule converge faster.

In [49]:

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

solvers = {}

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

  solver = Solver(model, small_data,
                  num_epochs=5, batch_size=100,
                  update_rule=update_rule,
                  optim_config={
                    'learning_rate': 1e-2,
                  },
                  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  sgd
(Iteration 1 / 200) loss: 2.559978
(Epoch 0 / 5) train acc: 0.103000; val_acc: 0.108000
(Iteration 11 / 200) loss: 2.291086
(Iteration 21 / 200) loss: 2.153591
(Iteration 31 / 200) loss: 2.082693
(Epoch 1 / 5) train acc: 0.277000; val_acc: 0.242000
(Iteration 41 / 200) loss: 2.004171
(Iteration 51 / 200) loss: 2.010409
(Iteration 61 / 200) loss: 2.023753
(Iteration 71 / 200) loss: 2.026621
(Epoch 2 / 5) train acc: 0.352000; val_acc: 0.312000
(Iteration 81 / 200) loss: 1.807163
(Iteration 91 / 200) loss: 1.914256
(Iteration 101 / 200) loss: 1.920494
(Iteration 111 / 200) loss: 1.708877
(Epoch 3 / 5) train acc: 0.399000; val_acc: 0.316000
(Iteration 121 / 200) loss: 1.701111
(Iteration 131 / 200) loss: 1.769697
(Iteration 141 / 200) loss: 1.788899
(Iteration 151 / 200) loss: 1.816437
(Epoch 4 / 5) train acc: 0.426000; val_acc: 0.321000
(Iteration 161 / 200) loss: 1.633853
(Iteration 171 / 200) loss: 1.903011
(Iteration 181 / 200) loss: 1.540134
(Iteration 191 / 200) loss: 1.712615
(Epoch 5 / 5) train acc: 0.437000; val_acc: 0.323000

running with  sgd_momentum
(Iteration 1 / 200) loss: 3.153777
(Epoch 0 / 5) train acc: 0.105000; val_acc: 0.093000
(Iteration 11 / 200) loss: 2.145874
(Iteration 21 / 200) loss: 2.032562
(Iteration 31 / 200) loss: 1.985848
(Epoch 1 / 5) train acc: 0.311000; val_acc: 0.281000
(Iteration 41 / 200) loss: 1.882354
(Iteration 51 / 200) loss: 1.855372
(Iteration 61 / 200) loss: 1.649133
(Iteration 71 / 200) loss: 1.806432
(Epoch 2 / 5) train acc: 0.415000; val_acc: 0.324000
(Iteration 81 / 200) loss: 1.907840
(Iteration 91 / 200) loss: 1.510681
(Iteration 101 / 200) loss: 1.546872
(Iteration 111 / 200) loss: 1.512046
(Epoch 3 / 5) train acc: 0.434000; val_acc: 0.321000
(Iteration 121 / 200) loss: 1.677301
(Iteration 131 / 200) loss: 1.504686
(Iteration 141 / 200) loss: 1.633253
(Iteration 151 / 200) loss: 1.745081
(Epoch 4 / 5) train acc: 0.460000; val_acc: 0.353000
(Iteration 161 / 200) loss: 1.485411
(Iteration 171 / 200) loss: 1.610417
(Iteration 181 / 200) loss: 1.528331
(Iteration 191 / 200) loss: 1.447238
(Epoch 5 / 5) train acc: 0.515000; val_acc: 0.384000
```

```
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:39: MatplotlibDeprecationWarning: Adding an axes using
the same arguments as a previous axes currently reuses the earlier inst
ance.  In a future version, a new instance will always be created and r
eturned.  Meanwhile, this warning can be suppressed, and the future beh
avior ensured, by passing a unique label to each axes instance.
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:42: MatplotlibDeprecationWarning: Adding an axes using
the same arguments as a previous axes currently reuses the earlier inst
ance.  In a future version, a new instance will always be created and r
eturned.  Meanwhile, this warning can be suppressed, and the future beh
avior ensured, by passing a unique label to each axes instance.
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:45: MatplotlibDeprecationWarning: Adding an axes using
the same arguments as a previous axes currently reuses the earlier inst
ance.  In a future version, a new instance will always be created and r
eturned.  Meanwhile, this warning can be suppressed, and the future beh
avior ensured, by passing a unique label to each axes instance.
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:49: MatplotlibDeprecationWarning: Adding an axes using
the same arguments as a previous axes currently reuses the earlier inst
ance.  In a future version, a new instance will always be created and r
eturned.  Meanwhile, this warning can be suppressed, and the future beh
avior ensured, by passing a unique label to each axes instance.
```



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 `cs682/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 [50]:
```
# Test RMSProp implementation
from cs682.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 [51]:
```
# Test Adam implementation
from cs682.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
```

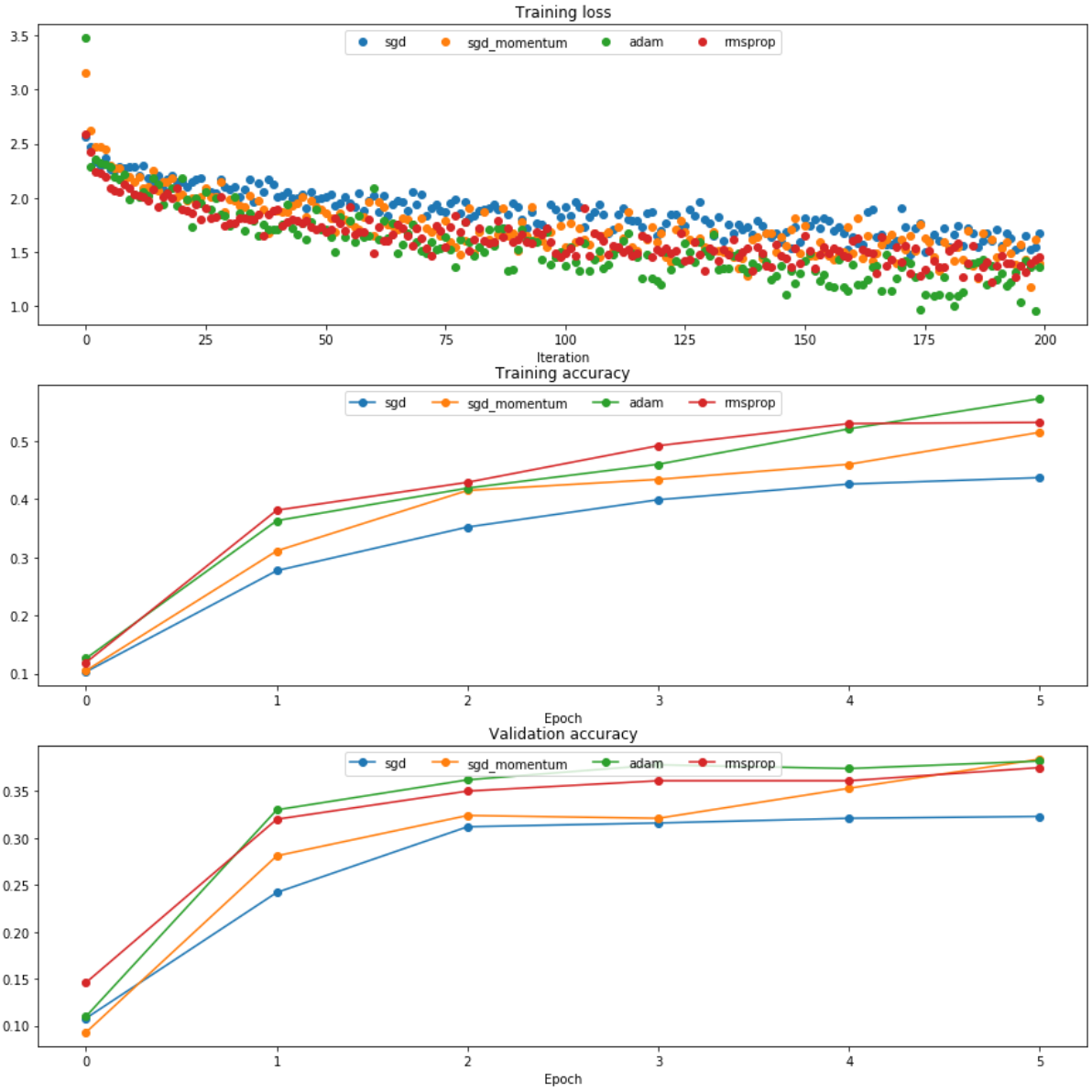
Once you have debugged your RMSProp and Adam implementations, run the following to train a pair of deep networks using these new update rules:

In [52]:

```
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: 1.505558
(Epoch 2 / 5) train acc: 0.419000; val_acc: 0.362000
(Iteration 81 / 200) loss: 1.594429
(Iteration 91 / 200) loss: 1.519017
(Iteration 101 / 200) loss: 1.368522
(Iteration 111 / 200) loss: 1.470400
(Epoch 3 / 5) train acc: 0.460000; val_acc: 0.378000
(Iteration 121 / 200) loss: 1.199064
(Iteration 131 / 200) loss: 1.464705
(Iteration 141 / 200) loss: 1.359863
(Iteration 151 / 200) loss: 1.415069
(Epoch 4 / 5) train acc: 0.521000; val_acc: 0.374000
(Iteration 161 / 200) loss: 1.382818
(Iteration 171 / 200) loss: 1.359900
(Iteration 181 / 200) loss: 1.095947
(Iteration 191 / 200) loss: 1.243088
(Epoch 5 / 5) train acc: 0.573000; val_acc: 0.382000

running with  rmsprop
(Iteration 1 / 200) loss: 2.589166
(Epoch 0 / 5) train acc: 0.119000; val_acc: 0.146000
(Iteration 11 / 200) loss: 2.032921
(Iteration 21 / 200) loss: 1.897278
(Iteration 31 / 200) loss: 1.770793
(Epoch 1 / 5) train acc: 0.381000; val_acc: 0.320000
(Iteration 41 / 200) loss: 1.895732
(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: 0.361000
(Iteration 121 / 200) loss: 1.497406
(Iteration 131 / 200) loss: 1.530736
(Iteration 141 / 200) loss: 1.550957
(Iteration 151 / 200) loss: 1.652046
(Epoch 4 / 5) train acc: 0.530000; val_acc: 0.361000
(Iteration 161 / 200) loss: 1.599574
(Iteration 171 / 200) loss: 1.401073
(Iteration 181 / 200) loss: 1.509582
(Iteration 191 / 200) loss: 1.368611
(Epoch 5 / 5) train acc: 0.532000; val_acc: 0.375000
```

```
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:30: MatplotlibDeprecationWarning: Adding an axes using
the same arguments as a previous axes currently reuses the earlier inst
ance.  In a future version, a new instance will always be created and r
eturned.  Meanwhile, this warning can be suppressed, and the future beh
avior ensured, by passing a unique label to each axes instance.
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:33: MatplotlibDeprecationWarning: Adding an axes using
the same arguments as a previous axes currently reuses the earlier inst
ance.  In a future version, a new instance will always be created and r
eturned.  Meanwhile, this warning can be suppressed, and the future beh
avior ensured, by passing a unique label to each axes instance.
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:36: MatplotlibDeprecationWarning: Adding an axes using
the same arguments as a previous axes currently reuses the earlier inst
ance.  In a future version, a new instance will always be created and r
eturned.  Meanwhile, this warning can be suppressed, and the future beh
avior ensured, by passing a unique label to each axes instance.
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:40: MatplotlibDeprecationWarning: Adding an axes using
the same arguments as a previous axes currently reuses the earlier inst
ance.  In a future version, a new instance will always be created and r
eturned.  Meanwhile, this warning can be suppressed, and the future beh
avior ensured, by passing a unique label to each axes instance.
```



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:

Adagrad accumulates the gradient and divides by it to compute the updates. This value can become too large after several iterations after which, the updates would become extremely small. Adam, however, takes a weighted average of the accumulated gradient (cache) and the current gradient (dw), hence it would not explode in as many iterations. Thus, Adam is more robust to this issue over several iterations of updates. Consider an example where the gradients are 10 at each step. With AdaGrad, the cache would become 1000 in 100 iterations whereas with Adam, the cache would remain 10. More formally, the Adam cache would never be greater than the max gradient. Thus, Adam does not suffer from this issue.

Alternatively, if the network suffers from exploding gradients (gradients becoming too large), then division by the accumulated value (in cache) could lead to a very small update (in very few iterations). The Adam update takes a weighted average, hence the updates would not be impacted by this.

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 [131]:
```
best_model = None
################################################################################
########
# TODO: Train the best FullyConnectedNet that you can on CIFAR-10. You m
ight   #
# find batch/layer normalization and dropout useful. Store your best mod
el in  #
# the best_model variable.
#
################################################################################
########
numTrials = 25
results = []
bestHyperparams = None
np.random.seed(123)
learning_rates = 10**np.random.uniform(-2,-4, numTrials)
regs = 10**np.random.uniform(0,-4, numTrials)
# dropouts = np.random.uniform(0.6, 1, numTrials)
weight_scales = np.random.uniform(1e-2,5e-2, numTrials)
for trial in range (numTrials):
    learning_rate = learning_rates[trial]
    reg = regs[trial]
    weight_scale = weight_scales[trial]
    dropout = 1#dropouts[trial]

    print ("Trial {}: lr={} reg={} weight_scale={} do={}".format(trial,
learning_rate, reg, weight_scale, dropout))
    model = FullyConnectedNet([100, 400, 400, 400, 100],
                              weight_scale=weight_scale,
                              normalization='batchnorm',
                              dtype=np.float64,
                              dropout=dropout,
                              reg=reg,
                              seed=123)

    solver = Solver(model, data,
                    num_epochs=20,
                    batch_size=50,
                    update_rule='adam',
                    optim_config={'learning_rate': learning_rate},
                    verbose=False,
                    lr_decay = 0.95,
                    print_every = 100)

    solver.train()
    val_acc = solver.best_val_acc
    print ("Best Train acc = {} Val acc = {}".format(max(solver.train_ac
c_history), val_acc))
#     print ("Min loss =", min(solver.loss_history))
#     print(solver.val_acc_history)
    if bestHyperparams is None or bestHyperparams[4] < val_acc:
        bestHyperparams = (learning_rate, reg, weight_scale, dropout, va
l_acc)
        best_model = model
    results.append((learning_rate, reg, weight_scale, dropout, val_acc))
```

```
print("Best hyperparams", bestHyperparams)
################################################################################
########
#                                END OF YOUR CODE
#
################################################################################
########
```

```
Trial 0: lr=0.0004046333073420584 reg=0.051069822050525036 weight_scale
=0.01482514663961295 do=1
Best Train acc = 0.522 Val acc = 0.519
Trial 1: lr=0.0026774497579933826 reg=0.035714566043029326 weight_scale
=0.04305363202027333 do=1
Best Train acc = 0.372 Val acc = 0.362
Trial 2: lr=0.0035180101884127587 reg=0.1221650779631915 weight_scale=
0.0341224051364371 do=1
Best Train acc = 0.279 Val acc = 0.281
Trial 3: lr=0.0007895333180807005 reg=0.066856527296119 weight_scale=0.
031802720258658594 do=1
Best Train acc = 0.47 Val acc = 0.446
Trial 4: lr=0.000363967043090007 reg=0.002992922730182325 weight_scale=
0.023710553350972337 do=1
Best Train acc = 0.774 Val acc = 0.581
Trial 5: lr=0.0014249088365594447 reg=0.42813451438371275 weight_scale=
0.022164831561087363 do=1
Best Train acc = 0.262 Val acc = 0.274
Trial 6: lr=0.00010926261824221895 reg=0.018416000127050833 weight_scal
e=0.026680888440988065 do=1
Best Train acc = 0.826 Val acc = 0.566
Trial 7: lr=0.00042691412362385033 reg=0.018903792722959698 weight_scal
e=0.03725203063171187 do=1
Best Train acc = 0.584 Val acc = 0.529
Trial 8: lr=0.0010917826715488564 reg=0.010598871074605358 weight_scale
=0.045018273671806996 do=1
Best Train acc = 0.529 Val acc = 0.492
Trial 9: lr=0.0016434820443355922 reg=0.019800622263578854 weight_scale
=0.030416893499120447 do=1
Best Train acc = 0.465 Val acc = 0.445
Trial 10: lr=0.0020589413120966965 reg=0.05635793970800434 weight_scale
=0.036772551318490894 do=1
Best Train acc = 0.385 Val acc = 0.388
Trial 11: lr=0.0003482575859315551 reg=0.01970583182808769 weight_scale
=0.03343746210248852 do=1
Best Train acc = 0.62 Val acc = 0.546
Trial 12: lr=0.0013269529083173167 reg=0.0002669582505040336 weight_sca
le=0.034996140083824 do=1
Best Train acc = 0.751 Val acc = 0.56
Trial 13: lr=0.007597036391571568 reg=0.00016724761263818577 weight_sca
le=0.03698756203951299 do=1
Best Train acc = 0.534 Val acc = 0.51
Trial 14: lr=0.001599232066581871 reg=0.009832258690034188 weight_scale
=0.043693697504810294 do=1
Best Train acc = 0.501 Val acc = 0.481
Trial 15: lr=0.0003342021107943263 reg=0.003192921143915423 weight_scal
e=0.013327799533297552 do=1
Best Train acc = 0.77 Val acc = 0.567
Trial 16: lr=0.004315355105388501 reg=0.3447675793771386 weight_scale=
0.04054731365773353 do=1
Best Train acc = 0.199 Val acc = 0.22
Trial 17: lr=0.004457552713588758 reg=0.05380939048839085 weight_scale=
0.01974665498147496 do=1
Best Train acc = 0.281 Val acc = 0.295
Trial 18: lr=0.0008647633042996515 reg=0.021912662622563427 weight_scal
e=0.017768918423150835 do=1
Best Train acc = 0.502 Val acc = 0.481
```

```
Trial 19: lr=0.0008636640168530538 reg=0.00034258107550713153 weight_sc
ale=0.032898278299658926 do=1
Best Train acc = 0.793 Val acc = 0.567
Trial 20: lr=0.0005385153448283213 reg=0.09958147125344827 weight_scale
=0.013828500664495485 do=1
Best Train acc = 0.463 Val acc = 0.462
Trial 21: lr=0.0002000490124667205 reg=0.011691303721755232 weight_scal
e=0.04541307305100559 do=1
Best Train acc = 0.766 Val acc = 0.556
Trial 22: lr=0.00035570449248140194 reg=0.00011422491868421907 weight_s
cale=0.03508995888205075 do=1
Best Train acc = 0.903 Val acc = 0.55
Trial 23: lr=0.0005997261399883596 reg=0.008357175510570808 weight_scal
e=0.03893665432759819 do=1
Best Train acc = 0.613 Val acc = 0.554
Trial 24: lr=0.00035901552960287584 reg=0.003535264375693929 weight_sca
le=0.010645168267800674 do=1
Best Train acc = 0.728 Val acc = 0.557
Best hyperparams (0.000363967043090007, 0.002992922730182325, 0.0237105
53350972337, 1, 0.581)
```

Test your model!

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

In [135]:
```
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:  0.551
Test set accuracy:  0.507
```

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 [3] 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 [3] hypothesize that the shifting distribution of features inside deep neural networks may make training deep networks more difficult. To overcome this problem, [3] 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.

[3] Sergey Ioffe and Christian Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015. (https://arxiv.org/abs/1502.03167)

In [188]:
```
# As usual, a bit of setup
import time
import numpy as np
import matplotlib.pyplot as plt
from cs682.classifiers.fc_net import *
from cs682.data_utils import get_CIFAR10_data
from cs682.gradient_check import eval_numerical_gradient, eval_numerical
_gradient_array
from cs682.solver import Solver

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-i
n-ipython
%load_ext autoreload
%autoreload 2

def rel_error(x, y):
    """ returns relative error """
    return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y
))))

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

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

In [160]:
```
# Load the (preprocessed) CIFAR10 data.
data = get_CIFAR10_data()
for k, v in data.items():
  print('%s: ' % k, v.shape)
```

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

Batch normalization: forward

In the file `cs682/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 would be helpful!

In [161]:
```
# Check the training-time forward pass by checking means and variances
# of features both before and after batch normalization

# Simulate the forward pass for a two-layer network
np.random.seed(231)
N, D1, D2, D3 = 200, 50, 60, 3
X = np.random.randn(N, D1)
W1 = np.random.randn(D1, D2)
W2 = np.random.randn(D2, D3)
a = np.maximum(0, X.dot(W1)).dot(W2)

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

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

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

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

After batch normalization (gamma=1, beta=0)
  means:  [5.32907052e-17 7.04991621e-17 4.11476409e-17]
  stds:   [0.99999999 1.         1.        ]

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

In [162]:
```
# 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 [163]:
```
# 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)
# print("Numerical dx", dx_num)

_, cache = batchnorm_forward(x, gamma, beta, bn_param)
dx, dgamma, dbeta = batchnorm_backward(dout, cache)
# print("Dx", dx)
#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:  1.7029246970364838e-09
dgamma error:  7.420414216247087e-13
dbeta error:  2.8795057655839487e-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.

Given a set of inputs $X = \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_N \end{bmatrix}$, we first calculate the mean $\mu = \frac{1}{N} \sum_{k=1}^{N} x_k$ and variance $v = \frac{1}{N} \sum_{k=1}^{N} (x_k - \mu)^2$.
With μ and v calculated, we can calculate the standard deviation $\sigma = \sqrt{v + \epsilon}$ and normalized data Y with $y_i = \frac{x_i - \mu}{\sigma}$.

The meat of our problem is to get $\frac{\partial L}{\partial X}$ from the upstream gradient $\frac{\partial L}{\partial Y}$. It might be challenging to directly reason about the gradients over X and Y - try reasoning about it in terms of x_i and y_i first.

You will need to come up with the derivations for $\frac{\partial L}{\partial x_i}$, by relying on the Chain Rule to first calculate the intermediate $\frac{\partial \mu}{\partial x_i}$, $\frac{\partial v}{\partial x_i}$, $\frac{\partial \sigma}{\partial x_i}$, then assemble these pieces to calculate $\frac{\partial y_i}{\partial x_i}$. You should make sure each of the intermediary steps are all as simple as possible.

After doing so, implement the simplified batch normalization backward pass in the function `batchnorm_backward_alt` and compare the two implementations by running the following. Your two implementations should compute nearly identical results, but the alternative implementation should be a bit faster.

In [164]:
```
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("dx1", dx1, "\ndx2", dx2)

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:  1.3951303266098162e-12
dgamma difference:  0.0
dbeta difference:  0.0
speedup: 5.47x
```

Fully Connected Nets with Batch Normalization

Now that you have a working implementation for batch normalization, go back to your `FullyConnectedNet` in the file `cs682/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 `cs682/layer_utils.py`. If you decide to do so, do it in the file `cs682/classifiers/fc_net.py`.

In [165]:
```
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=Fa
lse, h=1e-5)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[n
ame])))
  if reg == 0: print()
```

```
Running check with reg =  0
Initial loss:  2.2611955101340957
W1 relative error: 1.10e-04
W2 relative error: 2.85e-06
W3 relative error: 3.92e-10
b1 relative error: 8.88e-08
b2 relative error: 2.00e-07
b3 relative error: 4.78e-11
beta1 relative error: 7.33e-09
beta2 relative error: 1.89e-09
gamma1 relative error: 7.57e-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: 8.88e-08
b2 relative error: 2.22e-08
b3 relative error: 2.23e-10
beta1 relative error: 6.65e-09
beta2 relative error: 5.69e-09
gamma1 relative error: 8.80e-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 [166]:

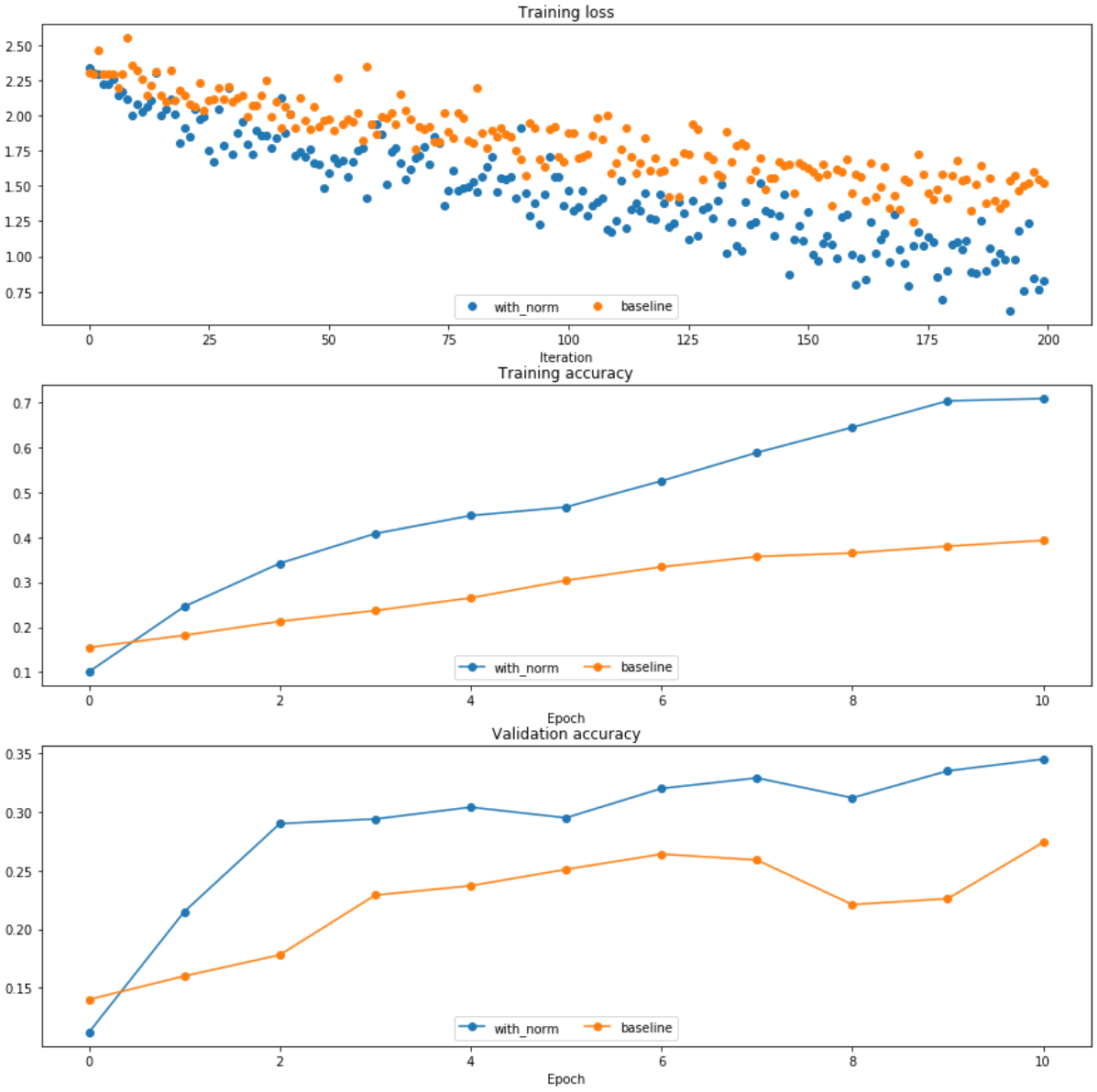
```
np.random.seed(231)
# Try training a very deep net with batchnorm
hidden_dims = [100, 100, 100, 100, 100]

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, nor
malization='batchnorm')
model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale, normal
ization=None)

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()

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()
```

```
(Iteration 1 / 200) loss: 2.340974
(Epoch 0 / 10) train acc: 0.101000; val_acc: 0.112000
(Epoch 1 / 10) train acc: 0.246000; val_acc: 0.215000
(Iteration 21 / 200) loss: 1.913055
(Epoch 2 / 10) train acc: 0.342000; val_acc: 0.290000
(Iteration 41 / 200) loss: 2.128057
(Epoch 3 / 10) train acc: 0.408000; val_acc: 0.294000
(Iteration 61 / 200) loss: 1.940800
(Epoch 4 / 10) train acc: 0.448000; val_acc: 0.304000
(Iteration 81 / 200) loss: 1.532883
(Epoch 5 / 10) train acc: 0.467000; val_acc: 0.295000
(Iteration 101 / 200) loss: 1.463726
(Epoch 6 / 10) train acc: 0.525000; val_acc: 0.320000
(Iteration 121 / 200) loss: 1.379170
(Epoch 7 / 10) train acc: 0.588000; val_acc: 0.329000
(Iteration 141 / 200) loss: 1.518723
(Epoch 8 / 10) train acc: 0.644000; val_acc: 0.312000
(Iteration 161 / 200) loss: 0.798684
(Epoch 9 / 10) train acc: 0.703000; val_acc: 0.335000
(Iteration 181 / 200) loss: 1.087987
(Epoch 10 / 10) train acc: 0.708000; val_acc: 0.345000
(Iteration 1 / 200) loss: 2.302332
(Epoch 0 / 10) train acc: 0.155000; val_acc: 0.140000
(Epoch 1 / 10) train acc: 0.182000; val_acc: 0.160000
(Iteration 21 / 200) loss: 2.143172
(Epoch 2 / 10) train acc: 0.213000; val_acc: 0.178000
(Iteration 41 / 200) loss: 1.915774
(Epoch 3 / 10) train acc: 0.237000; val_acc: 0.229000
(Iteration 61 / 200) loss: 1.865571
(Epoch 4 / 10) train acc: 0.265000; val_acc: 0.237000
(Iteration 81 / 200) loss: 1.802503
(Epoch 5 / 10) train acc: 0.304000; val_acc: 0.251000
(Iteration 101 / 200) loss: 1.876829
(Epoch 6 / 10) train acc: 0.334000; val_acc: 0.264000
(Iteration 121 / 200) loss: 1.611363
(Epoch 7 / 10) train acc: 0.357000; val_acc: 0.259000
(Iteration 141 / 200) loss: 1.696978
(Epoch 8 / 10) train acc: 0.365000; val_acc: 0.221000
(Iteration 161 / 200) loss: 1.581994
(Epoch 9 / 10) train acc: 0.380000; val_acc: 0.226000
(Iteration 181 / 200) loss: 1.573919
(Epoch 10 / 10) train acc: 0.393000; val_acc: 0.274000
```

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.

In [167]:

```
def plot_training_history(title, label, baseline, bn_solvers, plot_fn, b
l_marker='.', bn_marker='.', labels=None):
    """utility function for plotting training history"""
    plt.title(title)
    plt.xlabel(label)
    bn_plots = [plot_fn(bn_solver) for bn_solver in bn_solvers]
    bl_plot = plot_fn(baseline)
    num_bn = len(bn_plots)
    for i in range(num_bn):
        label='with_norm'
        if labels is not None:
            label += str(labels[i])
        plt.plot(bn_plots[i], bn_marker, label=label)
    label='baseline'
    if labels is not None:
        label += str(labels[0])
    plt.plot(bl_plot, bl_marker, label=label)
    plt.legend(loc='lower center', ncol=num_bn+1)


plt.subplot(3, 1, 1)
plot_training_history('Training loss','Iteration', solver, [bn_solver],
 \
                      lambda x: x.loss_history, bl_marker='o', bn_marker
='o')
plt.subplot(3, 1, 2)
plot_training_history('Training accuracy','Epoch', solver, [bn_solver],
 \
                      lambda x: x.train_acc_history, bl_marker='-o', bn_
marker='-o')
plt.subplot(3, 1, 3)
plot_training_history('Validation accuracy','Epoch', solver, [bn_solver
], \
                      lambda x: x.val_acc_history, bl_marker='-o', bn_ma
rker='-o')

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



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.

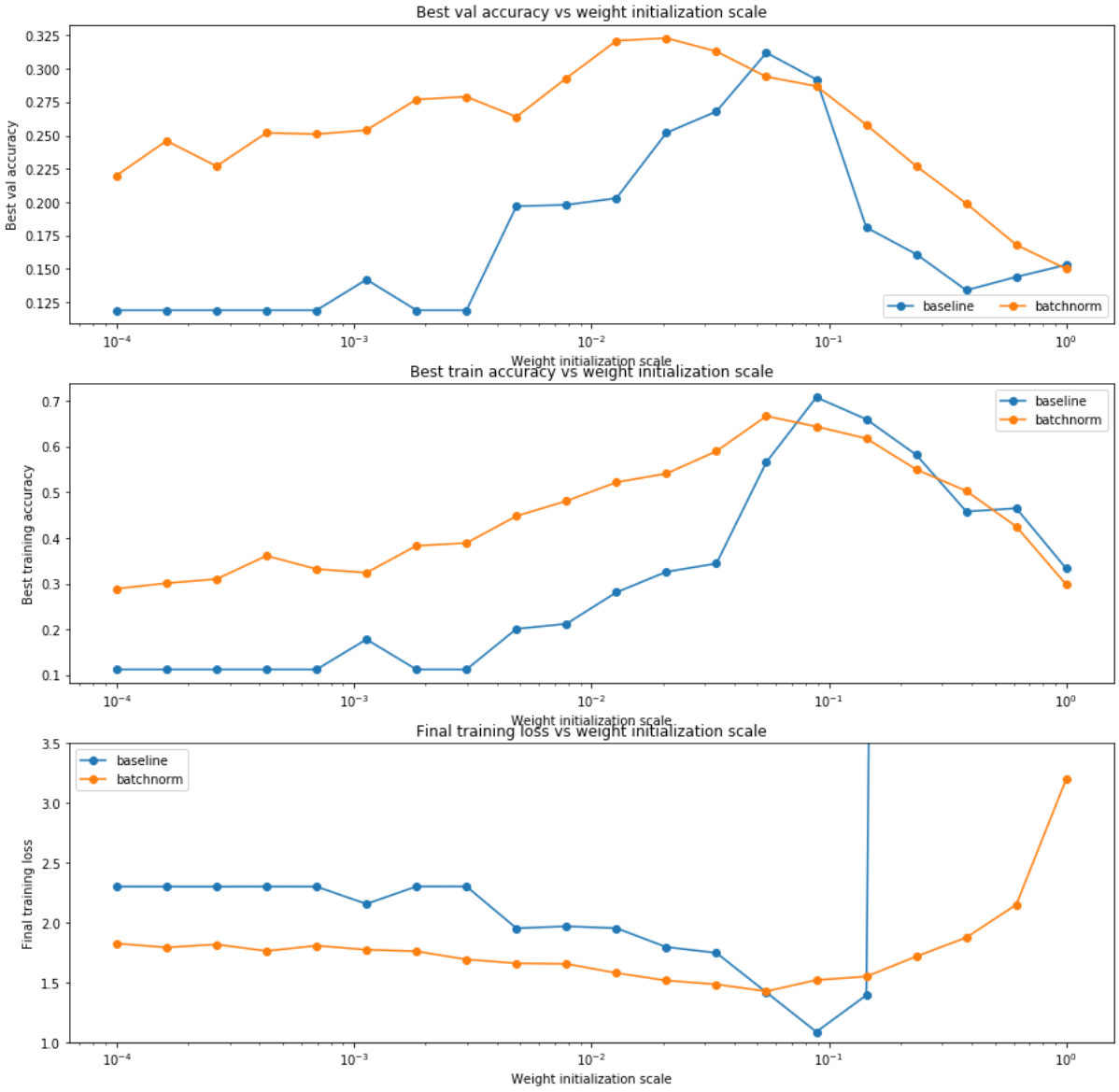
In [169]:

```
np.random.seed(231)
# Try training a very deep net with batchnorm
hidden_dims = [50, 50, 50, 50, 50, 50, 50]
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'],
}

bn_solvers_ws = {}
solvers_ws = {}
weight_scales = np.logspace(-4, 0, num=20)
for i, weight_scale in enumerate(weight_scales):
  print('Running weight scale %d / %d' % (i + 1, len(weight_scales)))
  bn_model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale, n
ormalization='batchnorm')
  model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale, norm
alization=None)

  bn_solver = Solver(bn_model, small_data,
                  num_epochs=10, batch_size=50,
                  update_rule='adam',
                  optim_config={
                    'learning_rate': 1e-3,
                  },
                  verbose=False, print_every=200)
  bn_solver.train()
  bn_solvers_ws[weight_scale] = bn_solver

  solver = Solver(model, small_data,
                  num_epochs=10, batch_size=50,
                  update_rule='adam',
                  optim_config={
                    'learning_rate': 1e-3,
                  },
                  verbose=False, print_every=200)
  solver.train()
  solvers_ws[weight_scale] = solver
```

```
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
```

In [170]:

```
# Plot results of weight scale experiment
best_train_accs, bn_best_train_accs = [], []
best_val_accs, bn_best_val_accs = [], []
final_train_loss, bn_final_train_loss = [], []

for ws in weight_scales:
  best_train_accs.append(max(solvers_ws[ws].train_acc_history))
  bn_best_train_accs.append(max(bn_solvers_ws[ws].train_acc_history))

  best_val_accs.append(max(solvers_ws[ws].val_acc_history))
  bn_best_val_accs.append(max(bn_solvers_ws[ws].val_acc_history))

  final_train_loss.append(np.mean(solvers_ws[ws].loss_history[-100:]))
  bn_final_train_loss.append(np.mean(bn_solvers_ws[ws].loss_history[-100
:]))

plt.subplot(3, 1, 1)
plt.title('Best val accuracy vs weight initialization scale')
plt.xlabel('Weight initialization scale')
plt.ylabel('Best val accuracy')
plt.semilogx(weight_scales, best_val_accs, '-o', label='baseline')
plt.semilogx(weight_scales, bn_best_val_accs, '-o', label='batchnorm')
plt.legend(ncol=2, loc='lower right')

plt.subplot(3, 1, 2)
plt.title('Best train accuracy vs weight initialization scale')
plt.xlabel('Weight initialization scale')
plt.ylabel('Best training accuracy')
plt.semilogx(weight_scales, best_train_accs, '-o', label='baseline')
plt.semilogx(weight_scales, bn_best_train_accs, '-o', label='batchnorm')
plt.legend()

plt.subplot(3, 1, 3)
plt.title('Final training loss vs weight initialization scale')
plt.xlabel('Weight initialization scale')
plt.ylabel('Final training loss')
plt.semilogx(weight_scales, final_train_loss, '-o', label='baseline')
plt.semilogx(weight_scales, bn_final_train_loss, '-o', label='batchnorm'
)
plt.legend()
plt.gca().set_ylim(1.0, 3.5)

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



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:

With batch normalization, the performance of the network is much less sensitive to the weight initialization. As we normalize the outputs periodically in the network (through the bacthnorm layer), the initial weights do not have a heavy bearing on the overall performance of the network. The network is able to learn appropriate values (by adjusting gamma dn beta) to overcome the restriction of this normalization while avoiding the impact of initialization.

Batch normalization and batch size

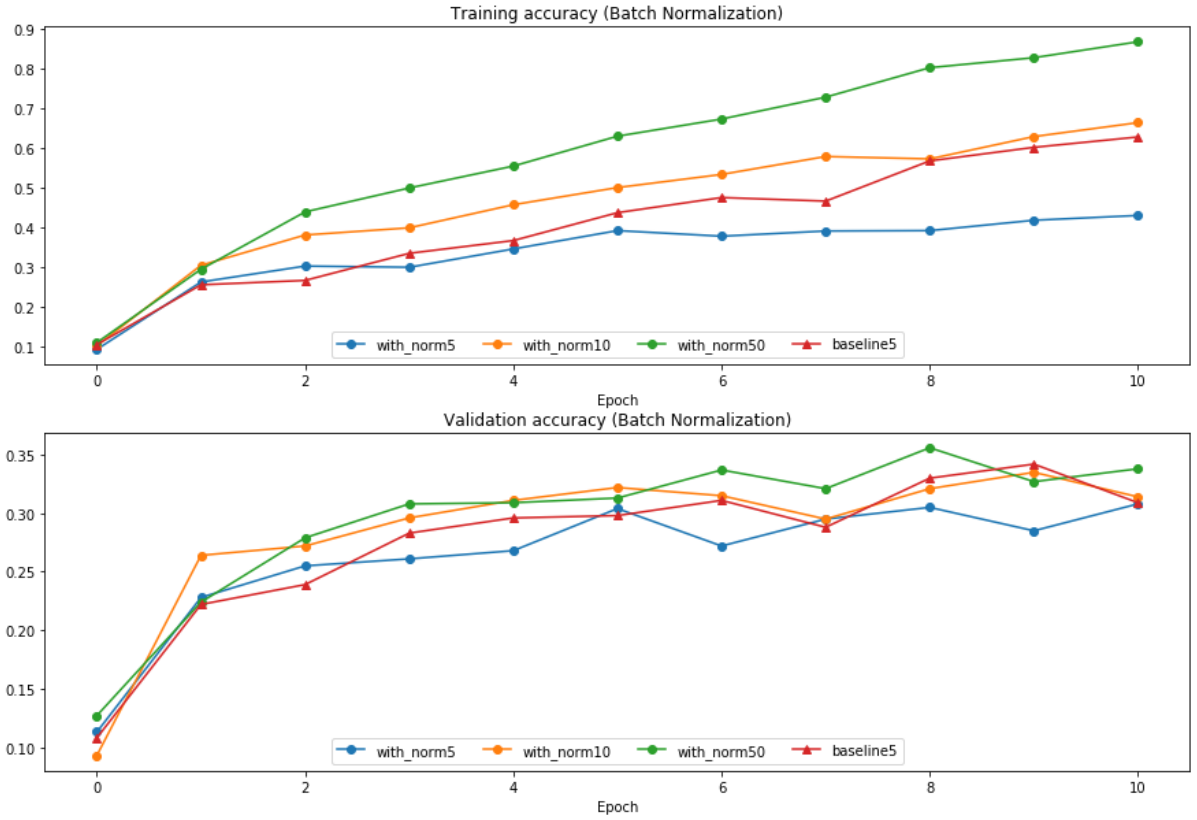
We will now run a small experiment to study the interaction of batch normalization and batch size.

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.

In [171]:
```
def run_batchsize_experiments(normalization_mode):
    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'],
    }
    n_epochs=10
    weight_scale = 2e-2
    batch_sizes = [5,10,50]
    lr = 10**(-3.5)
    solver_bsize = batch_sizes[0]

    print('No normalization: batch size = ',solver_bsize)
    model = FullyConnectedNet(hidden_dims, weight_scale=weight_scale, no
rmalization=None)
    solver = Solver(model, small_data,
                    num_epochs=n_epochs, batch_size=solver_bsize,
                    update_rule='adam',
                    optim_config={
                      'learning_rate': lr,
                    },
                    verbose=False)
    solver.train()

    bn_solvers = []
    for i in range(len(batch_sizes)):
        b_size=batch_sizes[i]
        print('Normalization: batch size = ',b_size)
        bn_model = FullyConnectedNet(hidden_dims, weight_scale=weight_sc
ale, normalization=normalization_mode)
        bn_solver = Solver(bn_model, small_data,
                           num_epochs=n_epochs, batch_size=b_size,
                           update_rule='adam',
                           optim_config={
                             'learning_rate': lr,
                           },
                           verbose=False)
        bn_solver.train()
        bn_solvers.append(bn_solver)

    return bn_solvers, solver, batch_sizes

batch_sizes = [5,10,50]
bn_solvers_bsize, solver_bsize, batch_sizes = run_batchsize_experiments(
'batchnorm')
```

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

In [172]:
```
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_sizes)
plt.subplot(2, 1, 2)
plot_training_history('Validation accuracy (Batch Normalization)','Epoc
h', solver_bsize, bn_solvers_bsize, \
                      lambda x: x.val_acc_history, bl_marker='-^', bn_ma
rker='-o', labels=batch_sizes)

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 training accuracy increases substantially with increase in batch size. Batch norm estimates the actual means and variance by computing it over just the samples in the batch. Hence, if the batch size is larger, the estimate would be closer to the actual mean and average of the training examples and hence the normalization would lead to a better training accuracy. At smaller batch sizes, the estimate would not be very accurate and the performance would be relatively low. The impact on the validation accuracy does not show any particular pattern as batchnorm estimates the statistics of the training set and not the validation set and hence may not have any deterministic impact on the validation accuracy.

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 [4]. 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.

[4] Ba, Jimmy Lei, Jamie Ryan Kiros, and Geoffrey E. Hinton. "Layer Normalization." stat 1050 (2016): 21. (https://arxiv.org/pdf/1607.06450.pdf)

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

Options 1, 2 are analogous to Layer Normalization

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 `cs682/layers.py`, implement the forward pass for layer normalization in the function `layernorm_backward`.

Run the cell below to check your results.

- In `cs682/layers.py`, implement the backward pass for layer normalization in the function `layernorm_backward`.

Run the second cell below to check your results.

- Modify `cs682/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 [181]:
```
# 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 -5.55111512e
-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 [182]:
```
# 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))
```

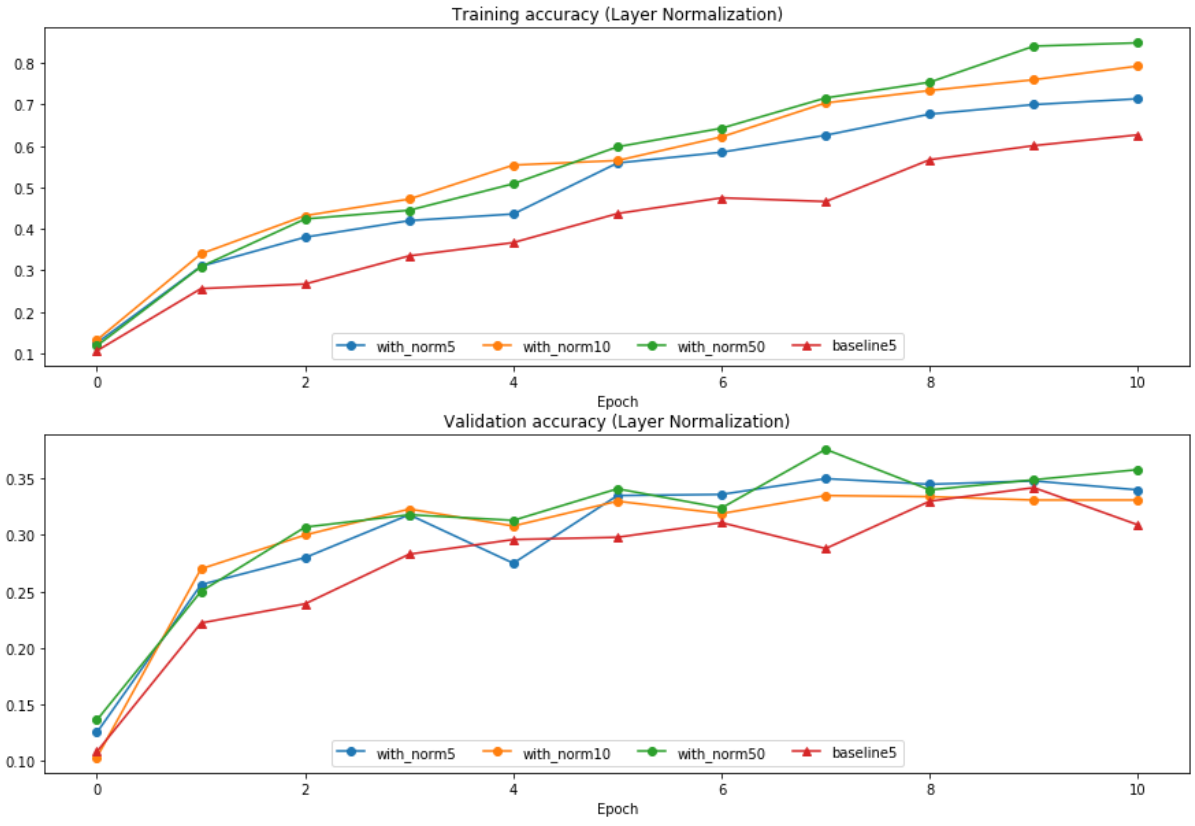
```
dx error:  1.4336158494902849e-09
dgamma error:  4.519489546032799e-12
dbeta error:  2.276445013433725e-12
```

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 [189]:
```
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_sizes)
plt.subplot(2, 1, 2)
plot_training_history('Validation accuracy (Layer Normalization)','Epoc
h', solver_bsize, ln_solvers_bsize, \
                      lambda x: x.val_acc_history, bl_marker='-^', bn_ma
rker='-o', labels=batch_sizes)

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 - Layer Normalization would likely not work well if the number of features is very low. This is because the calculated statistics would be noisy if the number of features is too low. This is analogous to the effect of small batch size on the performance of batchnorm.

In [ ]:

Dropout

Dropout [1] is a technique for regularizing neural networks by randomly setting some features 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 (https://arxiv.org/abs/1207.0580)

In [1]:
```
# As usual, a bit of setup
from __future__ import print_function
import time
import numpy as np
import matplotlib.pyplot as plt
from cs682.classifiers.fc_net import *
from cs682.data_utils import get_CIFAR10_data
from cs682.gradient_check import eval_numerical_gradient, eval_numerical
_gradient_array
from cs682.solver import Solver

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-i
n-ipython
%load_ext autoreload
%autoreload 2

def rel_error(x, y):
  """ returns relative error """
  return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y
))))
```

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

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

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

Dropout forward pass

In the file `cs682/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 [5]:
```
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).me
an())
  print()
```

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

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

Running tests with p =  0.7
Mean of input:  10.000207878477502
Mean of train-time output:  9.987811912159426
Mean of test-time output:  10.000207878477502
Fraction of train-time output set to zero:  0.30074
Fraction of test-time output set to zero:  0.0
```

Dropout backward pass

In the file `cs682/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, dr
opout_param)[0], x, dout)

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

```
dx relative error:  1.8928938043362133e-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:

On average, the activations after dropout are reduced by a factor of p if we do not divide by p. Therefore, during test, when there is no dropout, the activation would be larger than during train time and the network would not perform well. Hence, to make it consistent, we divide by p during the forward pass at train time. Alternatively, we could also multiply by p during test time.

Fully-connected nets with Dropout

In the file `cs682/classifiers/fc_net.py`, modify your implementation to use dropout. Specifically, if the constructor of the net receives a value that is not 1 for the `dropout` parameter, then the net should add dropout immediately after every ReLU nonlinearity. After doing so, run the following to numerically gradient-check your implementation.

In [8]:
```
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=Fa
lse, h=1e-5)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[n
ame])))
  print()
```

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

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

Running check with dropout =  0.5
Initial loss:  2.3042759220785896
W1 relative error: 3.11e-07
W2 relative error: 1.84e-08
W3 relative error: 5.35e-08
b1 relative error: 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.

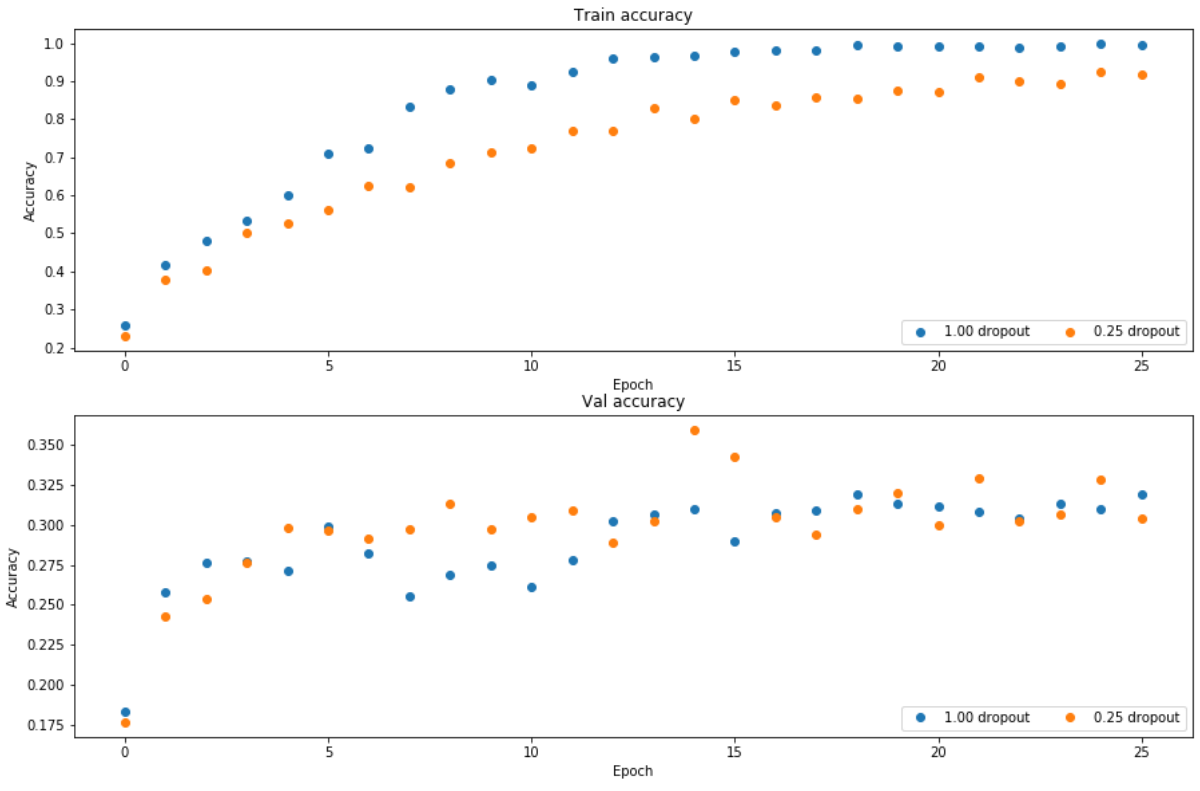
In [9]:

```
# 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
```

```
1
(Iteration 1 / 125) loss: 7.856643
(Epoch 0 / 25) train acc: 0.260000; val_acc: 0.184000
(Epoch 1 / 25) train acc: 0.416000; val_acc: 0.258000
(Epoch 2 / 25) train acc: 0.482000; val_acc: 0.276000
(Epoch 3 / 25) train acc: 0.532000; val_acc: 0.277000
(Epoch 4 / 25) train acc: 0.600000; val_acc: 0.271000
(Epoch 5 / 25) train acc: 0.708000; val_acc: 0.299000
(Epoch 6 / 25) train acc: 0.722000; val_acc: 0.282000
(Epoch 7 / 25) train acc: 0.832000; val_acc: 0.255000
(Epoch 8 / 25) train acc: 0.878000; val_acc: 0.269000
(Epoch 9 / 25) train acc: 0.902000; val_acc: 0.275000
(Epoch 10 / 25) train acc: 0.888000; val_acc: 0.261000
(Epoch 11 / 25) train acc: 0.926000; val_acc: 0.278000
(Epoch 12 / 25) train acc: 0.960000; val_acc: 0.302000
(Epoch 13 / 25) train acc: 0.964000; val_acc: 0.306000
(Epoch 14 / 25) train acc: 0.966000; val_acc: 0.310000
(Epoch 15 / 25) train acc: 0.978000; val_acc: 0.290000
(Epoch 16 / 25) train acc: 0.980000; val_acc: 0.307000
(Epoch 17 / 25) train acc: 0.982000; val_acc: 0.309000
(Epoch 18 / 25) train acc: 0.994000; val_acc: 0.319000
(Epoch 19 / 25) train acc: 0.990000; val_acc: 0.313000
(Epoch 20 / 25) train acc: 0.990000; val_acc: 0.311000
(Iteration 101 / 125) loss: 0.000313
(Epoch 21 / 25) train acc: 0.992000; val_acc: 0.308000
(Epoch 22 / 25) train acc: 0.986000; val_acc: 0.304000
(Epoch 23 / 25) train acc: 0.990000; val_acc: 0.313000
(Epoch 24 / 25) train acc: 0.998000; val_acc: 0.310000
(Epoch 25 / 25) train acc: 0.996000; val_acc: 0.319000
0.25
(Iteration 1 / 125) loss: 17.318480
(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: 0.296000
(Epoch 6 / 25) train acc: 0.626000; val_acc: 0.291000
(Epoch 7 / 25) train acc: 0.622000; val_acc: 0.297000
(Epoch 8 / 25) train acc: 0.686000; val_acc: 0.313000
(Epoch 9 / 25) train acc: 0.712000; val_acc: 0.297000
(Epoch 10 / 25) train acc: 0.724000; val_acc: 0.305000
(Epoch 11 / 25) train acc: 0.768000; val_acc: 0.309000
(Epoch 12 / 25) train acc: 0.768000; val_acc: 0.289000
(Epoch 13 / 25) train acc: 0.830000; val_acc: 0.302000
(Epoch 14 / 25) train acc: 0.802000; val_acc: 0.359000
(Epoch 15 / 25) train acc: 0.852000; val_acc: 0.342000
(Epoch 16 / 25) train acc: 0.838000; val_acc: 0.305000
(Epoch 17 / 25) train acc: 0.856000; val_acc: 0.294000
(Epoch 18 / 25) train acc: 0.854000; val_acc: 0.310000
(Epoch 19 / 25) train acc: 0.874000; val_acc: 0.320000
(Epoch 20 / 25) train acc: 0.872000; val_acc: 0.300000
(Iteration 101 / 125) loss: 4.683146
(Epoch 21 / 25) train acc: 0.910000; val_acc: 0.329000
(Epoch 22 / 25) train acc: 0.900000; val_acc: 0.302000
(Epoch 23 / 25) train acc: 0.894000; val_acc: 0.306000
```

```
(Epoch 24 / 25) train acc: 0.924000; val_acc: 0.328000
(Epoch 25 / 25) train acc: 0.918000; val_acc: 0.304000
```

In [10]:
```
# 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:

With dropout, the difference between training and validation accuracies falls, hence dropout acts as a regularizer. Without dropout, the model overfits on the training data and there is a larger gap between training and validation accuracies.

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). How should we modify p, if at all, if we decide to decrease the size of the hidden layers (that is, the number of nodes in each layer)?

Answer:

p should be increased. Reducing the number of hidden layers would decrease the capacity of the model and thus, the regularization should be reduced by increasing p by dropping lesser values.

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.

In [45]:
```
# As usual, a bit of setup
import numpy as np
import matplotlib.pyplot as plt
from cs682.classifiers.cnn import *
from cs682.data_utils import get_CIFAR10_data
from cs682.gradient_check import eval_numerical_gradient_array, eval_num
erical_gradient
from cs682.layers import *
from cs682.fast_layers import *
from cs682.solver import Solver

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-i
n-ipython
%load_ext autoreload
%autoreload 2

def rel_error(x, y):
  """ returns relative error """
  return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y
))))
```

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

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

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

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

Convolution: Naive forward pass

The core of a convolutional network is the convolution operation. In the file `cs682/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 (correct_out.shape, correct_out[:,:,1,1])
# print(out.shape, out[:,:,1,1])
print('difference: ', rel_error(out, correct_out))
```

```
Testing conv_forward_naive
difference:  2.212147649671884e-08
```

Aside: Image processing via convolutions

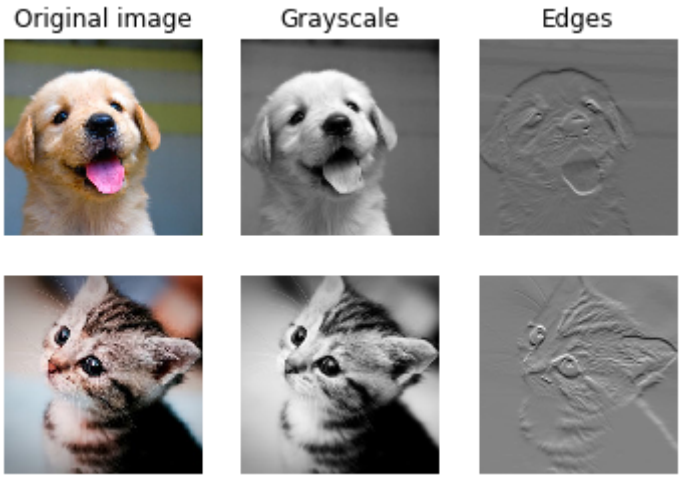
As fun way to both check your implementation and gain a better understanding of the type of operation that convolutional layers can perform, we will set up an input containing two images and manually set up filters that perform common image processing operations (grayscale conversion and edge detection).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

In [4]:

```
from scipy.misc import imread, imresize

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

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

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

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

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

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

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

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

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

```
plt.subplot(2, 3, 5)
imshow_noax(out[1, 0])
plt.subplot(2, 3, 6)
imshow_noax(out[1, 1])
plt.show()
```

```
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:3: DeprecationWarning: `imread` is deprecated!
`imread` is deprecated in SciPy 1.0.0, and will be removed in 1.2.0.
Use ``imageio.imread`` instead.
  This is separate from the ipykernel package so we can avoid doing imp
orts until
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:10: DeprecationWarning: `imresize` is deprecated!
`imresize` is deprecated in SciPy 1.0.0, and will be removed in 1.3.0.
Use Pillow instead: ``numpy.array(Image.fromarray(arr).resize())``.
  # Remove the CWD from sys.path while we load stuff.
/Users/anshuman/anaconda3/envs/cs682/lib/python3.6/site-packages/ipyker
nel_launcher.py:11: DeprecationWarning: `imresize` is deprecated!
`imresize` is deprecated in SciPy 1.0.0, and will be removed in 1.3.0.
Use Pillow instead: ``numpy.array(Image.fromarray(arr).resize())``.
  # This is added back by InteractiveShellApp.init_path()
```



Convolution: Naive backward pass

Implement the backward pass for the convolution operation in the function `conv_backward_naive` in the file `cs682/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 [7]:
```
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, dout)
dw_num = eval_numerical_gradient_array(lambda w: conv_forward_naive(x, w
, b, conv_param)[0], w, dout)
db_num = eval_numerical_gradient_array(lambda b: conv_forward_naive(x, w
, b, conv_param)[0], b, dout)

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:  4.885873245262464e-09
dw error:  1.2171605452970947e-09
db error:  1.1987330644595476e-10
```

Max-Pooling: Naive forward

Implement the forward pass for the max-pooling operation in the function `max_pool_forward_naive` in the file `cs682/layers.py`. Again, don't worry too much about computational efficiency.

Check your implementation by running the following:

In [12]:
```
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 `cs682/layers.py` . You don't need to worry about computational efficiency.

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

In [22]:
```
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 `cs682/fast_layers.py`.

The fast convolution implementation depends on a Cython extension; to compile it you need to run the following from the `cs682` 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 [23]:
```
# Rel errors should be around e-9 or less
from cs682.fast_layers import conv_forward_fast, conv_backward_fast
from time import time
np.random.seed(231)
x = np.random.randn(100, 3, 31, 31)
w = np.random.randn(25, 3, 3, 3)
b = np.random.randn(25,)
dout = np.random.randn(100, 25, 16, 16)
conv_param = {'stride': 2, 'pad': 1}

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

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

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

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

```
Testing conv_forward_fast:
Naive: 0.095110s
Fast: 0.033375s
Speedup: 2.849734x
Difference:  4.926407851494105e-11

Testing conv_backward_fast:
Naive: 0.106962s
Fast: 0.014177s
Speedup: 7.544708x
dx difference:  3.0189906199222895e-11
dw difference:  3.684308639594534e-13
db difference:  1.2340192272300884e-14
```

In [24]:
```
# Relative errors should be close to 0.0
from cs682.fast_layers import max_pool_forward_fast, max_pool_backward_f
ast
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: 0.009937s
fast: 0.004588s
speedup: 2.165766x
difference:  0.0

Testing pool_backward_fast:
Naive: 0.021426s
fast: 0.011407s
speedup: 1.878294x
dx difference:  0.0
```

Convolutional "sandwich" layers

Previously we introduced the concept of "sandwich" layers that combine multiple operations into commonly used patterns. In the file `cs682/layer_utils.py` you will find sandwich layers that implement a few commonly used patterns for convolutional networks.

In [25]:
```
from cs682.layer_utils import conv_relu_pool_forward, conv_relu_pool_bac
kward
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_param)[0], x, dout)
dw_num = eval_numerical_gradient_array(lambda w: conv_relu_pool_forward(
x, w, b, conv_param, pool_param)[0], w, dout)
db_num = eval_numerical_gradient_array(lambda b: conv_relu_pool_forward(
x, w, b, conv_param, pool_param)[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:  5.828178746516271e-09
dw error:  8.443628091870788e-09
db error:  3.57960501324485e-10
```

In [26]:
```
from cs682.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 `cs682/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 this should go up.

In [46]:
```
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):  2.3025850635890874
Initial loss (with regularization):  2.508600062137286
```

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 [47]:
```
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_gra
d_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.

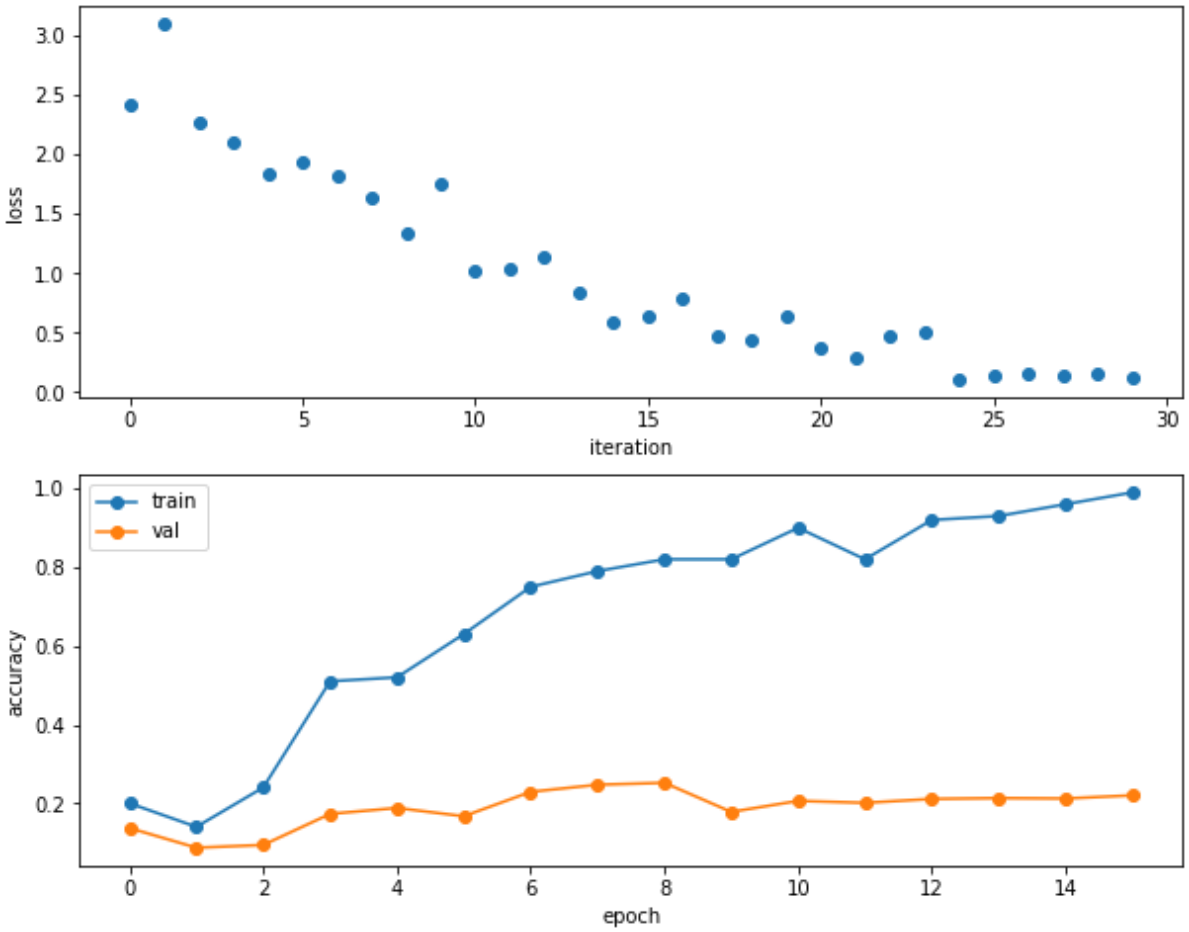
In [48]:

```
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 [49]:
```
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:

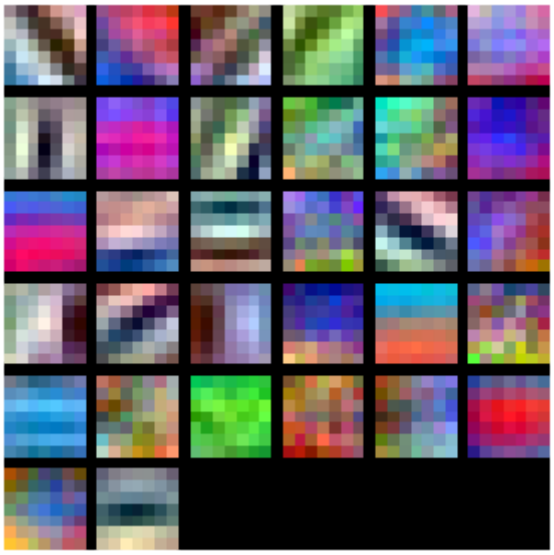
In [50]:
```
model = ThreeLayerConvNet(weight_scale=0.001, hidden_dim=500, reg=0.001)

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 [51]:
```
from cs682.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 [3], 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 the statistics of each feature channel to be relatively consistent both between different imagesand different locations within the same image. Therefore spatial batch normalization computes a mean and variance for each of the `C` feature channels by computing statistics over both the minibatch dimension `N` and the spatial dimensions `H` and `W`.

[3] Sergey Ioffe and Christian Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015. (https://arxiv.org/abs/1502.03167)

Spatial batch normalization: forward

In the file `cs682/layers.py` , implement the forward pass for spatial batch normalization in the function `spatial_batchnorm_forward` . Check your implementation by running the following:

In [68]:
```
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:  [ 6.18949336e-16  5.99520433e-16 -1.22124533e-16]
  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 [69]:
```
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 `cs682/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 [70]:
```
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))
```

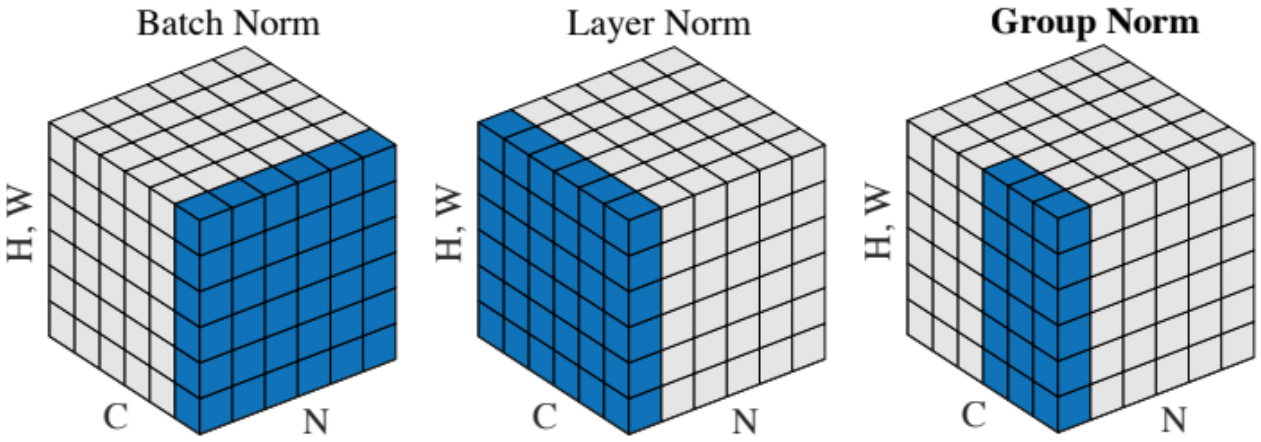
```
dx error:  2.7866481890178303e-07
dgamma error:  7.0974817113608705e-12
dbeta error:  3.275608725278405e-12
```

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 [4] 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 [5] 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 [5])

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 [6]-- 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 arXiv *less than a month ago* -- this truly is still an ongoing and excitingly active field of research!

[4] Ba, Jimmy Lei, Jamie Ryan Kiros, and Geoffrey E. Hinton. "Layer Normalization." stat 1050 (2016): 21. (https://arxiv.org/pdf/1607.06450.pdf)

[5] Wu, Yuxin, and Kaiming He. "Group Normalization." arXiv preprint arXiv:1803.08494 (2018). (https://arxiv.org/abs/1803.08494)

[6] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In Computer Vision and Pattern Recognition (CVPR), 2005. (https://ieeexplore.ieee.org/abstract/document/1467360/)

Group normalization: forward

In the file `cs682/layers.py`, implement the forward pass for group normalization in the function `spatial_groupnorm_forward`. Check your implementation by running the following:

In [90]:
```
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:  [ 0.0353638  -0.0353638   0.03878463 -0.03878463]
  Stds:  [1.05136914 0.94452101 1.02890674 0.96868012]
```

Spatial group normalization: backward

In the file `cs682/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 [89]:
```
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(da_num.shape, "\n", dgamma.shape)
print('dbeta error: ', rel_error(db_num, dbeta))
# print (db_num.shape, "\n", dbeta.shape)
```

```
dx error:  4.718196569920716e-08
dgamma error:  4.594351017568041e-12
dbeta error:  4.934654120638732e-12
```

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 switch over to that notebook).

What is PyTorch?

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

Why?

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

PyTorch versions

This notebook assumes that you are using **PyTorch version 0.4**. Prior to this version, Tensors had to be wrapped in Variable objects to be used in autograd; however Variables have now been deprecated. In addition 0.4 also separates a Tensor's datatype from its device, and uses numpy-style factories for constructing Tensors rather than directly invoking Tensor constructors.

How will I learn PyTorch?

Justin Johnson has made an excellent tutorial (https://github.com/jcjohnson/pytorch-examples) for PyTorch.

You can also find the detailed API doc (http://pytorch.org/docs/stable/index.html) here. If you have other questions that are not addressed by the API docs, the PyTorch forum (https://discuss.pytorch.org/) is a much better place to ask than StackOverflow.

Table of Contents

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

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

Here is a table of comparison:

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

Part I. Preparation

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

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

In [3]:

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

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

import numpy as np

import os
os.environ['KMP_DUPLICATE_LIB_OK']='True'
```

In [4]:
```
NUM_TRAIN = 49000

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

# We set up a Dataset object for each split (train / val / test); Datase
ts load
# training examples one at a time, so we wrap each Dataset in a DataLoad
er which
# iterates through the Dataset and forms minibatches. We divide the CIFA
R-10
# training set into train and val sets by passing a Sampler object to th
e
# DataLoader telling how it should sample from the underlying Dataset.
cifar10_train = dset.CIFAR10('./cs682/datasets', train=True, download=Tr
ue,
                             transform=transform)
loader_train = DataLoader(cifar10_train, batch_size=64,
                          sampler=sampler.SubsetRandomSampler(range(NUM_
TRAIN)))

cifar10_val = dset.CIFAR10('./cs682/datasets', train=True, download=True
,
                           transform=transform)
loader_val = DataLoader(cifar10_val, batch_size=64,
                        sampler=sampler.SubsetRandomSampler(range(NUM_TR
AIN, 50000)))

cifar10_test = dset.CIFAR10('./cs682/datasets', train=False, download=Tr
ue,
                            transform=transform)
loader_test = DataLoader(cifar10_test, batch_size=64)
```

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

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

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

In [5]:
```
USE_GPU = True

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

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

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

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

```
using device: 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.

PyTorch Tensors: Flatten Function

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

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

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

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

In [6]:
```
def flatten(x):
    N = x.shape[0] # read in N, C, H, W
    return x.view(N, -1)  # "flatten" the C * H * W values into a single vector per image

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

test_flatten()
```

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


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

Barebones PyTorch: Two-Layer Network

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

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

In [7]:
```
import torch.nn.functional as F  # useful stateless functions

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

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

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

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

    w1, w2 = params

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


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

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

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.

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

In [24]:
```
def three_layer_convnet(x, params):
    """
    Performs the forward pass of a three-layer convolutional network wit
h the
    architecture defined above.

    Inputs:
    - x: A PyTorch Tensor of shape (N, 3, H, W) giving a minibatch of im
ages
    - params: A list of PyTorch Tensors giving the weights and biases fo
r 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, KW
2) 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 laye
r. Can you
        figure out what the shape should be?
      - fc_b: PyTorch Tensor giving biases for the fully-connected laye
r. Can you
        figure out what the shape should be?

    Returns:
    - scores: PyTorch Tensor of shape (N, C) giving classification score
s 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.
#
    ################################################################################
############
    z1 = F.conv2d(x, conv_w1, bias=conv_b1, padding=2)
    z2 = F.relu(z1)
#     print("z2", z2.shape)
    z3 = F.conv2d(z2, conv_w2, bias=conv_b2, padding=1)
    z4 = F.relu(z3)
    z4 = flatten(z4)
#     print ("z4", z4.shape)
    scores = z4.mm(fc_w) + fc_b
    ################################################################################
############
    #                                 END OF YOUR CODE
#
    ################################################################################
```

```
    ############
    return scores
```

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

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

In [25]:
```
def three_layer_convnet_test():
    x = torch.zeros((64, 3, 32, 32), dtype=dtype)  # minibatch size 64, image size [3, 32, 32]

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

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

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

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

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 (https://arxiv.org/abs/1502.01852)

In [26]:
```
def random_weight(shape):
    """
    Create random Tensors for weights; setting requires_grad=True means
 that we
    want to compute gradients for these Tensors during the backward pas
s.
    We use Kaiming normalization: sqrt(2 / fan_in)
    """
    if len(shape) == 2:  # FC weight
        fan_in = shape[0]
    else:
        fan_in = np.prod(shape[1:]) # conv weight [out_channel, in_chann
el, kH, kW]
    # randn is standard normal distribution generator.
    w = torch.randn(shape, device=device, dtype=dtype) * np.sqrt(2. / fa
n_in)
    w.requires_grad = True
    return w

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

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

Out[26]:
```
tensor([[-0.8634,  1.2359,  0.0678, -1.0635,  1.6025],
        [ 0.2004, -0.5486, -0.5235,  0.0680,  1.0950],
        [-0.9561,  0.4455,  0.5152,  0.2006,  1.0745]], requires_grad=T
rue)
```

Barebones PyTorch: Check Accuracy

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

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

In [27]:
```
def check_accuracy_part2(loader, model_fn, params):
    """
    Check the accuracy of a classification model.

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

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

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 (http://pytorch.org/docs/stable/nn.html#cross-entropy)](http://pytorch.org/docs/stable/nn.html#cross-entropy).

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

In [28]:
```
def train_part2(model_fn, params, learning_rate):
    """
    Train a model on CIFAR-10.

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

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

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

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

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

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

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

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 [29]:
```
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 = 3.5956
Checking accuracy on the val set
Got 103 / 1000 correct (10.30%)

Iteration 100, loss = 2.4938
Checking accuracy on the val set
Got 290 / 1000 correct (29.00%)

Iteration 200, loss = 1.7095
Checking accuracy on the val set
Got 393 / 1000 correct (39.30%)

Iteration 300, loss = 2.1934
Checking accuracy on the val set
Got 370 / 1000 correct (37.00%)

Iteration 400, loss = 1.8438
Checking accuracy on the val set
Got 383 / 1000 correct (38.30%)

Iteration 500, loss = 1.7035
Checking accuracy on the val set
Got 414 / 1000 correct (41.40%)

Iteration 600, loss = 1.8732
Checking accuracy on the val set
Got 437 / 1000 correct (43.70%)

Iteration 700, loss = 1.5101
Checking accuracy on the val set
Got 419 / 1000 correct (41.90%)
```

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 [30]:

```
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.
#
################################################################################
########
# 3 x 32 x 32
conv_w1 = random_weight ((channel_1, 3, 5, 5))
conv_b1 = zero_weight ((channel_1))
# after 1st conv layer (pad=2) => channel_1 x 32 x 32
conv_w2 = random_weight ((channel_2, channel_1, 3, 3))
conv_b2 = zero_weight ((channel_2))
# after 2nd conv layer (pad=1) => channel_2 x 32 x 32
fc_w = random_weight ((channel_2 * 32 * 32, 10))
fc_b = zero_weight ((10))
################################################################################
########
#                                       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 = 3.4746
Checking accuracy on the val set
Got 128 / 1000 correct (12.80%)

Iteration 100, loss = 2.1287
Checking accuracy on the val set
Got 357 / 1000 correct (35.70%)

Iteration 200, loss = 1.7476
Checking accuracy on the val set
Got 419 / 1000 correct (41.90%)

Iteration 300, loss = 1.4640
Checking accuracy on the val set
Got 410 / 1000 correct (41.00%)

Iteration 400, loss = 1.5675
Checking accuracy on the val set
Got 457 / 1000 correct (45.70%)

Iteration 500, loss = 1.6361
Checking accuracy on the val set
Got 458 / 1000 correct (45.80%)

Iteration 600, loss = 1.4654
Checking accuracy on the val set
Got 470 / 1000 correct (47.00%)

Iteration 700, loss = 1.6182
Checking accuracy on the val set
Got 478 / 1000 correct (47.80%)
```

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 (http://pytorch.org/docs/master/optim.html) 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 (http://pytorch.org/docs/master/nn.html) 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 [31]:
```
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 (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 [34]:
```
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 wit
h the  #
        # architecture defined above.
#
        ########################################################################
        self.conv1 = nn.Conv2d (in_channel, channel_1, (5,5), padding=2)
        nn.init.kaiming_normal_(self.conv1.weight)
        self.conv2 = nn.Conv2d (channel_1, channel_2, (3,3), padding=1)
        nn.init.kaiming_normal_(self.conv2.weight)
        self.fc = nn.Linear (channel_2*32*32, num_classes)
        ########################################################################
        #                               END OF YOUR CODE
#
        ########################################################################

    def forward(self, x):
        scores = None
        ########################################################################
        # TODO: Implement the forward function for a 3-layer ConvNet. yo
u      #
        # should use the layers you defined in __init__ and specify the
#
        # connectivity of those layers in forward()
#
        ########################################################################
        z1 = F.relu(self.conv1(x))
        z2 = F.relu(self.conv2(z1))
        scores = self.fc(flatten(z2))
        ########################################################################
        #                                 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, n
um_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 [35]:
```
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 [36]:
```
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 lo
ss with
            # respect to each  parameter of the model.
            loss.backward()

            # Actually update the parameters of the model using the grad
ients
            # 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 [37]:
```
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 = 3.7192
Checking accuracy on validation set
Got 138 / 1000 correct (13.80)

Iteration 100, loss = 2.3288
Checking accuracy on validation set
Got 333 / 1000 correct (33.30)

Iteration 200, loss = 1.7268
Checking accuracy on validation set
Got 357 / 1000 correct (35.70)

Iteration 300, loss = 2.5014
Checking accuracy on validation set
Got 399 / 1000 correct (39.90)

Iteration 400, loss = 1.9137
Checking accuracy on validation set
Got 442 / 1000 correct (44.20)

Iteration 500, loss = 1.9807
Checking accuracy on validation set
Got 408 / 1000 correct (40.80)

Iteration 600, loss = 1.7959
Checking accuracy on validation set
Got 434 / 1000 correct (43.40)

Iteration 700, loss = 1.8260
Checking accuracy on validation set
Got 441 / 1000 correct (44.10)
```

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 [38]:
```
learning_rate = 3e-3
channel_1 = 32
channel_2 = 16

model = None
optimizer = None
################################################################################
########
# TODO: Instantiate your ThreeLayerConvNet model and a corresponding opt
imizer #
################################################################################
########
model = ThreeLayerConvNet(in_channel=3, channel_1=20, channel_2=20, num_
classes=10)
optimizer = optim.Adam(model.parameters(), lr=1e-3)
################################################################################
########
#                                END OF YOUR CODE
################################################################################
########

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.3925
Checking accuracy on validation set
Got 129 / 1000 correct (12.90)

Iteration 100, loss = 1.6374
Checking accuracy on validation set
Got 430 / 1000 correct (43.00)

Iteration 200, loss = 1.6120
Checking accuracy on validation set
Got 487 / 1000 correct (48.70)

Iteration 300, loss = 1.2784
Checking accuracy on validation set
Got 514 / 1000 correct (51.40)

Iteration 400, loss = 1.4642
Checking accuracy on validation set
Got 542 / 1000 correct (54.20)

Iteration 500, loss = 1.3801
Checking accuracy on validation set
Got 547 / 1000 correct (54.70)

Iteration 600, loss = 1.1941
Checking accuracy on validation set
Got 570 / 1000 correct (57.00)

Iteration 700, loss = 1.2486
Checking accuracy on validation set
Got 597 / 1000 correct (59.70)
```

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 [39]:
```
# 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 = 2.3838
Checking accuracy on validation set
Got 182 / 1000 correct (18.20)

Iteration 100, loss = 1.7808
Checking accuracy on validation set
Got 391 / 1000 correct (39.10)

Iteration 200, loss = 1.7499
Checking accuracy on validation set
Got 367 / 1000 correct (36.70)

Iteration 300, loss = 1.9528
Checking accuracy on validation set
Got 404 / 1000 correct (40.40)

Iteration 400, loss = 1.8237
Checking accuracy on validation set
Got 415 / 1000 correct (41.50)

Iteration 500, loss = 1.5825
Checking accuracy on validation set
Got 441 / 1000 correct (44.10)

Iteration 600, loss = 1.6609
Checking accuracy on validation set
Got 436 / 1000 correct (43.60)

Iteration 700, loss = 1.7796
Checking accuracy on validation set
Got 432 / 1000 correct (43.20)
```

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 [44]:

```
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.
#
################################################################################
########
model = nn.Sequential(
    nn.Conv2d(3, 20, (5,5),padding=2),
    nn.ReLU(),
    nn.Conv2d(20, 20, (3,3),padding=1),
    nn.ReLU(),
    Flatten(),
    nn.Linear(20*32*32, 10),
)

optimizer = optim.Adam(model.parameters(), lr=1e-3)
################################################################################
########
#                                END OF YOUR CODE
################################################################################
########

train_part34(model, optimizer)
```

```
Iteration 0, loss = 2.3349
Checking accuracy on validation set
Got 129 / 1000 correct (12.90)

Iteration 100, loss = 1.9342
Checking accuracy on validation set
Got 473 / 1000 correct (47.30)

Iteration 200, loss = 1.5828
Checking accuracy on validation set
Got 487 / 1000 correct (48.70)

Iteration 300, loss = 1.4545
Checking accuracy on validation set
Got 532 / 1000 correct (53.20)

Iteration 400, loss = 1.2852
Checking accuracy on validation set
Got 556 / 1000 correct (55.60)

Iteration 500, loss = 1.5161
Checking accuracy on validation set
Got 554 / 1000 correct (55.40)

Iteration 600, loss = 1.0615
Checking accuracy on validation set
Got 566 / 1000 correct (56.60)

Iteration 700, loss = 1.3529
Checking accuracy on validation set
Got 586 / 1000 correct (58.60)
```

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 (http://pytorch.org/docs/stable/nn.html)
- Activations: http://pytorch.org/docs/stable/nn.html#non-linear-activations (http://pytorch.org/docs/stable/nn.html#non-linear-activations)
- Loss functions: http://pytorch.org/docs/stable/nn.html#loss-functions (http://pytorch.org/docs/stable/nn.html#loss-functions)
- Optimizers: http://pytorch.org/docs/stable/optim.html (http://pytorch.org/docs/stable/optim.html)

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 (https://arxiv.org/abs/1512.00567) (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 (https://arxiv.org/abs/1512.03385) where the input from the previous layer is added to the output.
  - DenseNets (https://arxiv.org/abs/1608.06993) where inputs into previous layers are concatenated together.
  - This blog has an in-depth overview (https://chatbotslife.com/resnets-highwaynets-and-densenets-oh-my-9bb15918ee32)

In [60]:
```
################################################################################
########
# TODO:
#
# Experiment with any architectures, optimizers, and hyperparameters.
#
# Achieve AT LEAST 70% accuracy on the *validation set* within 10 epoch
s.      #
#
#
# Note that you can use the check_accuracy function to evaluate on eithe
r      #
# 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 to
uch    #
# the test set until you have finished your architecture and  hyperparam
eter   #
# tuning, and only run the test set once at the end to report a final va
lue.   #
################################################################################
########
model = None
optimizer = None

model = nn.Sequential(
    nn.Conv2d(3, 20, (5,5),padding=2),
    nn.BatchNorm2d(20),
    nn.ReLU(),
    nn.MaxPool2d((2,2)), # 32x32 => 16x16
    nn.Conv2d(20, 50, (5,5),padding=2),
    nn.BatchNorm2d(50),
    nn.ReLU(),
    nn.MaxPool2d((2,2)), # 16x16 => 8x8
    nn.Conv2d(50, 50, (3,3),padding=1),
    nn.BatchNorm2d(50),
    nn.ReLU(),
    Flatten(),
    nn.Linear(50*8*8, 1024),
    nn.Linear(1024,10)
)

optimizer = optim.Adam(model.parameters(), lr=1e-3)
################################################################################
########
#                                END OF YOUR CODE
################################################################################
########

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

```
Iteration 0, loss = 2.3497
Checking accuracy on validation set
Got 109 / 1000 correct (10.90)

Iteration 100, loss = 1.6936
Checking accuracy on validation set
Got 454 / 1000 correct (45.40)

Iteration 200, loss = 1.4230
Checking accuracy on validation set
Got 514 / 1000 correct (51.40)

Iteration 300, loss = 1.1730
Checking accuracy on validation set
Got 554 / 1000 correct (55.40)

Iteration 400, loss = 1.1308
Checking accuracy on validation set
Got 557 / 1000 correct (55.70)

Iteration 500, loss = 1.3258
Checking accuracy on validation set
Got 570 / 1000 correct (57.00)

Iteration 600, loss = 1.4640
Checking accuracy on validation set
Got 574 / 1000 correct (57.40)

Iteration 700, loss = 1.0723
Checking accuracy on validation set
Got 602 / 1000 correct (60.20)

Iteration 0, loss = 0.9848
Checking accuracy on validation set
Got 614 / 1000 correct (61.40)

Iteration 100, loss = 1.1298
Checking accuracy on validation set
Got 578 / 1000 correct (57.80)

Iteration 200, loss = 1.0836
Checking accuracy on validation set
Got 617 / 1000 correct (61.70)

Iteration 300, loss = 0.8377
Checking accuracy on validation set
Got 628 / 1000 correct (62.80)

Iteration 400, loss = 0.9715
Checking accuracy on validation set
Got 640 / 1000 correct (64.00)

Iteration 500, loss = 0.9843
Checking accuracy on validation set
Got 656 / 1000 correct (65.60)

Iteration 600, loss = 0.9773
```

```
Checking accuracy on validation set
Got 622 / 1000 correct (62.20)

Iteration 700, loss = 0.6761
Checking accuracy on validation set
Got 629 / 1000 correct (62.90)

Iteration 0, loss = 0.8370
Checking accuracy on validation set
Got 636 / 1000 correct (63.60)

Iteration 100, loss = 0.9479
Checking accuracy on validation set
Got 671 / 1000 correct (67.10)

Iteration 200, loss = 0.8476
Checking accuracy on validation set
Got 675 / 1000 correct (67.50)

Iteration 300, loss = 0.8792
Checking accuracy on validation set
Got 681 / 1000 correct (68.10)

Iteration 400, loss = 1.0242
Checking accuracy on validation set
Got 692 / 1000 correct (69.20)

Iteration 500, loss = 0.9149
Checking accuracy on validation set
Got 696 / 1000 correct (69.60)

Iteration 600, loss = 0.8583
Checking accuracy on validation set
Got 693 / 1000 correct (69.30)

Iteration 700, loss = 0.6781
Checking accuracy on validation set
Got 693 / 1000 correct (69.30)

Iteration 0, loss = 0.6042
Checking accuracy on validation set
Got 698 / 1000 correct (69.80)

Iteration 100, loss = 0.6293
Checking accuracy on validation set
Got 703 / 1000 correct (70.30)

Iteration 200, loss = 0.7063
Checking accuracy on validation set
Got 701 / 1000 correct (70.10)

Iteration 300, loss = 0.7640
Checking accuracy on validation set
Got 687 / 1000 correct (68.70)

Iteration 400, loss = 0.6097
Checking accuracy on validation set
```

```
Got 695 / 1000 correct (69.50)

Iteration 500, loss = 0.6942
Checking accuracy on validation set
Got 712 / 1000 correct (71.20)

Iteration 600, loss = 0.5115
Checking accuracy on validation set
Got 699 / 1000 correct (69.90)

Iteration 700, loss = 0.5922
Checking accuracy on validation set
Got 694 / 1000 correct (69.40)

Iteration 0, loss = 0.5485
Checking accuracy on validation set
Got 714 / 1000 correct (71.40)

Iteration 100, loss = 0.4997
Checking accuracy on validation set
Got 702 / 1000 correct (70.20)

Iteration 200, loss = 0.5262
Checking accuracy on validation set
Got 736 / 1000 correct (73.60)

Iteration 300, loss = 0.5172
Checking accuracy on validation set
Got 712 / 1000 correct (71.20)

Iteration 400, loss = 0.6746
Checking accuracy on validation set
Got 744 / 1000 correct (74.40)

Iteration 500, loss = 0.5279
Checking accuracy on validation set
Got 724 / 1000 correct (72.40)

Iteration 600, loss = 0.5852
Checking accuracy on validation set
Got 739 / 1000 correct (73.90)

Iteration 700, loss = 0.6247
Checking accuracy on validation set
Got 741 / 1000 correct (74.10)

Iteration 0, loss = 0.7368
Checking accuracy on validation set
Got 732 / 1000 correct (73.20)

Iteration 100, loss = 0.4470
Checking accuracy on validation set
Got 735 / 1000 correct (73.50)

Iteration 200, loss = 0.6347
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)
```

```
Iteration 300, loss = 0.8925
Checking accuracy on validation set
Got 724 / 1000 correct (72.40)

Iteration 400, loss = 0.7596
Checking accuracy on validation set
Got 731 / 1000 correct (73.10)

Iteration 500, loss = 0.5915
Checking accuracy on validation set
Got 733 / 1000 correct (73.30)

Iteration 600, loss = 0.4848
Checking accuracy on validation set
Got 710 / 1000 correct (71.00)

Iteration 700, loss = 0.5966
Checking accuracy on validation set
Got 712 / 1000 correct (71.20)

Iteration 0, loss = 0.4044
Checking accuracy on validation set
Got 755 / 1000 correct (75.50)

Iteration 100, loss = 0.5634
Checking accuracy on validation set
Got 729 / 1000 correct (72.90)

Iteration 200, loss = 0.6137
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)

Iteration 300, loss = 0.4423
Checking accuracy on validation set
Got 759 / 1000 correct (75.90)

Iteration 400, loss = 0.4145
Checking accuracy on validation set
Got 721 / 1000 correct (72.10)

Iteration 500, loss = 0.4775
Checking accuracy on validation set
Got 751 / 1000 correct (75.10)

Iteration 600, loss = 0.4411
Checking accuracy on validation set
Got 748 / 1000 correct (74.80)

Iteration 700, loss = 0.4563
Checking accuracy on validation set
Got 731 / 1000 correct (73.10)

Iteration 0, loss = 0.2930
Checking accuracy on validation set
Got 766 / 1000 correct (76.60)
```

```
Iteration 100, loss = 0.5990
Checking accuracy on validation set
Got 729 / 1000 correct (72.90)

Iteration 200, loss = 0.4143
Checking accuracy on validation set
Got 718 / 1000 correct (71.80)

Iteration 300, loss = 0.2678
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 400, loss = 0.4067
Checking accuracy on validation set
Got 723 / 1000 correct (72.30)

Iteration 500, loss = 0.4766
Checking accuracy on validation set
Got 736 / 1000 correct (73.60)

Iteration 600, loss = 0.5136
Checking accuracy on validation set
Got 750 / 1000 correct (75.00)

Iteration 700, loss = 0.3405
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 0, loss = 0.3297
Checking accuracy on validation set
Got 751 / 1000 correct (75.10)

Iteration 100, loss = 0.5637
Checking accuracy on validation set
Got 753 / 1000 correct (75.30)

Iteration 200, loss = 0.3968
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 300, loss = 0.2474
Checking accuracy on validation set
Got 747 / 1000 correct (74.70)

Iteration 400, loss = 0.5851
Checking accuracy on validation set
Got 760 / 1000 correct (76.00)

Iteration 500, loss = 0.6267
Checking accuracy on validation set
Got 750 / 1000 correct (75.00)

Iteration 600, loss = 0.5335
Checking accuracy on validation set
Got 758 / 1000 correct (75.80)

Iteration 700, loss = 0.4673
```

```
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 0, loss = 0.2662
Checking accuracy on validation set
Got 754 / 1000 correct (75.40)

Iteration 100, loss = 0.5627
Checking accuracy on validation set
Got 743 / 1000 correct (74.30)

Iteration 200, loss = 0.5520
Checking accuracy on validation set
Got 753 / 1000 correct (75.30)

Iteration 300, loss = 0.3652
Checking accuracy on validation set
Got 757 / 1000 correct (75.70)

Iteration 400, loss = 0.3019
Checking accuracy on validation set
Got 771 / 1000 correct (77.10)

Iteration 500, loss = 0.2220
Checking accuracy on validation set
Got 730 / 1000 correct (73.00)

Iteration 600, loss = 0.4130
Checking accuracy on validation set
Got 756 / 1000 correct (75.60)

Iteration 700, loss = 0.3751
Checking accuracy on validation set
Got 738 / 1000 correct (73.80)
```

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.

Answer:

I started with a basic conv-batchnorm-relu-pool set followed by a fully connected layer. I was able to get close to 65% accuracy with it. I then incrementally added another conv-batchnorm-relu-pool set and then another fully connected layer after which the model was able to get above 75% accuracy on the validation set.

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 [61]:
```
best_model = model
check_accuracy_part34(loader_test, best_model)
```

```
Checking accuracy on test set
Got 7340 / 10000 correct (73.40)
```

In [ ]: