FullyConnectedNets

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1 Fully-Connected Neural Nets

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

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

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

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

  return out, cache
```

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

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

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

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

  return dx, dw
```

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

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

In [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-in-ipython
%load_ext autoreload
%autoreload 2

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

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

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

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

2 Affine layer: 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 [3]:
```
# Test the affine_forward function

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

input_size = num_inputs * np.prod(input_shape)
```

```
weight_size = output_dim * np.prod(input_shape)

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

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

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

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

3 Affine layer: backward

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

In [4]:
```
# Test the affine_backward function
np.random.seed(231)
x = np.random.randn(10, 2, 3)
w = np.random.randn(6, 5)
b = np.random.randn(5)
dout = np.random.randn(10, 5)

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

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

# The error should be around e-10 or less
print('Testing affine_backward function:')
print('dx error: ', rel_error(dx_num, dx))
print('dw error: ', rel_error(dw_num, dw))
print('db error: ', rel_error(db_num, db))
```

```
Testing affine_backward function:
dx error:  5.399100368651805e-11
dw error:  9.904211865398145e-11
db error:  2.4122867568119087e-11
```

4 ReLU activation: forward

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

In [5]:
```
# Test the relu_forward function

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

out, _ = relu_forward(x)
correct_out = np.array([[ 0.,          0.,          0.,          0.,        ],
```

```
                                  [ 0.,          0.,          0.04545455,  0.13636364,],
                                  [ 0.22727273,  0.31818182,  0.40909091,  0.5,       ]])

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

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

5 ReLU activation: backward

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

```
In [6]: np.random.seed(231)
        x = np.random.randn(10, 10)
        dout = np.random.randn(*x.shape)

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

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

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

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

5.1 Inline Question 1:

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

5.2 Answer:

Sigmoid and ReLU are both capable of producing zero gradient flow during backpropagation.

Sigmoid will have zero gradient if the input is too large in magnitude (either potitive or negative). In the one-dimensional case, the gradient would be zero if the input were a large positive or negative number.

ReLU will have zero gradient if the input is negative. In the one-dimensional case, the gradient would be zero if the input were a negative number.

Leaky ReLU could also potentially produce *close to zero* gradient flow during backpropagation if the slope of the "leaky part" isn't high enough (i.e. if the small positive constant that negative inputs are multiplied by is *too* small).

6 "Sandwich" layers

There are some common patterns of layers that are frequently used in neural nets. For example, affine layers are frequently followed by a ReLU nonlinearity. To make these common patterns easy, we define several convenience layers in the file `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 [7]: 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:  2.299579177309368e-11
dw error:  8.162011105764925e-11
db error:  7.826724021458994e-12
```

7 Loss layers: Softmax and SVM

You implemented these loss functions in the last assignment, so we'll give them to you for free here. You should still make sure you understand how they work by looking at the implementations in `cs682/layers.py`.

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

```
In [8]: np.random.seed(231)
        num_classes, num_inputs = 10, 50
        x = 0.001 * np.random.randn(num_inputs, num_classes)
        y = np.random.randint(num_classes, size=num_inputs)

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

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

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

```
# Test softmax_loss function. Loss should be close to 2.3 and dx error should be around
e-8
print('\nTesting softmax_loss:')
print('loss: ', loss)
print('dx error: ', rel_error(dx_num, dx))
```

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

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

8 Two-layer network

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

Open the file `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 [9]: np.random.seed(231)
        N, D, H, C = 3, 5, 50, 7
        X = np.random.randn(N, D)
        y = np.random.randint(C, size=N)

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

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

        print('Testing test-time forward pass ... ')
        model.params['W1'] = np.linspace(-0.7, 0.3, num=D*H).reshape(D, H)
        model.params['b1'] = np.linspace(-0.1, 0.9, num=H)
        model.params['W2'] = np.linspace(-0.3, 0.4, num=H*C).reshape(H, C)
        model.params['b2'] = np.linspace(-0.9, 0.1, num=C)
        X = np.linspace(-5.5, 4.5, num=N*D).reshape(D, N).T
        scores = model.loss(X)
        correct_scores = np.asarray(
          [[11.53165108,  12.2917344,   13.05181771,  13.81190102,  14.57198434, 15.33206765,
        16.09215096],
           [12.05769098,  12.74614105,  13.43459113,  14.1230412,   14.81149128, 15.49994135,
        16.18839143],
           [12.58373087,  13.20054771,  13.81736455,  14.43418138,  15.05099822, 15.66781506,
        16.2846319 ]])
        scores_diff = np.abs(scores - correct_scores).sum()
        assert scores_diff < 1e-6, 'Problem with test-time forward pass'
```

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

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

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

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

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

9 Solver

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

Open the file `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.

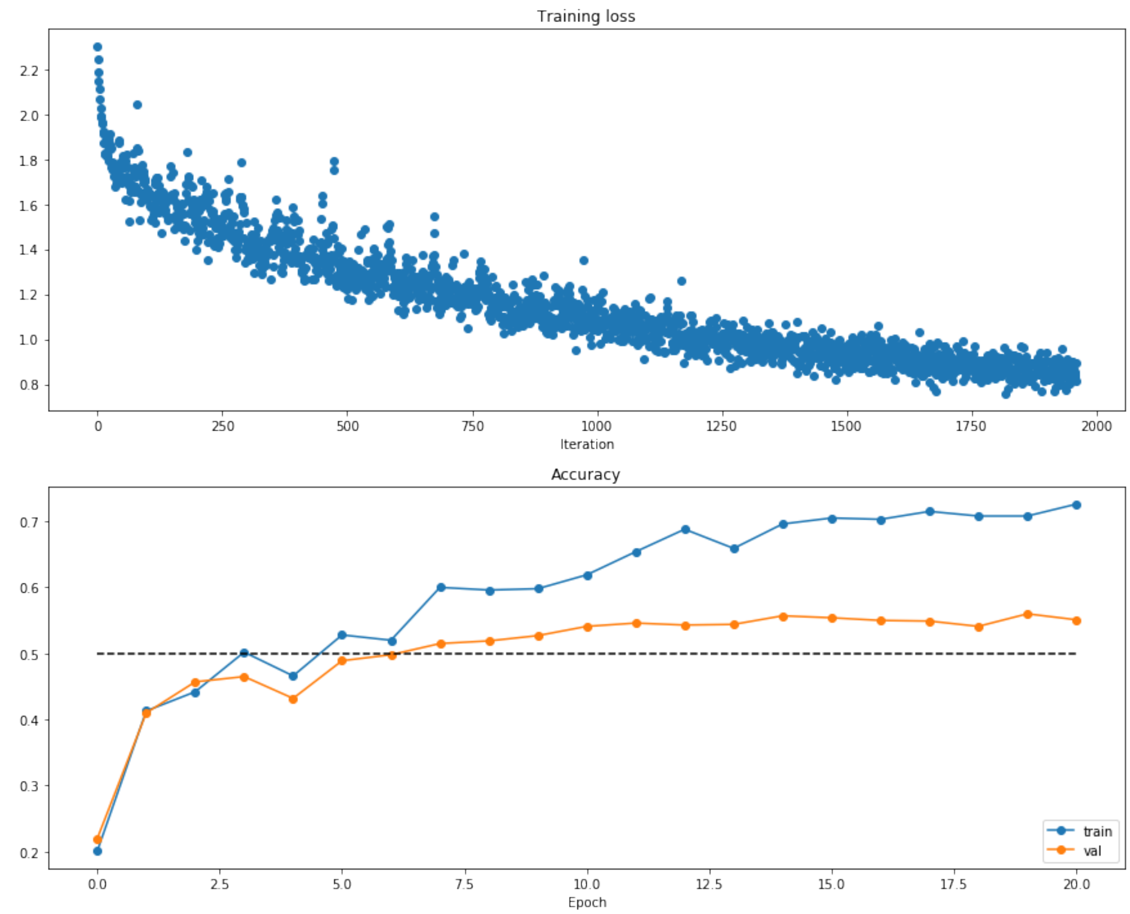
```
In [10]: ##############################################################################
         # TODO: Use a Solver instance to train a TwoLayerNet that achieves at least  #
         # 50% accuracy on the validation set.                                        #
         ##############################################################################

         solver_data = {'X_train': data['X_train'],
                        'y_train': data['y_train'],
                        'X_val': data['X_val'],
                        'y_val': data['y_val']
                       }

         def hyperparameter_search():
             learning_rates = np.arange(1e-3, 5e-3, 5e-4)
             reg_strengths = np.arange(1e-5, 1e-4, 5e-6)
             lr_decays = np.arange(0.75, 0.95, 0.01)
```

```python
    best_acc = -np.Infinity
    best_model = None
    best_params = None

    while best_acc < 0.5:
        learning_rate = np.random.choice(learning_rates)
        reg_strength = np.random.choice(reg_strengths)
        lr_decay = np.random.choice(lr_decays)
        optim_config = {'learning_rate': learning_rate}

        print('learning rate = %e, reg strength = %e, lr decay = %f' % (learning_rate,
reg_strength, lr_decay))

        # preselected parameters based on manual tuning
        batch_size = 500
        hidden_dim = 500
        num_epochs = 20

        model = TwoLayerNet(hidden_dim=hidden_dim,
                            reg=reg_strength)

        solver = Solver(model,
                        solver_data,
                        optim_config=optim_config,
                        lr_decay=lr_decay,
                        batch_size=batch_size,
                        num_epochs=num_epochs,
                        print_every=np.Infinity)

        solver.train()

        test_acc = solver.check_accuracy(data['X_test'], data['y_test'])
        print('test set accuracy = ', test_acc)

        if test_acc > best_acc:
            print('----- updating parameters -----')
            best_params = tuple([learning_rate, reg_strength, lr_decay])
            best_acc = test_acc
            best_model = model

    return best_model, best_params

# By default, the notebook will run the parameters found on a previous run of the
hyperparameter_search()
# function defined above, which resulted in a test accuracy of 55.8%. If you want to
perform hyperparameter
# search, change the value of the following variable to True
do_hyperparameter_search = False

if do_hyperparameter_search:
    model, params = hyperparameter_search()
else:
    # parameters found by running hyperparameter_search() resulting in a test accuracy
of 55.8%
    optim_config = {'learning_rate': 3e-3}
    reg_strength = 5e-5
    lr_decay = 0.9
    hidden_dim = 500
    batch_size=500
    num_epochs = 20

    model = TwoLayerNet(hidden_dim=500, reg=reg_strength)
    solver = Solver(model,
                    solver_data,
                    optim_config=optim_config,
                    lr_decay=lr_decay,
                    batch_size=500,
```

```
                     num_epochs=20,
                     print_every=np.Infinity)
    solver.train()

    test_acc = solver.check_accuracy(data['X_test'], data['y_test'])
    print('test set accuracy = ', test_acc)

################################################################################
#                              END OF YOUR CODE                                #
################################################################################
```

```
(Iteration 1 / 1960) loss: 2.311008
(Epoch 0 / 20) train acc: 0.211000; val_acc: 0.251000
(Epoch 1 / 20) train acc: 0.419000; val_acc: 0.407000
(Epoch 2 / 20) train acc: 0.426000; val_acc: 0.428000
(Epoch 3 / 20) train acc: 0.457000; val_acc: 0.426000
(Epoch 4 / 20) train acc: 0.501000; val_acc: 0.456000
(Epoch 5 / 20) train acc: 0.500000; val_acc: 0.461000
(Epoch 6 / 20) train acc: 0.554000; val_acc: 0.500000
(Epoch 7 / 20) train acc: 0.559000; val_acc: 0.510000
(Epoch 8 / 20) train acc: 0.632000; val_acc: 0.539000
(Epoch 9 / 20) train acc: 0.606000; val_acc: 0.527000
(Epoch 10 / 20) train acc: 0.633000; val_acc: 0.521000
(Epoch 11 / 20) train acc: 0.646000; val_acc: 0.546000
(Epoch 12 / 20) train acc: 0.664000; val_acc: 0.560000
(Epoch 13 / 20) train acc: 0.646000; val_acc: 0.532000
(Epoch 14 / 20) train acc: 0.695000; val_acc: 0.552000
(Epoch 15 / 20) train acc: 0.688000; val_acc: 0.555000
(Epoch 16 / 20) train acc: 0.709000; val_acc: 0.555000
(Epoch 17 / 20) train acc: 0.737000; val_acc: 0.555000
(Epoch 18 / 20) train acc: 0.705000; val_acc: 0.563000
(Epoch 19 / 20) train acc: 0.719000; val_acc: 0.564000
(Epoch 20 / 20) train acc: 0.739000; val_acc: 0.555000
test set accuracy =  0.546
```

In [45]:
```
# Run this cell to visualize training loss and train / val accuracy

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

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



10 Multilayer network

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

Read through the `FullyConnectedNet` class in the file `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.

10.1 Initial loss and gradient check

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

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

```
In [106]: np.random.seed(231)
          N, D, H1, H2, C = 2, 15, 20, 30, 10
          X = np.random.randn(N, D)
          y = np.random.randint(C, size=(N,))

          for reg in [0, 3.14]:
```

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

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

# Most of the errors should be on the order of e-7 or smaller.
# NOTE: It is fine however to see an error for W2 on the order of e-5
# for the check when reg = 0.0
for name in sorted(grads):
  f = lambda _: model.loss(X, y)[0]
  grad_num = eval_numerical_gradient(f, model.params[name], verbose=False, h=1e-5)
  print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[name])))
```

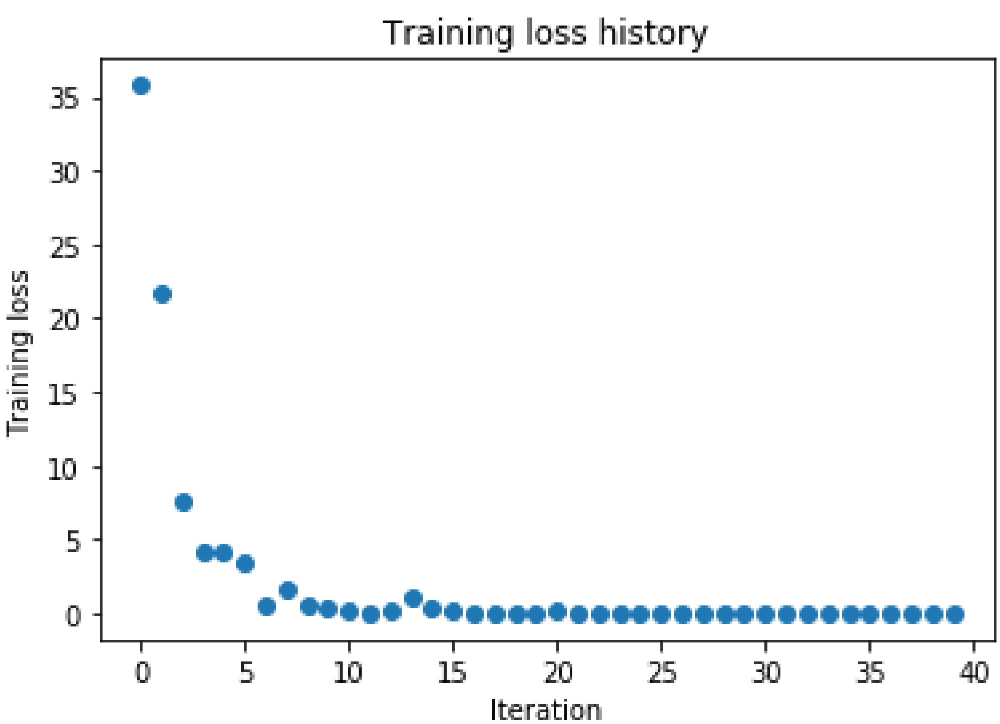
```
Running check with reg =  0
Initial loss:  2.2658787769555633
W1 relative error: 1.81e-08
W2 relative error: 3.73e-07
W3 relative error: 5.55e-07
b1 relative error: 3.13e-10
b2 relative error: 4.67e-11
b3 relative error: 8.06e-11
Running check with reg =  3.14
Initial loss:  450.6109940039681
W1 relative error: 2.57e-07
W2 relative error: 1.69e-06
W3 relative error: 4.11e-08
b1 relative error: 2.68e-08
b2 relative error: 5.54e-09
b3 relative error: 7.75e-09
```

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 [107]:
```
# TODO: Use a three-layer Net to overfit 50 training examples by
# tweaking just the learning rate and initialization scale.

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

weight_scale = 1e-2
learning_rate = 1e-4
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: 35.790877
(Epoch 0 / 20) train acc: 0.180000; val_acc: 0.119000
(Epoch 1 / 20) train acc: 0.340000; val_acc: 0.120000
(Epoch 2 / 20) train acc: 0.640000; val_acc: 0.140000
(Epoch 3 / 20) train acc: 0.840000; val_acc: 0.157000
(Epoch 4 / 20) train acc: 0.820000; val_acc: 0.150000
(Epoch 5 / 20) train acc: 0.900000; val_acc: 0.147000
(Iteration 11 / 40) loss: 0.100810
(Epoch 6 / 20) train acc: 0.920000; val_acc: 0.154000
(Epoch 7 / 20) train acc: 0.900000; val_acc: 0.170000
(Epoch 8 / 20) train acc: 0.980000; val_acc: 0.158000
(Epoch 9 / 20) train acc: 0.980000; val_acc: 0.158000
(Epoch 10 / 20) train acc: 0.980000; val_acc: 0.158000
(Iteration 21 / 40) loss: 0.121191
(Epoch 11 / 20) train acc: 1.000000; val_acc: 0.160000
(Epoch 12 / 20) train acc: 1.000000; val_acc: 0.160000
(Epoch 13 / 20) train acc: 1.000000; val_acc: 0.159000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.159000
(Epoch 15 / 20) train acc: 1.000000; val_acc: 0.158000
(Iteration 31 / 40) loss: 0.000467
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.158000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.158000
```

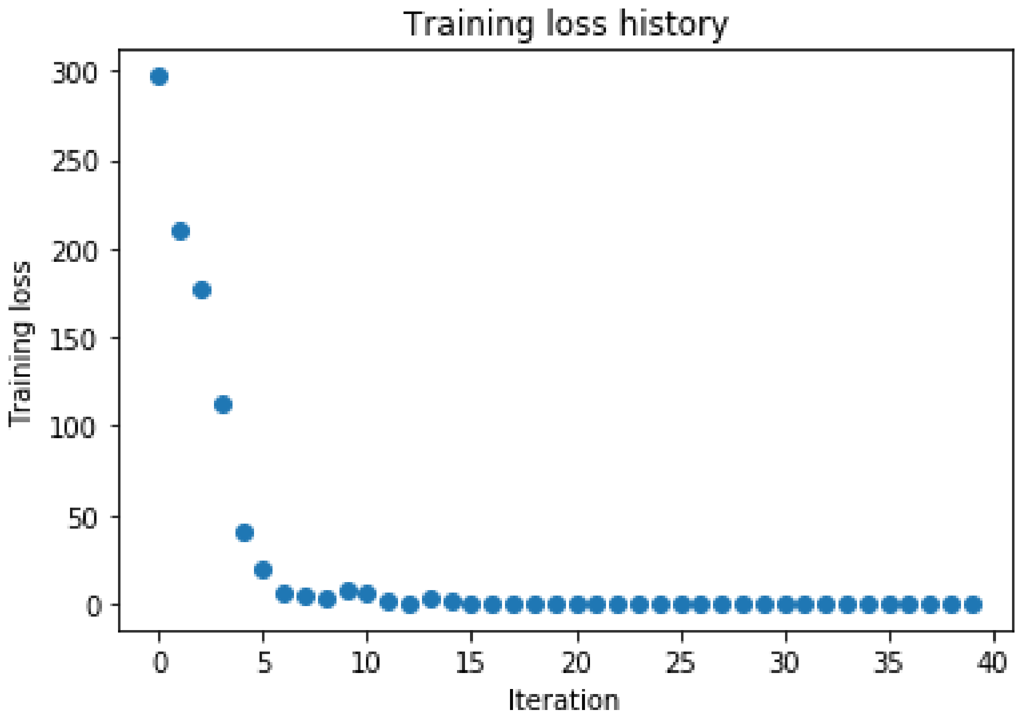


Now try to use a five-layer network with 100 units on each layer to overfit 50 training examples. Again you will have to adjust the learning rate and weight initialization, but you should be able to achieve 100% training accuracy within 20 epochs.

In [108]:
```
# 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'],
}

weight_scale = 6.5e-2
learning_rate = 3.5e-4
model = FullyConnectedNet([100, 100, 100, 100],
                          weight_scale=weight_scale,
                          dtype=np.float64)

solver = Solver(model,
                small_data,
                print_every=10,
                num_epochs=20,
                batch_size=25,
                update_rule='sgd',
                optim_config={'learning_rate': learning_rate
                             }
               )
solver.train()

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

```
(Iteration 1 / 40) loss: 297.208644
(Epoch 0 / 20) train acc: 0.200000; val_acc: 0.116000
(Epoch 1 / 20) train acc: 0.320000; val_acc: 0.106000
(Epoch 2 / 20) train acc: 0.440000; val_acc: 0.105000
(Epoch 3 / 20) train acc: 0.660000; val_acc: 0.114000
(Epoch 4 / 20) train acc: 0.780000; val_acc: 0.103000
(Epoch 5 / 20) train acc: 0.780000; val_acc: 0.120000
(Iteration 11 / 40) loss: 5.387502
(Epoch 6 / 20) train acc: 0.920000; val_acc: 0.121000
(Epoch 7 / 20) train acc: 0.920000; val_acc: 0.123000
(Epoch 8 / 20) train acc: 0.960000; val_acc: 0.124000
(Epoch 9 / 20) train acc: 0.980000; val_acc: 0.129000
(Epoch 10 / 20) train acc: 0.980000; val_acc: 0.129000
(Iteration 21 / 40) loss: 0.419520
(Epoch 11 / 20) train acc: 1.000000; val_acc: 0.125000
(Epoch 12 / 20) train acc: 1.000000; val_acc: 0.129000
(Epoch 13 / 20) train acc: 1.000000; val_acc: 0.129000
(Epoch 14 / 20) train acc: 1.000000; val_acc: 0.129000
(Epoch 15 / 20) train acc: 1.000000; val_acc: 0.129000
(Iteration 31 / 40) loss: 0.000006
(Epoch 16 / 20) train acc: 1.000000; val_acc: 0.129000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.129000
```

```
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.129000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.129000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.129000
```



10.2 Inline Question 2:

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

10.3 Answer:

The five layer net was more difficult to train, as it was more sensitive to both weight initialization and changes in the learning rate. Smaller initialization weights result in lower gradient flow through ReLU nonlinearities, and because a deeper network has more ReLU layers, there is a higer probability of "dead" ReLU units, as activations become smaller after passing through each affine layer, and are more likely to become zero after passing through each ReLU layer.

11 Update rules

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

12 SGD+Momentum

Stochastic gradient descent with momentum is a widely used update rule that tends to make deep networks converge faster than vanilla stochastic gradient descent. See the Momentum Update section at 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 [11]: 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.

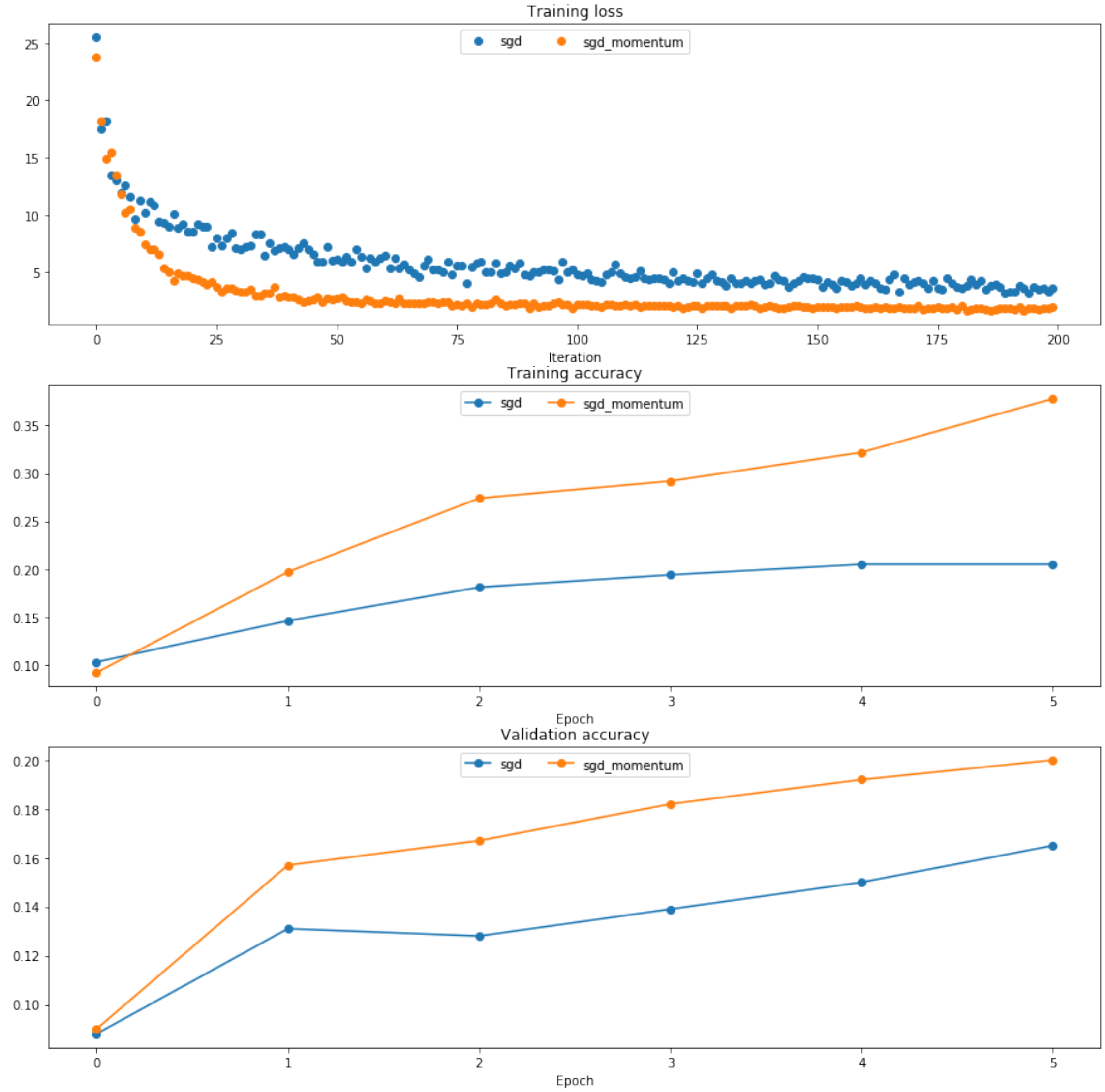
```
In [115]: num_train = 4000
          small_data = {
            'X_train': data['X_train'][:num_train],
            'y_train': data['y_train'][:num_train],
            'X_val': data['X_val'],
            'y_val': data['y_val'],
          }

          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-4,
                                           }
```

```python
                        )

            solver.train()
            solvers[update_rule] = solver

            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: 25.495220
(Epoch 0 / 5) train acc: 0.103000; val_acc: 0.088000
(Iteration 11 / 200) loss: 10.229651
(Iteration 21 / 200) loss: 8.493636
(Iteration 31 / 200) loss: 6.999047
(Epoch 1 / 5) train acc: 0.146000; val_acc: 0.131000
(Iteration 41 / 200) loss: 7.036191
(Iteration 51 / 200) loss: 6.139806
(Iteration 61 / 200) loss: 6.453247
(Iteration 71 / 200) loss: 5.219362
(Epoch 2 / 5) train acc: 0.181000; val_acc: 0.128000
(Iteration 81 / 200) loss: 5.961541
(Iteration 91 / 200) loss: 4.688865
(Iteration 101 / 200) loss: 4.820385
(Iteration 111 / 200) loss: 4.603017
(Epoch 3 / 5) train acc: 0.194000; val_acc: 0.139000
(Iteration 121 / 200) loss: 5.014280
(Iteration 131 / 200) loss: 4.214131
(Iteration 141 / 200) loss: 4.028232
(Iteration 151 / 200) loss: 4.427943
(Epoch 4 / 5) train acc: 0.205000; val_acc: 0.150000
(Iteration 161 / 200) loss: 3.957780
(Iteration 171 / 200) loss: 4.123300
(Iteration 181 / 200) loss: 3.588122
(Iteration 191 / 200) loss: 3.231773
(Epoch 5 / 5) train acc: 0.205000; val_acc: 0.165000

running with  sgd_momentum
```

```
(Iteration 1 / 200) loss: 23.816016
(Epoch 0 / 5) train acc: 0.092000; val_acc: 0.090000
(Iteration 11 / 200) loss: 7.469200
(Iteration 21 / 200) loss: 4.539695
(Iteration 31 / 200) loss: 3.297007
(Epoch 1 / 5) train acc: 0.197000; val_acc: 0.157000
(Iteration 41 / 200) loss: 2.896729
(Iteration 51 / 200) loss: 2.685854
(Iteration 61 / 200) loss: 2.481272
(Iteration 71 / 200) loss: 2.445718
(Epoch 2 / 5) train acc: 0.274000; val_acc: 0.167000
(Iteration 81 / 200) loss: 2.150510
(Iteration 91 / 200) loss: 1.867980
(Iteration 101 / 200) loss: 2.174606
(Iteration 111 / 200) loss: 2.172702
(Epoch 3 / 5) train acc: 0.292000; val_acc: 0.182000
(Iteration 121 / 200) loss: 1.953552
(Iteration 131 / 200) loss: 2.079026
(Iteration 141 / 200) loss: 2.056502
(Iteration 151 / 200) loss: 1.943504
(Epoch 4 / 5) train acc: 0.322000; val_acc: 0.192000
(Iteration 161 / 200) loss: 1.881984
(Iteration 171 / 200) loss: 1.889364
(Iteration 181 / 200) loss: 2.086546
(Iteration 191 / 200) loss: 1.856802
(Epoch 5 / 5) train acc: 0.378000; val_acc: 0.200000
```

```
/home/brendan/Desktop/school/grad/f19/cs682/assignment2/env/lib/python3.6/site-packages/
↪ipykernel_launcher.py:42:
MatplotlibDeprecationWarning: Adding an axes using the same arguments as a previous axes currently␣
↪reuses the earlier
instance.  In a future version, a new instance will always be created and returned.  Meanwhile,␣
↪this warning can be
suppressed, and the future behavior ensured, by passing a unique label to each axes instance.
/home/brendan/Desktop/school/grad/f19/cs682/assignment2/env/lib/python3.6/site-packages/
↪ipykernel_launcher.py:45:
MatplotlibDeprecationWarning: Adding an axes using the same arguments as a previous axes currently␣
↪reuses the earlier
instance.  In a future version, a new instance will always be created and returned.  Meanwhile,␣
↪this warning can be
suppressed, and the future behavior ensured, by passing a unique label to each axes instance.
/home/brendan/Desktop/school/grad/f19/cs682/assignment2/env/lib/python3.6/site-packages/
↪ipykernel_launcher.py:48:
MatplotlibDeprecationWarning: Adding an axes using the same arguments as a previous axes currently␣
↪reuses the earlier
instance.  In a future version, a new instance will always be created and returned.  Meanwhile,␣
↪this warning can be
suppressed, and the future behavior ensured, by passing a unique label to each axes instance.
/home/brendan/Desktop/school/grad/f19/cs682/assignment2/env/lib/python3.6/site-packages/
↪ipykernel_launcher.py:52:
MatplotlibDeprecationWarning: Adding an axes using the same arguments as a previous axes currently␣
↪reuses the earlier
instance.  In a future version, a new instance will always be created and returned.  Meanwhile,␣
↪this warning can be
suppressed, and the future behavior ensured, by passing a unique label to each axes instance.
```



13 RMSProp and Adam

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

In the file `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 [12]:
```
# 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 [13]:
```
# 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:

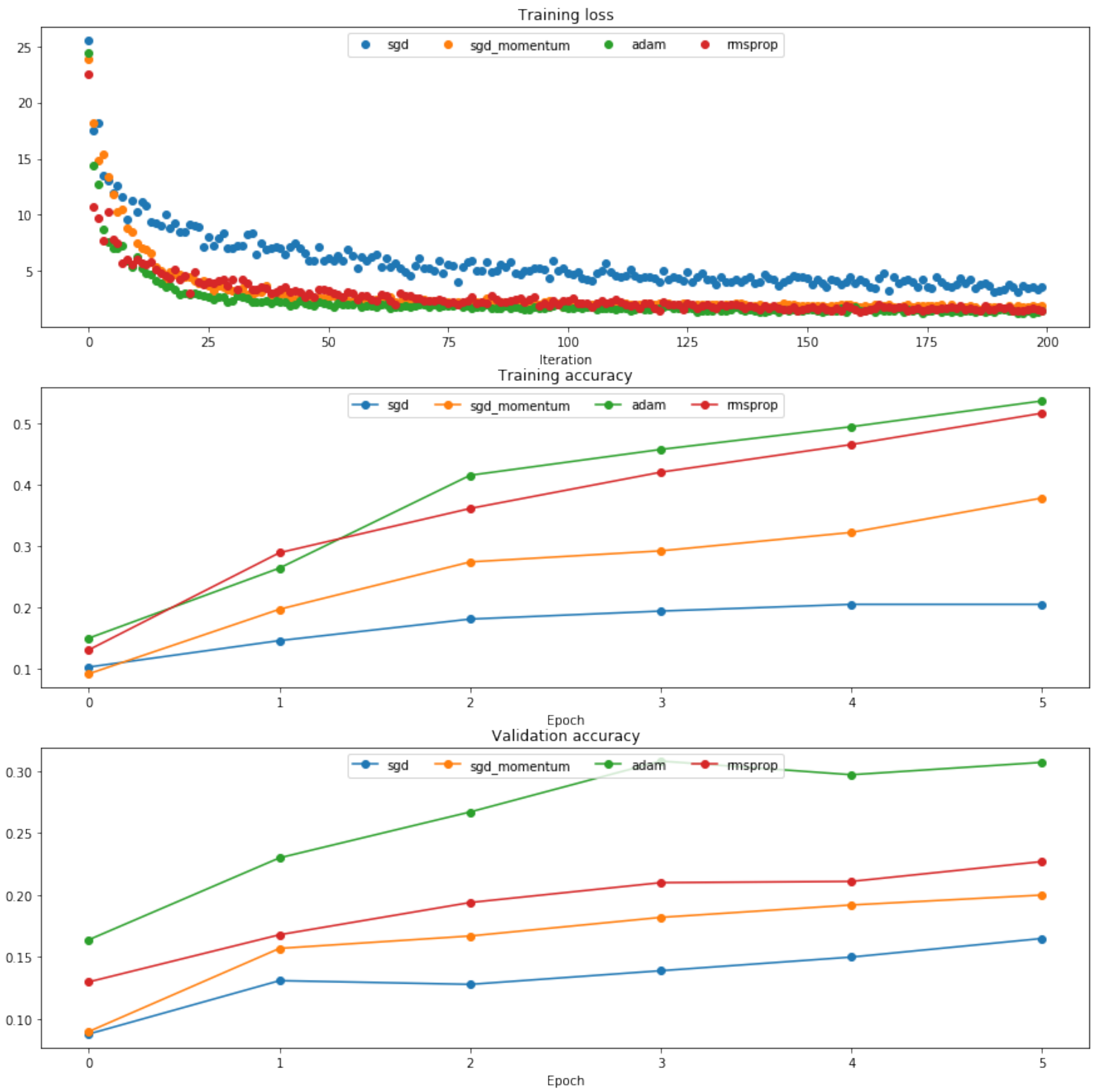
```
In [128]: learning_rates = {'rmsprop': 1e-4, 'adam': 1e-3}
          for update_rule in ['adam', 'rmsprop']:
            print('running with ', update_rule)
            model = FullyConnectedNet([100, 100, 100, 100, 100], weight_scale=5e-2)

            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: 24.367495
(Epoch 0 / 5) train acc: 0.150000; val_acc: 0.164000
(Iteration 11 / 200) loss: 6.222972
(Iteration 21 / 200) loss: 2.998138
(Iteration 31 / 200) loss: 2.333535
(Epoch 1 / 5) train acc: 0.264000; val_acc: 0.230000
(Iteration 41 / 200) loss: 2.256579
(Iteration 51 / 200) loss: 2.053400
(Iteration 61 / 200) loss: 1.794105
(Iteration 71 / 200) loss: 2.074381
(Epoch 2 / 5) train acc: 0.415000; val_acc: 0.267000
```

```
(Iteration 81 / 200) loss: 1.659071
(Iteration 91 / 200) loss: 1.684889
(Iteration 101 / 200) loss: 1.673981
(Iteration 111 / 200) loss: 1.644885
(Epoch 3 / 5) train acc: 0.457000; val_acc: 0.308000
(Iteration 121 / 200) loss: 1.827878
(Iteration 131 / 200) loss: 1.517418
(Iteration 141 / 200) loss: 1.380265
(Iteration 151 / 200) loss: 1.576847
(Epoch 4 / 5) train acc: 0.494000; val_acc: 0.297000
(Iteration 161 / 200) loss: 1.793351
(Iteration 171 / 200) loss: 1.357383
(Iteration 181 / 200) loss: 1.407575
(Iteration 191 / 200) loss: 1.588814
(Epoch 5 / 5) train acc: 0.536000; val_acc: 0.307000

running with  rmsprop
(Iteration 1 / 200) loss: 22.469834
(Epoch 0 / 5) train acc: 0.131000; val_acc: 0.130000
(Iteration 11 / 200) loss: 6.077731
(Iteration 21 / 200) loss: 4.551940
(Iteration 31 / 200) loss: 4.246853
(Epoch 1 / 5) train acc: 0.289000; val_acc: 0.168000
(Iteration 41 / 200) loss: 3.365351
(Iteration 51 / 200) loss: 3.206939
(Iteration 61 / 200) loss: 2.367928
(Iteration 71 / 200) loss: 2.319942
(Epoch 2 / 5) train acc: 0.361000; val_acc: 0.194000
(Iteration 81 / 200) loss: 2.705558
(Iteration 91 / 200) loss: 2.645353
(Iteration 101 / 200) loss: 2.411135
(Iteration 111 / 200) loss: 2.467196
(Epoch 3 / 5) train acc: 0.420000; val_acc: 0.210000
(Iteration 121 / 200) loss: 2.233731
(Iteration 131 / 200) loss: 1.815985
(Iteration 141 / 200) loss: 1.587860
(Iteration 151 / 200) loss: 1.745673
(Epoch 4 / 5) train acc: 0.465000; val_acc: 0.211000
(Iteration 161 / 200) loss: 1.567292
(Iteration 171 / 200) loss: 1.809110
(Iteration 181 / 200) loss: 1.795550
(Iteration 191 / 200) loss: 1.860653
(Epoch 5 / 5) train acc: 0.516000; val_acc: 0.227000
```

```
/home/brendan/Desktop/school/grad/f19/cs682/assignment2/env/lib/python3.6/site-packages/
 ↪ipykernel_launcher.py:30:
MatplotlibDeprecationWarning: Adding an axes using the same arguments as a previous axes currently␣
 ↪reuses the earlier
instance.  In a future version, a new instance will always be created and returned.  Meanwhile,␣
 ↪this warning can be
suppressed, and the future behavior ensured, by passing a unique label to each axes instance.
/home/brendan/Desktop/school/grad/f19/cs682/assignment2/env/lib/python3.6/site-packages/
 ↪ipykernel_launcher.py:33:
MatplotlibDeprecationWarning: Adding an axes using the same arguments as a previous axes currently␣
 ↪reuses the earlier
instance.  In a future version, a new instance will always be created and returned.  Meanwhile,␣
 ↪this warning can be
```

```
suppressed, and the future behavior ensured, by passing a unique label to each axes instance.
/home/brendan/Desktop/school/grad/f19/cs682/assignment2/env/lib/python3.6/site-packages/
↪ipykernel_launcher.py:36:
MatplotlibDeprecationWarning: Adding an axes using the same arguments as a previous axes currently␣
↪reuses the earlier
instance.  In a future version, a new instance will always be created and returned.  Meanwhile,␣
↪this warning can be
suppressed, and the future behavior ensured, by passing a unique label to each axes instance.
/home/brendan/Desktop/school/grad/f19/cs682/assignment2/env/lib/python3.6/site-packages/
↪ipykernel_launcher.py:40:
MatplotlibDeprecationWarning: Adding an axes using the same arguments as a previous axes currently␣
↪reuses the earlier
instance.  In a future version, a new instance will always be created and returned.  Meanwhile,␣
↪this warning can be
suppressed, and the future behavior ensured, by passing a unique label to each axes instance.
```



13.1 Inline Question 3:

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

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

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

13.2 Answer:

Both Adagrad and Adam update the learning rate based on a per-weight basis, however Adagrad does so in such a way that the learning rate decays monotonically, causing learning to slow down, while Adam allows learning rates to increase along with weights.

14 Train a good model!

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

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

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

```
In [18]: ################################################################################
         # TODO: Train the best FullyConnectedNet that you can on CIFAR-10. You might   #
         # find batch/layer normalization and dropout useful. Store your best model in  #
         # the best_model variable.                                                     #
         ################################################################################

         solver_data = {'X_train': data['X_train'],
                        'y_train': data['y_train'],
                        'X_val': data['X_val'],
                        'y_val': data['y_val']
                       }

         def hyperparameter_search():
             learning_rates = np.arange(1e-3, 5e-3, 5e-4)
             reg_strengths = np.arange(1e-5, 1e-4, 5e-6)
             lr_decays = np.arange(0.85, 0.95, 0.01)
             decay_rates = np.arange(0.95, 0.99, 0.01)
             epsilons = np.arange(1e-8, 1e-7, 2e-9)
             weight_scales = np.arange(5e-4, 1e-1, 1e-4)

             best_acc = -np.Infinity
             best_model = None
             best_params = None

             while best_acc < 0.5:
                 learning_rate = np.random.choice(learning_rates)
                 reg_strength = np.random.choice(reg_strengths)
                 lr_decay = np.random.choice(lr_decays)
```

```
        epsilon = np.random.choice(epsilons)
        decay_rate = np.random.choice(decay_rates)
        weight_scale = np.random.choice(weight_scales)

        optim_config = {'learning_rate': learning_rate,
                        'decay_rate': decay_rate,
                        'epsilon': epsilon}

        # preselected parameters based on manual tuning
        batch_size = 500
        hidden_dim = 100
        num_epochs = 20

        print('lr = %e, reg = %e, lr decay = %f, eps = %e, rms decay = %e' %
(learning_rate,
reg_strength,
                                                                               lr_decay,
                                                                               epsilon,
decay_rate))

        # model = FullyConnectedNet([100, 100, 100, 100, 100], weight_scale=5e-2)
        model = FullyConnectedNet([hidden_dim, hidden_dim, hidden_dim, hidden_dim,
hidden_dim], weight_scale=weight_scale)

        solver = Solver(model,
                        solver_data,
                        optim_config=optim_config,
                        update_rule='rmsprop',
                        lr_decay=lr_decay,
                        batch_size=batch_size,
                        num_epochs=num_epochs,
                        print_every=np.Infinity)

        solver.train()
        test_acc = solver.check_accuracy(data['X_test'], data['y_test'])
        print('test set accuracy = ', test_acc)

        if test_acc > best_acc:
            print('----- updating parameters -----')
            best_params = tuple([learning_rate, reg_strength, lr_decay])
            best_acc = test_acc
            best_model = model

    return best_model, best_params

# By default, the notebook will run the parameters found on a previous run of the
hyperparameter_search()
# function defined above, which resulted in a test accuracy of 55.8%. If you want to
perform hyperparameter
# search, change the value of the following variable to True
do_hyperparameter_search = False

if do_hyperparameter_search:
    model, params = hyperparameter_search()
else:
    # parameters found by running hyperparameter_search() resulting in a test accuracy
of 52.4%
    learning_rate = 3.3e-3
    reg_strength = 5.1e-5
    lr_decay = 0.87
    epsilon = 4e-8
    decay_rate = 0.96
    weight_scale = 5e-3

    optim_config = {'learning_rate': learning_rate,
                    'decay_rate': decay_rate,
                    'epsilon': epsilon}
```

```python
    # preselected parameters based on manual tuning
    batch_size = 500
    hidden_dim = 100
    num_epochs = 20

    print('lr = %e, reg = %e, lr decay = %f, eps = %e, rms decay = %e' % (learning_rate,
                                                                          reg_strength,
                                                                          lr_decay,
                                                                          epsilon,
                                                                          decay_rate))

    model = FullyConnectedNet([hidden_dim, hidden_dim, hidden_dim, hidden_dim,
hidden_dim], weight_scale=weight_scale)

    solver = Solver(model,
                    solver_data,
                    optim_config=optim_config,
                    update_rule='rmsprop',
                    lr_decay=lr_decay,
                    batch_size=batch_size,
                    num_epochs=num_epochs,
                    print_every=np.Infinity)

    solver.train()
    test_acc = solver.check_accuracy(data['X_test'], data['y_test'])
    print('test set accuracy = ', test_acc)

################################################################################
#                               END OF YOUR CODE                               #
################################################################################
```

```
lr = 3.300000e-03, reg = 5.100000e-05, lr decay = 0.870000, eps = 4.000000e-08, rms decay = 9.
↪600000e-01
(Iteration 1 / 1960) loss: 2.302585
(Epoch 0 / 20) train acc: 0.103000; val_acc: 0.087000
(Epoch 1 / 20) train acc: 0.253000; val_acc: 0.286000
(Epoch 2 / 20) train acc: 0.394000; val_acc: 0.395000
(Epoch 3 / 20) train acc: 0.384000; val_acc: 0.379000
(Epoch 4 / 20) train acc: 0.415000; val_acc: 0.419000
(Epoch 5 / 20) train acc: 0.476000; val_acc: 0.451000
(Epoch 6 / 20) train acc: 0.502000; val_acc: 0.495000
(Epoch 7 / 20) train acc: 0.540000; val_acc: 0.517000
(Epoch 8 / 20) train acc: 0.545000; val_acc: 0.508000
(Epoch 9 / 20) train acc: 0.569000; val_acc: 0.531000
(Epoch 10 / 20) train acc: 0.585000; val_acc: 0.512000
(Epoch 11 / 20) train acc: 0.577000; val_acc: 0.509000
(Epoch 12 / 20) train acc: 0.582000; val_acc: 0.523000
(Epoch 13 / 20) train acc: 0.610000; val_acc: 0.513000
(Epoch 14 / 20) train acc: 0.593000; val_acc: 0.508000
(Epoch 15 / 20) train acc: 0.617000; val_acc: 0.524000
(Epoch 16 / 20) train acc: 0.620000; val_acc: 0.525000
(Epoch 17 / 20) train acc: 0.640000; val_acc: 0.546000
(Epoch 18 / 20) train acc: 0.652000; val_acc: 0.542000
(Epoch 19 / 20) train acc: 0.650000; val_acc: 0.550000
(Epoch 20 / 20) train acc: 0.628000; val_acc: 0.531000
test set accuracy =  0.512
```

15 Test your model!

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

```
In [20]: y_test_pred = np.argmax(model.loss(data['X_test']), axis=1)
         y_val_pred = np.argmax(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:  0.55
Test set accuracy:  0.512
```