Extra 1 - Update rules

March 13, 2019

0.1 # NOTICE

- You are **NOT required** to complete this exercise. However, you are highly recommended to complete this exercise as it is very helpful. Additionally, *some bonus points will be given.*
- If you do not have enough time to complete this exercise. Don't worry. You will have chance to understand the update rules later with built-in **Tensorflow** batch normalization function.

---

1 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.

Acknowledgement: This exercise is adapted from Stanford CS231n.

```
In [1]: # As usual, a bit of setup

        import time
        import numpy as np
        import matplotlib.pyplot as plt
        from libs.classifiers.fc_net import *
        from libs.data_utils import get_CIFAR10_data
        from libs.gradient_check import eval_numerical_gradient, eval_numerical_gradient_array
        from libs.solver import Solver

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

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

        def rel_error(x, y):
```

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

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

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

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

1.1 Difficulty in training deep networks

First we will try a three-layer network with 100 units in each hidden layer.

TODO: You will need to `tweak the learning rate and initialization scale`, but you should be able to overfit and achieve 100% training accuracy within 20 epochs.

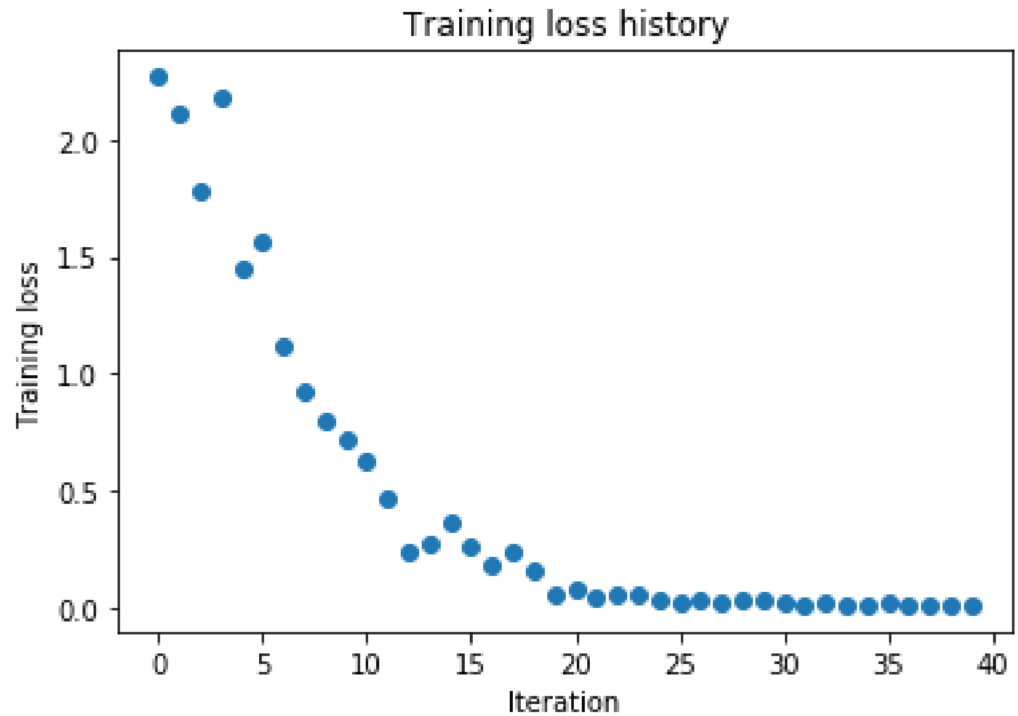
```
In [3]: N, D, H1, H2, C = 2, 15, 20, 30, 10
        X = np.random.randn(N, D)
        y = np.random.randint(C, size=(N,))

        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)

            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-
                print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[name])))
```

```
Running check with reg =  0
Initial loss:  2.2976849712277883
W1 relative error: 2.92e-06
W2 relative error: 1.04e-06
W3 relative error: 6.51e-07
b1 relative error: 1.55e-08
b2 relative error: 4.81e-09
b3 relative error: 1.15e-10
Running check with reg =  3.14
```

```
Initial loss:  7.047153455818023
W1 relative error: 7.71e-09
W2 relative error: 9.05e-08
W3 relative error: 5.05e-08
b1 relative error: 8.73e-08
b2 relative error: 2.00e-09
b3 relative error: 2.78e-10
```

```
In [4]: # TODO: Use a three-layer Net to overfit 50 training examples.

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

        learning_rate = 1e-2
        weight_scale = 1e-2

        model = FullyConnectedNet([200, 200],
                      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()
```

```
(Epoch 0 / 20) (Iteration 1 / 40) loss: 2.269489 train acc: 0.160000 val_acc: 0.080000
(Epoch 5 / 20) (Iteration 11 / 40) loss: 0.629569 train acc: 0.900000 val_acc: 0.206000
(Epoch 10 / 20) (Iteration 21 / 40) loss: 0.078320 train acc: 1.000000 val_acc: 0.188000
(Epoch 15 / 20) (Iteration 31 / 40) loss: 0.020225 train acc: 1.000000 val_acc: 0.193000
```



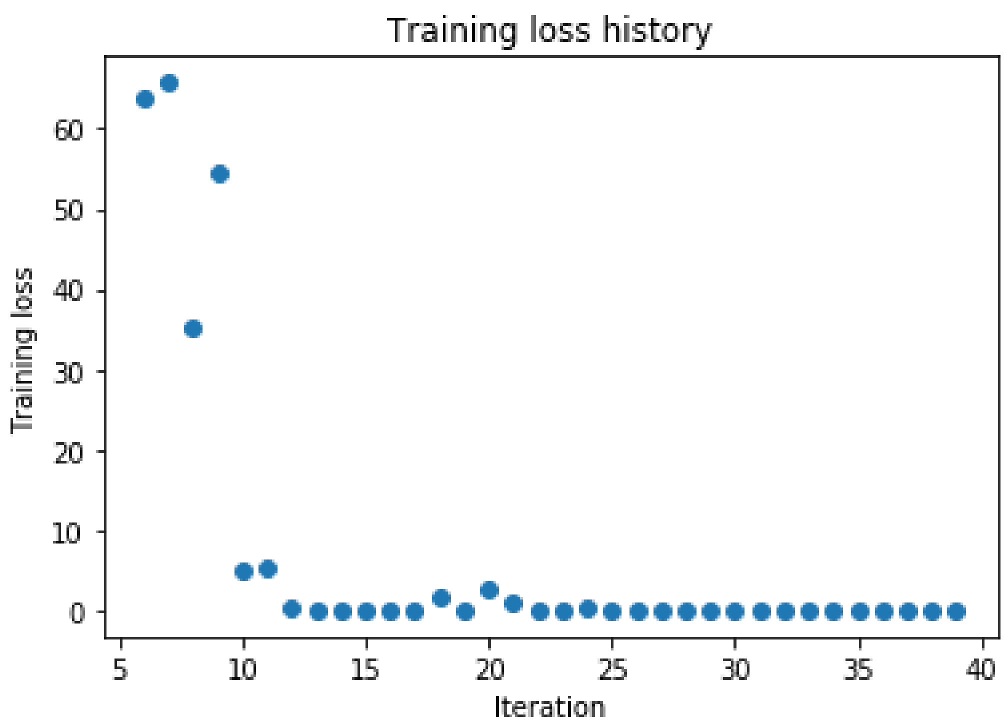
Now try to use a five-layer network with 100 units on each layer to overfit 50 training examples.

TODO: 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 [6]: # TODO: Use a five-layer Net to overfit 50 training examples.

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

        learning_rate = 0.0001
        weight_scale = 0.1
        model = FullyConnectedNet([200, 200, 200, 200, 200],
                        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()
```

```
(Epoch 0 / 20) (Iteration 1 / 40) loss: inf train acc: 0.120000 val_acc: 0.108000
(Epoch 5 / 20) (Iteration 11 / 40) loss: 4.854955 train acc: 0.840000 val_acc: 0.127000
(Epoch 10 / 20) (Iteration 21 / 40) loss: 2.581516 train acc: 0.960000 val_acc: 0.125000
(Epoch 15 / 20) (Iteration 31 / 40) loss: 0.000000 train acc: 1.000000 val_acc: 0.122000
```



2 Inline question:

Did you notice anything about the comparative difficulty of training the three-layer net vs training the five layer net?

3 Answer:

It was relatively harder to fine tune to overfit. In a three-layer, The first try I could overfit it. For the five layer, I had to run a double for loop, looping over different weight scale and learning rate to find it.

4 SGD+Momentum

Stochastic gradient descent with momentum is a widely used update rule that tends to make deep networks converge faster than vanilla stochstic gradient descent.

Open the file `libs/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 1e-8.

```
In [7]: from libs.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    ]])

        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
```

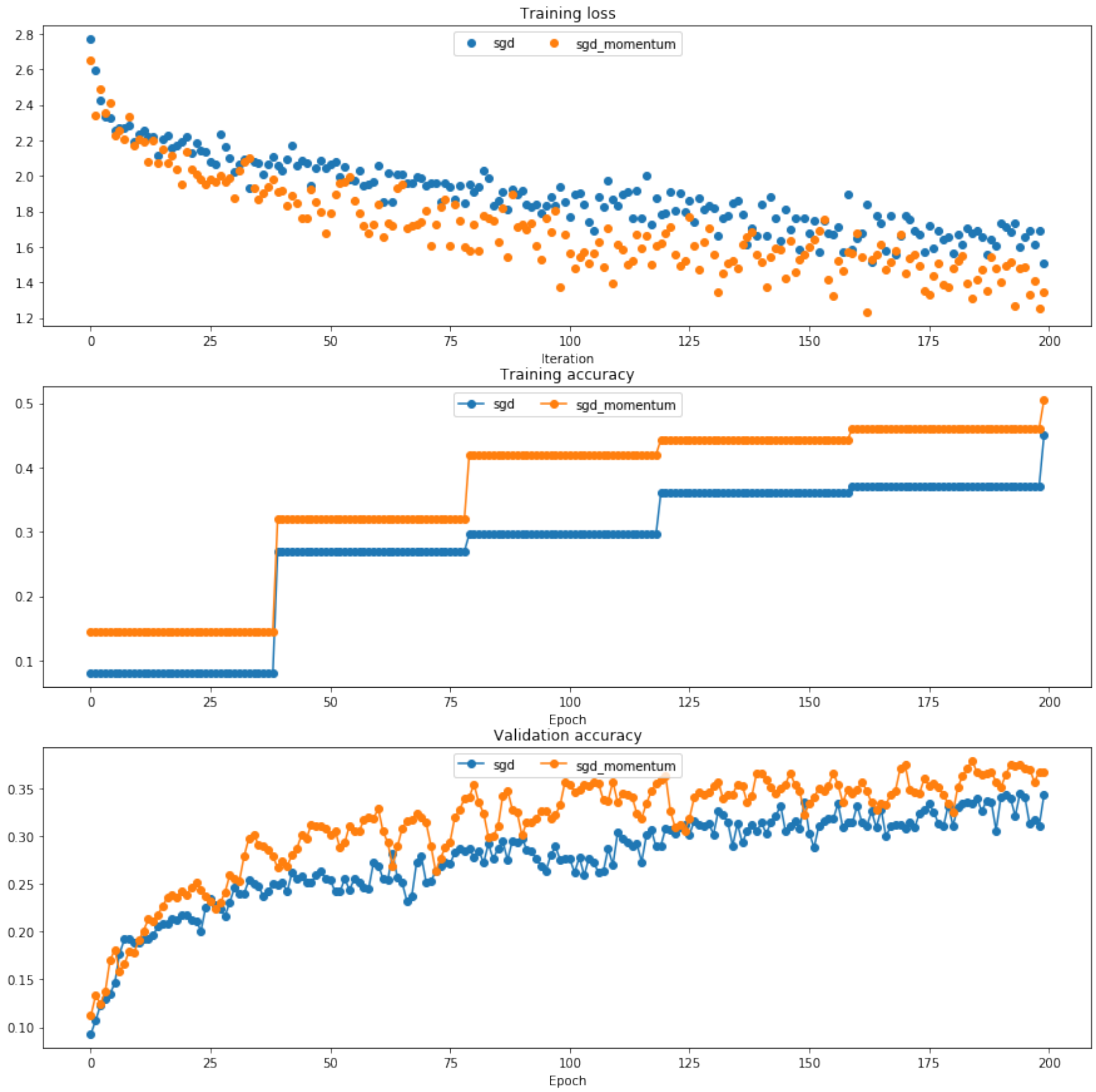
```
In [8]: num_train = 4000
        small_data = {
          'X_train': data['X_train'][:num_train],
          'y_train': data['y_train'][:num_train],
          'X_val': data['X_val'],
          'y_val': data['y_val'],
        }

        solvers = {}
```

```python
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 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
(Epoch 0 / 5) (Iteration 1 / 200) loss: 2.768939 train acc: 0.080000 val_acc: 0.093000
(Epoch 0 / 5) (Iteration 11 / 200) loss: 2.232598 train acc: 0.080000 val_acc: 0.188000
(Epoch 0 / 5) (Iteration 21 / 200) loss: 2.220102 train acc: 0.080000 val_acc: 0.218000
(Epoch 0 / 5) (Iteration 31 / 200) loss: 2.023023 train acc: 0.080000 val_acc: 0.246000
```

```
(Epoch 1 / 5) (Iteration 41 / 200) loss: 2.030687 train acc: 0.270000 val_acc: 0.251000
(Epoch 1 / 5) (Iteration 51 / 200) loss: 2.062255 train acc: 0.270000 val_acc: 0.254000
(Epoch 1 / 5) (Iteration 61 / 200) loss: 2.057339 train acc: 0.270000 val_acc: 0.269000
(Epoch 1 / 5) (Iteration 71 / 200) loss: 1.949063 train acc: 0.270000 val_acc: 0.252000
(Epoch 2 / 5) (Iteration 81 / 200) loss: 1.906796 train acc: 0.296000 val_acc: 0.278000
(Epoch 2 / 5) (Iteration 91 / 200) loss: 1.913908 train acc: 0.296000 val_acc: 0.298000
(Epoch 2 / 5) (Iteration 101 / 200) loss: 1.768143 train acc: 0.296000 val_acc: 0.276000
(Epoch 2 / 5) (Iteration 111 / 200) loss: 1.836087 train acc: 0.296000 val_acc: 0.304000
(Epoch 3 / 5) (Iteration 121 / 200) loss: 1.787209 train acc: 0.360000 val_acc: 0.308000
(Epoch 3 / 5) (Iteration 131 / 200) loss: 1.815735 train acc: 0.360000 val_acc: 0.302000
(Epoch 3 / 5) (Iteration 141 / 200) loss: 1.836709 train acc: 0.360000 val_acc: 0.314000
(Epoch 3 / 5) (Iteration 151 / 200) loss: 1.679561 train acc: 0.360000 val_acc: 0.303000
(Epoch 4 / 5) (Iteration 161 / 200) loss: 1.651747 train acc: 0.371000 val_acc: 0.332000
(Epoch 4 / 5) (Iteration 171 / 200) loss: 1.775608 train acc: 0.371000 val_acc: 0.308000
(Epoch 4 / 5) (Iteration 181 / 200) loss: 1.565286 train acc: 0.371000 val_acc: 0.311000
(Epoch 4 / 5) (Iteration 191 / 200) loss: 1.735860 train acc: 0.371000 val_acc: 0.341000
running with  sgd_momentum
(Epoch 0 / 5) (Iteration 1 / 200) loss: 2.651714 train acc: 0.145000 val_acc: 0.112000
(Epoch 0 / 5) (Iteration 11 / 200) loss: 2.205419 train acc: 0.145000 val_acc: 0.191000
(Epoch 0 / 5) (Iteration 21 / 200) loss: 2.134072 train acc: 0.145000 val_acc: 0.238000
(Epoch 0 / 5) (Iteration 31 / 200) loss: 1.871657 train acc: 0.145000 val_acc: 0.255000
(Epoch 1 / 5) (Iteration 41 / 200) loss: 1.919462 train acc: 0.320000 val_acc: 0.274000
(Epoch 1 / 5) (Iteration 51 / 200) loss: 1.787215 train acc: 0.320000 val_acc: 0.301000
(Epoch 1 / 5) (Iteration 61 / 200) loss: 1.836813 train acc: 0.320000 val_acc: 0.329000
(Epoch 1 / 5) (Iteration 71 / 200) loss: 1.801691 train acc: 0.320000 val_acc: 0.314000
(Epoch 2 / 5) (Iteration 81 / 200) loss: 1.724366 train acc: 0.420000 val_acc: 0.354000
(Epoch 2 / 5) (Iteration 91 / 200) loss: 1.725871 train acc: 0.420000 val_acc: 0.301000
(Epoch 2 / 5) (Iteration 101 / 200) loss: 1.566536 train acc: 0.420000 val_acc: 0.354000
(Epoch 2 / 5) (Iteration 111 / 200) loss: 1.613371 train acc: 0.420000 val_acc: 0.335000
(Epoch 3 / 5) (Iteration 121 / 200) loss: 1.678331 train acc: 0.443000 val_acc: 0.363000
(Epoch 3 / 5) (Iteration 131 / 200) loss: 1.554155 train acc: 0.443000 val_acc: 0.353000
(Epoch 3 / 5) (Iteration 141 / 200) loss: 1.512614 train acc: 0.443000 val_acc: 0.366000
(Epoch 3 / 5) (Iteration 151 / 200) loss: 1.597238 train acc: 0.443000 val_acc: 0.334000
(Epoch 4 / 5) (Iteration 161 / 200) loss: 1.676180 train acc: 0.461000 val_acc: 0.349000
(Epoch 4 / 5) (Iteration 171 / 200) loss: 1.448435 train acc: 0.461000 val_acc: 0.375000
(Epoch 4 / 5) (Iteration 181 / 200) loss: 1.479058 train acc: 0.461000 val_acc: 0.325000
(Epoch 4 / 5) (Iteration 191 / 200) loss: 1.400371 train acc: 0.461000 val_acc: 0.351000
```

```
/anaconda3/envs/aienv/lib/python3.6/site-packages/matplotlib/figure.py:98: MatplotlibDeprecatio
Adding an axes using the same arguments as a previous axes currently reuses the earlier instanc
  "Adding an axes using the same arguments as a previous axes "
```



5 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 `libs/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.

[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 [9]:
```python
# Test RMSProp implementation; you should see errors less than 1e-7
from libs.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    ]])

print('next_w error: ', rel_error(expected_next_w, next_w))
print('cache error: ', rel_error(expected_cache, config['cache']))
```

```
next_w error:  1.0007967647444523e-07
cache error:  2.6477955807156126e-09
```

In [18]:
```python
# Test Adam implementation; you should see errors around 1e-7 or less
from libs.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      ]])

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:  1.139887467333134e-07
v error:  4.208314038113071e-09
m error:  4.214963193114416e-09
```

In [19]:
```
learning_rates = {'rmsprop': 1e-4, 'adam': 1e-3}
for update_rule in ['adam', 'rmsprop']:
    print('running with ', update_rule)
    model = FullyConnectedNet([100, 100, 100, 100, 100], weight_scale=5e-2)

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

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

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

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

for update_rule, solver in solvers.items():
    plt.subplot(3, 1, 1)
```

```python
            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
(Epoch 0 / 5) (Iteration 1 / 200) loss: 3.346106 train acc: 0.106000 val_acc: 0.078000
(Epoch 0 / 5) (Iteration 11 / 200) loss: 1.992866 train acc: 0.106000 val_acc: 0.226000
(Epoch 0 / 5) (Iteration 21 / 200) loss: 1.942513 train acc: 0.106000 val_acc: 0.290000
(Epoch 0 / 5) (Iteration 31 / 200) loss: 1.935746 train acc: 0.106000 val_acc: 0.309000
(Epoch 1 / 5) (Iteration 41 / 200) loss: 1.812209 train acc: 0.349000 val_acc: 0.302000
(Epoch 1 / 5) (Iteration 51 / 200) loss: 1.793806 train acc: 0.349000 val_acc: 0.344000
(Epoch 1 / 5) (Iteration 61 / 200) loss: 1.757146 train acc: 0.349000 val_acc: 0.322000
(Epoch 1 / 5) (Iteration 71 / 200) loss: 1.565659 train acc: 0.349000 val_acc: 0.354000
(Epoch 2 / 5) (Iteration 81 / 200) loss: 1.543933 train acc: 0.424000 val_acc: 0.349000
(Epoch 2 / 5) (Iteration 91 / 200) loss: 1.456761 train acc: 0.424000 val_acc: 0.334000
(Epoch 2 / 5) (Iteration 101 / 200) loss: 1.673966 train acc: 0.424000 val_acc: 0.347000
(Epoch 2 / 5) (Iteration 111 / 200) loss: 1.640201 train acc: 0.424000 val_acc: 0.355000
(Epoch 3 / 5) (Iteration 121 / 200) loss: 1.475435 train acc: 0.505000 val_acc: 0.388000
(Epoch 3 / 5) (Iteration 131 / 200) loss: 1.421125 train acc: 0.505000 val_acc: 0.382000
(Epoch 3 / 5) (Iteration 141 / 200) loss: 1.463064 train acc: 0.505000 val_acc: 0.378000
(Epoch 3 / 5) (Iteration 151 / 200) loss: 1.316374 train acc: 0.505000 val_acc: 0.384000
(Epoch 4 / 5) (Iteration 161 / 200) loss: 1.238981 train acc: 0.563000 val_acc: 0.401000
(Epoch 4 / 5) (Iteration 171 / 200) loss: 1.270081 train acc: 0.563000 val_acc: 0.385000
(Epoch 4 / 5) (Iteration 181 / 200) loss: 1.218125 train acc: 0.563000 val_acc: 0.390000
(Epoch 4 / 5) (Iteration 191 / 200) loss: 1.168553 train acc: 0.563000 val_acc: 0.381000
running with  rmsprop
(Epoch 0 / 5) (Iteration 1 / 200) loss: 3.119525 train acc: 0.092000 val_acc: 0.095000
(Epoch 0 / 5) (Iteration 11 / 200) loss: 2.135162 train acc: 0.092000 val_acc: 0.207000
(Epoch 0 / 5) (Iteration 21 / 200) loss: 1.994246 train acc: 0.092000 val_acc: 0.245000
(Epoch 0 / 5) (Iteration 31 / 200) loss: 1.815473 train acc: 0.092000 val_acc: 0.273000
(Epoch 1 / 5) (Iteration 41 / 200) loss: 1.882904 train acc: 0.350000 val_acc: 0.301000
(Epoch 1 / 5) (Iteration 51 / 200) loss: 1.709493 train acc: 0.350000 val_acc: 0.327000
(Epoch 1 / 5) (Iteration 61 / 200) loss: 1.718911 train acc: 0.350000 val_acc: 0.319000
(Epoch 1 / 5) (Iteration 71 / 200) loss: 1.733985 train acc: 0.350000 val_acc: 0.324000
(Epoch 2 / 5) (Iteration 81 / 200) loss: 1.618223 train acc: 0.432000 val_acc: 0.338000
(Epoch 2 / 5) (Iteration 91 / 200) loss: 1.570802 train acc: 0.432000 val_acc: 0.351000
(Epoch 2 / 5) (Iteration 101 / 200) loss: 1.524798 train acc: 0.432000 val_acc: 0.350000
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(Epoch 2 / 5) (Iteration 111 / 200) loss: 1.623369 train acc: 0.432000 val_acc: 0.351000
(Epoch 3 / 5) (Iteration 121 / 200) loss: 1.594561 train acc: 0.460000 val_acc: 0.366000
(Epoch 3 / 5) (Iteration 131 / 200) loss: 1.467020 train acc: 0.460000 val_acc: 0.353000
(Epoch 3 / 5) (Iteration 141 / 200) loss: 1.527898 train acc: 0.460000 val_acc: 0.343000
(Epoch 3 / 5) (Iteration 151 / 200) loss: 1.588350 train acc: 0.460000 val_acc: 0.357000
(Epoch 4 / 5) (Iteration 161 / 200) loss: 1.537924 train acc: 0.466000 val_acc: 0.350000
(Epoch 4 / 5) (Iteration 171 / 200) loss: 1.371988 train acc: 0.466000 val_acc: 0.365000
(Epoch 4 / 5) (Iteration 181 / 200) loss: 1.285116 train acc: 0.466000 val_acc: 0.359000
(Epoch 4 / 5) (Iteration 191 / 200) loss: 1.401383 train acc: 0.466000 val_acc: 0.372000
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