Experiments are performed by a two layer NN with ReLU activation and Softmax Loss at the end. The skeleton of the model has been provided by Stanford CS231n. I do not give the codes because it is an active assignment for the students and I don't want to violate the honor code.¶

In [ ]:

```
# Create some toy data to check your implementations
input_size
hidden_size
num_classes
num_inputs

 init_toy_model
  model
  model  linspace  input_sizehidden_sizereshapeinput_size hidden_size
  model  linspace  hidden_size
  model  linspace  hidden_sizenum_classesreshapehidden_size num_classes
  model  linspace  num_classes
  return model

 init_toy_data
    linspace  num_inputsinput_sizereshapenum_inputs input_size
    array
  return

model  init_toy_model
   init_toy_data
```

Train the network¶

Here we compare naive sgd, momentum, rmsprop and rmsprop+momentum

In [10]:

```
 cs231n.classifier_trainer import ClassifierTrainer

model  init_toy_model
trainer  ClassifierTrainer
# call the trainer to optimize the loss
# Notice that we're using sample_batches=False, so we're performing Gradient Descent (no sampled batches of data)
best_model loss_history    trainertrain
                                        model two_layer_net
                                        0.001
                                        learning_rate momentum learning_rate_decay
                                        update'sgd' sample_batchesFalse
                                        num_epochs
                                        verboseFalse
print 'Final loss with vanilla SGD: %f'  loss_history

starting iteration  0
```

```
starting iteration  10
starting iteration  20
starting iteration  30
starting iteration  40
starting iteration  50
starting iteration  60
starting iteration  70
starting iteration  80
starting iteration  90
Final loss with vanilla SGD: 0.940686
```

Momentum Update

In [18]:

```
model  init_toy_model
trainer  ClassifierTrainer
# call the trainer to optimize the loss
# Notice that we're using sample_batches=False, so we're performing Gradient Descent (no sampled batches of data)
best_model loss_history    trainertrain
                                        model two_layer_net
                                        0.001
                                        learning_rate momentum learning_rate_decay
                                        update'momentum' sample_batchesFalse
                                        num_epochs
                                        verboseFalse
correct_loss  0.494394
print 'Final loss with momentum SGD: %f'  loss_history

starting iteration  0
starting iteration  10
starting iteration  20
starting iteration  30
starting iteration  40
starting iteration  50
starting iteration  60
starting iteration  70
starting iteration  80
starting iteration  90
Final loss with momentum SGD: 0.494394
```

RMSprop

In [17]:

```
model  init_toy_model
trainer  ClassifierTrainer
# call the trainer to optimize the loss
# Notice that we're using sample_batches=False, so we're performing Gradient Descent (no sampled batches of data)
best_model loss_history    trainertrain
                                        model two_layer_net
                                        0.001
                                        learning_rate momentum learning_rate_decay
                                        update'rmsprop' sample_batchesFalse
                                        num_epochs
                                        verboseFalse
correct_loss  0.439368
```

```
print 'Final loss with RMSProp: %f'  loss_history

starting iteration  0
starting iteration  10
starting iteration  20
starting iteration  30
starting iteration  40
starting iteration  50
starting iteration  60
starting iteration  70
starting iteration  80
starting iteration  90
Final loss with RMSProp: 0.439368
```

RMS+Momentum best of the this naive experiment

In [14]:

```
model  init_toy_model
trainer  ClassifierTrainer
# call the trainer to optimize the loss
# Notice that we're using sample_batches=False, so we're performing Gradient Descent (no sampled batches of data)
best_model loss_history    trainertrain
                                        model two_layer_net
                                        0.001
                                        learning_rate momentum learning_rate_decay
                                        update'rmsprop+momentum' sample_batchesFalse
                                        num_epochs
                                        verboseFalse
correct_loss  0.439368
print 'Final loss with RMSProp+momentum: %f'  loss_history

starting iteration  0
starting iteration  10
starting iteration  20
starting iteration  30
starting iteration  40
starting iteration  50
starting iteration  60
starting iteration  70
starting iteration  80
starting iteration  90
Final loss with RMSProp+momentum: 0.435519
```

AdaGrad is better than SGD but not that RMS and Momentum

In [42]:

```
model  init_toy_model
trainer  ClassifierTrainer
# call the trainer to optimize the loss
# Notice that we're using sample_batches=False, so we're performing Gradient Descent (no sampled batches of data)
best_model loss_history    trainertrain
                                        model two_layer_net
                                        0.001
                                        learning_rate momentum learning_rate_decay
                                        update'adagrad' sample_batchesFalse
```

```
                                        num_epochs
                                        verboseFalse
correct_loss  0.439368
print 'Final loss with Adagrad: %f'  loss_history

Final loss with Adagrad: 0.643385
```

RESULT: Even in a very simple toy dataset results are so demanding for the favor of RMSprop and Momentum against SGD. Best performance is observed by RMSprop+Momentum

Load the data¶

In [20]:

```
 cs231n.data_utils import load_CIFAR10

 get_CIFAR10_datanum_training49000 num_validation num_test

    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for the two-layer neural net classifier. These are the same steps as
    we used for the SVM, but condensed to a single function.

    # Load the raw CIFAR-10 data
    cifar10_dir  'cs231n/datasets/cifar-10-batches-py'
    X_train y_train X_test y_test  load_CIFAR10cifar10_dir

    # Subsample the data
      rangenum_training num_training  num_validation
    X_val  X_train
    y_val  y_train
      rangenum_training
    X_train  X_train
    y_train  y_train
      rangenum_test
    X_test  X_test
    y_test  y_test

    # Normalize the data: subtract the mean image
    mean_image  X_train
    X_train  mean_image
    X_val  mean_image
    X_test  mean_image

    # Reshape data to rows
    X_train  X_trainreshapenum_training
    X_val  X_valreshapenum_validation
    X_test  X_testreshapenum_test

    return X_train y_train X_val y_val X_test y_test


# Invoke the above function to get our data.
X_train y_train X_val y_val X_test y_test  get_CIFAR10_data
print 'Train data shape: ' X_trainshape
print 'Train labels shape: ' y_trainshape
print 'Validation data shape: ' X_valshape
```

```
print 'Validation labels shape: ' y_valshape
print 'Test data shape: ' X_testshape
print 'Test labels shape: ' y_testshape

Train data shape:  (49000, 3072)
Train labels shape:  (49000,)
Validation data shape:  (1000, 3072)
Validation labels shape:  (1000,)
Test data shape:  (1000, 3072)
Test labels shape:  (1000,)
```

Train a network¶

Train this simple model with different update rules.

In [55]:

```
# use SGD
 cs231n.classifiers.neural_net import init_two_layer_model

model  init_two_layer_model   # input size, hidden size, number of classes
trainer  ClassifierTrainer
best_model1 loss_history1 train_acc1 val_acc1  trainertrainX_train y_train X_val y_val
                                          model two_layer_net
                                          num_epochs
                                          update  'sgd'
                                          momentum learning_rate_decay
                                          learning_rate verbose

Finished epoch 0 / 20: cost 2.302593, train: 0.120000, val 0.158000, lr 1.000000e-05
Finished epoch 1 / 20: cost 2.302591, train: 0.129000, val 0.130000, lr 9.500000e-06
Finished epoch 2 / 20: cost 2.302589, train: 0.139000, val 0.174000, lr 9.025000e-06
Finished epoch 3 / 20: cost 2.302574, train: 0.166000, val 0.177000, lr 8.573750e-06
Finished epoch 4 / 20: cost 2.302539, train: 0.170000, val 0.193000, lr 8.145063e-06
Finished epoch 5 / 20: cost 2.302430, train: 0.188000, val 0.199000, lr 7.737809e-06
Finished epoch 6 / 20: cost 2.302224, train: 0.195000, val 0.193000, lr 7.350919e-06
Finished epoch 7 / 20: cost 2.301709, train: 0.177000, val 0.181000, lr 6.983373e-06
Finished epoch 8 / 20: cost 2.300819, train: 0.165000, val 0.179000, lr 6.634204e-06
Finished epoch 9 / 20: cost 2.296373, train: 0.151000, val 0.181000, lr 6.302494e-06
Finished epoch 10 / 20: cost 2.290793, train: 0.169000, val 0.197000, lr 5.987369e-06
Finished epoch 11 / 20: cost 2.284688, train: 0.184000, val 0.187000, lr 5.688001e-06
Finished epoch 12 / 20: cost 2.244895, train: 0.184000, val 0.193000, lr 5.403601e-06
Finished epoch 13 / 20: cost 2.196050, train: 0.156000, val 0.180000, lr 5.133421e-06
Finished epoch 14 / 20: cost 2.254494, train: 0.135000, val 0.183000, lr 4.876750e-06
Finished epoch 15 / 20: cost 2.185508, train: 0.196000, val 0.185000, lr 4.632912e-06
Finished epoch 16 / 20: cost 2.192414, train: 0.163000, val 0.186000, lr 4.401267e-06
Finished epoch 17 / 20: cost 2.227328, train: 0.179000, val 0.188000, lr 4.181203e-06
Finished epoch 18 / 20: cost 2.073986, train: 0.181000, val 0.188000, lr 3.972143e-06
Finished epoch 19 / 20: cost 2.080279, train: 0.186000, val 0.190000, lr 3.773536e-06
Finished epoch 20 / 20: cost 2.142814, train: 0.198000, val 0.199000, lr 3.584859e-06
finished optimization. best validation accuracy: 0.199000
```

In [56]:

```
# use Momentum
 cs231n.classifiers.neural_net import init_two_layer_model
```

```
model  init_two_layer_model   # input size, hidden size, number of classes
trainer  ClassifierTrainer
best_model2 loss_history2 train_acc2 val_acc2  trainertrainX_train y_train X_val y_val
                                          model two_layer_net
                                          num_epochs
                                          update  'momentum'
                                          momentum learning_rate_decay
                                          learning_rate verbose

Finished epoch 0 / 20: cost 2.302593, train: 0.110000, val 0.109000, lr 1.000000e-05
Finished epoch 1 / 20: cost 2.273101, train: 0.133000, val 0.154000, lr 9.500000e-06
Finished epoch 2 / 20: cost 2.057101, train: 0.201000, val 0.241000, lr 9.025000e-06
Finished epoch 3 / 20: cost 1.888748, train: 0.311000, val 0.288000, lr 8.573750e-06
Finished epoch 4 / 20: cost 1.839703, train: 0.344000, val 0.339000, lr 8.145063e-06
Finished epoch 5 / 20: cost 1.942659, train: 0.333000, val 0.366000, lr 7.737809e-06
Finished epoch 6 / 20: cost 1.847249, train: 0.361000, val 0.389000, lr 7.350919e-06
Finished epoch 7 / 20: cost 1.742119, train: 0.407000, val 0.391000, lr 6.983373e-06
Finished epoch 8 / 20: cost 1.523142, train: 0.392000, val 0.397000, lr 6.634204e-06
Finished epoch 9 / 20: cost 1.710355, train: 0.411000, val 0.411000, lr 6.302494e-06
Finished epoch 10 / 20: cost 1.675986, train: 0.426000, val 0.417000, lr 5.987369e-06
Finished epoch 11 / 20: cost 1.759964, train: 0.449000, val 0.433000, lr 5.688001e-06
Finished epoch 12 / 20: cost 1.400295, train: 0.445000, val 0.430000, lr 5.403601e-06
Finished epoch 13 / 20: cost 1.473600, train: 0.441000, val 0.430000, lr 5.133421e-06
Finished epoch 14 / 20: cost 1.665528, train: 0.437000, val 0.447000, lr 4.876750e-06
Finished epoch 15 / 20: cost 1.608525, train: 0.471000, val 0.445000, lr 4.632912e-06
Finished epoch 16 / 20: cost 1.420895, train: 0.454000, val 0.450000, lr 4.401267e-06
Finished epoch 17 / 20: cost 1.560292, train: 0.472000, val 0.444000, lr 4.181203e-06
Finished epoch 18 / 20: cost 1.585418, train: 0.450000, val 0.449000, lr 3.972143e-06
Finished epoch 19 / 20: cost 1.623252, train: 0.503000, val 0.445000, lr 3.773536e-06
Finished epoch 20 / 20: cost 1.554016, train: 0.476000, val 0.454000, lr 3.584859e-06
finished optimization. best validation accuracy: 0.454000
```

In [57]:

```
# use RMSprop
 cs231n.classifiers.neural_net import init_two_layer_model

model  init_two_layer_model   # input size, hidden size, number of classes
trainer  ClassifierTrainer
best_model3 loss_history3 train_acc3 val_acc3  trainertrainX_train y_train X_val y_val
                                          model two_layer_net
                                          num_epochs
                                          update  'rmsprop'
                                          momentum learning_rate_decay
                                          learning_rate verbose

Finished epoch 0 / 20: cost 2.302593, train: 0.102000, val 0.098000, lr 1.000000e-05
Finished epoch 1 / 20: cost 1.948840, train: 0.356000, val 0.329000, lr 9.500000e-06
Finished epoch 2 / 20: cost 1.933427, train: 0.383000, val 0.359000, lr 9.025000e-06
Finished epoch 3 / 20: cost 1.866497, train: 0.390000, val 0.395000, lr 8.573750e-06
Finished epoch 4 / 20: cost 1.748220, train: 0.420000, val 0.414000, lr 8.145063e-06
Finished epoch 5 / 20: cost 1.647285, train: 0.417000, val 0.427000, lr 7.737809e-06
Finished epoch 6 / 20: cost 1.636752, train: 0.406000, val 0.438000, lr 7.350919e-06
Finished epoch 7 / 20: cost 1.683645, train: 0.433000, val 0.439000, lr 6.983373e-06
Finished epoch 8 / 20: cost 1.727223, train: 0.455000, val 0.444000, lr 6.634204e-06
Finished epoch 9 / 20: cost 1.771403, train: 0.446000, val 0.454000, lr 6.302494e-06
```

```
Finished epoch 10 / 20: cost 1.662157, train: 0.484000, val 0.450000, lr 5.987369e-06
Finished epoch 11 / 20: cost 1.783750, train: 0.451000, val 0.451000, lr 5.688001e-06
Finished epoch 12 / 20: cost 1.572829, train: 0.455000, val 0.459000, lr 5.403601e-06
Finished epoch 13 / 20: cost 1.539926, train: 0.457000, val 0.459000, lr 5.133421e-06
Finished epoch 14 / 20: cost 1.699544, train: 0.439000, val 0.458000, lr 4.876750e-06
Finished epoch 15 / 20: cost 1.600255, train: 0.443000, val 0.463000, lr 4.632912e-06
Finished epoch 16 / 20: cost 1.619370, train: 0.468000, val 0.464000, lr 4.401267e-06
Finished epoch 17 / 20: cost 1.571197, train: 0.476000, val 0.464000, lr 4.181203e-06
Finished epoch 18 / 20: cost 1.608766, train: 0.468000, val 0.469000, lr 3.972143e-06
Finished epoch 19 / 20: cost 1.630492, train: 0.484000, val 0.477000, lr 3.773536e-06
Finished epoch 20 / 20: cost 1.481858, train: 0.489000, val 0.470000, lr 3.584859e-06
finished optimization. best validation accuracy: 0.477000
```

In [58]:

```
# use RMSprop+Momentum
 cs231n.classifiers.neural_net import init_two_layer_model

model  init_two_layer_model   # input size, hidden size, number of classes
trainer  ClassifierTrainer
best_model4 loss_history4 train_acc4 val_acc4  trainertrainX_train y_train X_val y_val
                                          model two_layer_net
                                          num_epochs
                                          update  'rmsprop+momentum'
                                          momentum learning_rate_decay
                                          learning_rate verbose

Finished epoch 0 / 20: cost 2.302593, train: 0.166000, val 0.165000, lr 1.000000e-05
Finished epoch 1 / 20: cost 1.800040, train: 0.373000, val 0.390000, lr 9.500000e-06
Finished epoch 2 / 20: cost 1.636812, train: 0.459000, val 0.437000, lr 9.025000e-06
Finished epoch 3 / 20: cost 1.609279, train: 0.472000, val 0.450000, lr 8.573750e-06
Finished epoch 4 / 20: cost 1.540035, train: 0.467000, val 0.451000, lr 8.145063e-06
Finished epoch 5 / 20: cost 1.507733, train: 0.487000, val 0.460000, lr 7.737809e-06
Finished epoch 6 / 20: cost 1.642292, train: 0.518000, val 0.473000, lr 7.350919e-06
Finished epoch 7 / 20: cost 1.497452, train: 0.504000, val 0.468000, lr 6.983373e-06
Finished epoch 8 / 20: cost 1.533577, train: 0.502000, val 0.473000, lr 6.634204e-06
Finished epoch 9 / 20: cost 1.442068, train: 0.482000, val 0.464000, lr 6.302494e-06
Finished epoch 10 / 20: cost 1.549564, train: 0.486000, val 0.473000, lr 5.987369e-06
Finished epoch 11 / 20: cost 1.494527, train: 0.502000, val 0.471000, lr 5.688001e-06
Finished epoch 12 / 20: cost 1.462458, train: 0.495000, val 0.483000, lr 5.403601e-06
Finished epoch 13 / 20: cost 1.515679, train: 0.543000, val 0.480000, lr 5.133421e-06
Finished epoch 14 / 20: cost 1.510962, train: 0.525000, val 0.485000, lr 4.876750e-06
Finished epoch 15 / 20: cost 1.541044, train: 0.508000, val 0.492000, lr 4.632912e-06
Finished epoch 16 / 20: cost 1.577317, train: 0.536000, val 0.493000, lr 4.401267e-06
Finished epoch 17 / 20: cost 1.525123, train: 0.538000, val 0.491000, lr 4.181203e-06
Finished epoch 18 / 20: cost 1.351778, train: 0.552000, val 0.503000, lr 3.972143e-06
Finished epoch 19 / 20: cost 1.590443, train: 0.536000, val 0.499000, lr 3.773536e-06
Finished epoch 20 / 20: cost 1.448961, train: 0.530000, val 0.507000, lr 3.584859e-06
finished optimization. best validation accuracy: 0.507000
```

In [59]:

```
# AdaGrad
# use RMSprop+Momentum
 cs231n.classifiers.neural_net import init_two_layer_model

model  init_two_layer_model   # input size, hidden size, number of classes
```

```
trainer  ClassifierTrainer
best_model5 loss_history5 train_acc5 val_acc5  trainertrainX_train y_train X_val y_val
                                          model two_layer_net
                                          num_epochs
                                          update  'adagrad'
                                          momentum learning_rate_decay
                                          learning_rate verbose

Finished epoch 0 / 20: cost 2.302593, train: 0.117000, val 0.108000, lr 1.000000e-02
Finished epoch 1 / 20: cost 1.976317, train: 0.375000, val 0.393000, lr 9.500000e-03
Finished epoch 2 / 20: cost 1.819465, train: 0.396000, val 0.360000, lr 9.025000e-03
Finished epoch 3 / 20: cost 1.946780, train: 0.393000, val 0.396000, lr 8.573750e-03
Finished epoch 4 / 20: cost 1.948320, train: 0.429000, val 0.388000, lr 8.145062e-03
Finished epoch 5 / 20: cost 1.817160, train: 0.445000, val 0.463000, lr 7.737809e-03
Finished epoch 6 / 20: cost 1.781161, train: 0.433000, val 0.433000, lr 7.350919e-03
Finished epoch 7 / 20: cost 1.726162, train: 0.437000, val 0.431000, lr 6.983373e-03
Finished epoch 8 / 20: cost 1.945575, train: 0.467000, val 0.438000, lr 6.634204e-03
Finished epoch 9 / 20: cost 1.717542, train: 0.463000, val 0.468000, lr 6.302494e-03
Finished epoch 10 / 20: cost 1.653255, train: 0.472000, val 0.443000, lr 5.987369e-03
Finished epoch 11 / 20: cost 1.757400, train: 0.487000, val 0.448000, lr 5.688001e-03
Finished epoch 12 / 20: cost 1.612132, train: 0.487000, val 0.470000, lr 5.403601e-03
Finished epoch 13 / 20: cost 1.575829, train: 0.462000, val 0.453000, lr 5.133421e-03
Finished epoch 14 / 20: cost 1.739385, train: 0.465000, val 0.471000, lr 4.876750e-03
Finished epoch 15 / 20: cost 1.649168, train: 0.497000, val 0.461000, lr 4.632912e-03
Finished epoch 16 / 20: cost 1.844438, train: 0.482000, val 0.483000, lr 4.401267e-03
Finished epoch 17 / 20: cost 1.755178, train: 0.502000, val 0.466000, lr 4.181203e-03
Finished epoch 18 / 20: cost 1.623927, train: 0.494000, val 0.476000, lr 3.972143e-03
Finished epoch 19 / 20: cost 1.760897, train: 0.502000, val 0.474000, lr 3.773536e-03
Finished epoch 20 / 20: cost 1.795621, train: 0.501000, val 0.469000, lr 3.584859e-03
finished optimization. best validation accuracy: 0.483000
```

RESULT: In a real dataset perfomance differences are more significant. SGD gets 0.18 and we can scale ti to up to 0.46 by RMSprop+Momentum with the smae number of iterations.

Look at the results¶

SGD results ---

Plots show that SGD takes so much time to reduce the loss and it only achives 0.19 accuracy at validation set. In addition, train and validation accuracies are very dispersed at many segments of the learning. I think SGD is not very reliable by these observations.

In [60]:

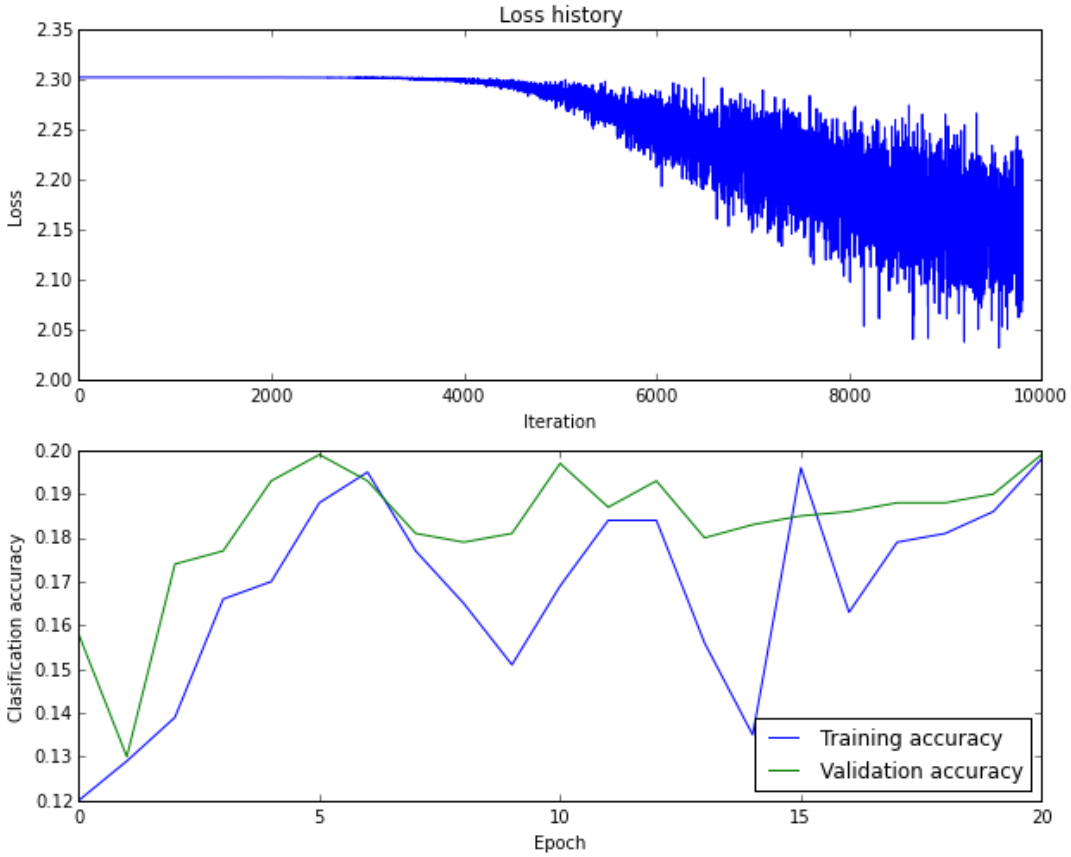
```
# Plot the loss function and train / validation accuracies
subplot
loss_history1
title'Loss history'
xlabel'Iteration'
ylabel'Loss'

subplot
train_acc1
val_acc1
legend'Training accuracy' 'Validation accuracy' 'lower right'
```

```
xlabel'Epoch'
ylabel'Clasification accuracy'
```

Out[60]:

```
<matplotlib.text.Text at 0x7fbb51db12d0>
```



Momentum Results ---

Better than SGD. However, still it needs a set of epochs to find a way to the minima. It is observed through the stationary Loss at the begining. Validation and Train accurcies much more correlated as well.

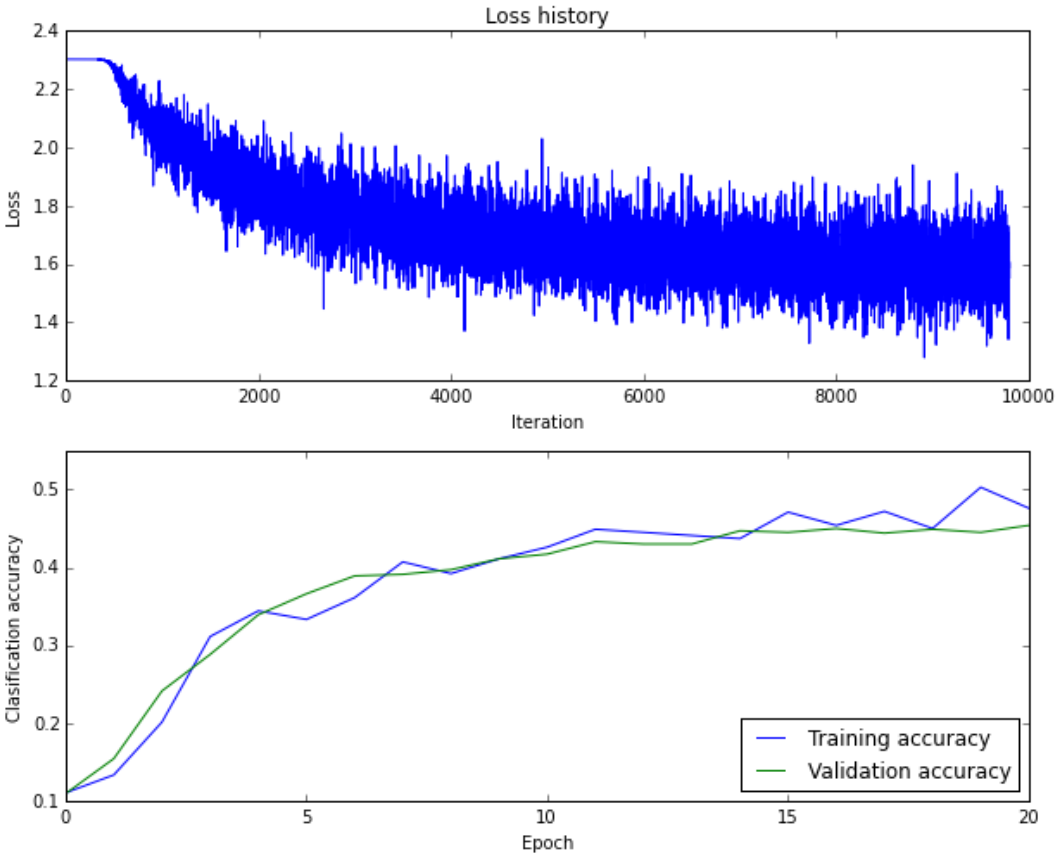
In [61]:

```
# Plot the loss function and train / validation accuracies
subplot
loss_history2
title'Loss history'
xlabel'Iteration'
ylabel'Loss'

subplot
train_acc2
val_acc2
legend'Training accuracy' 'Validation accuracy' 'lower right'
xlabel'Epoch'
ylabel'Clasification accuracy'
```

Out[61]:

```
<matplotlib.text.Text at 0x7fbb51f9d890>
```



RMSprop results

Main difference here is the convergende of the algorithm compared to others. You can see a very declined slope at he beginning of the Loss value. It starts to optimize very quickly. Also, accuracy is peaked from the begining of the training.

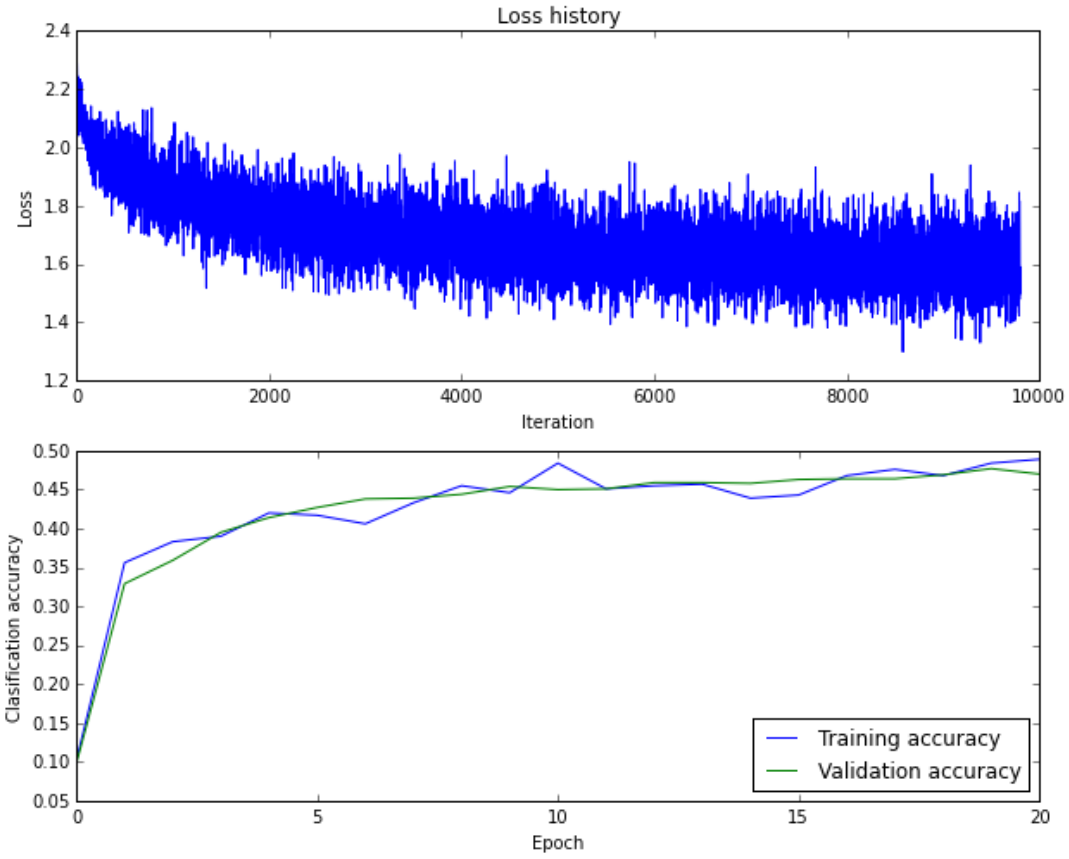
In [62]:

```
# Plot the loss function and train / validation accuracies
subplot
loss_history3
title'Loss history'
xlabel'Iteration'
ylabel'Loss'

subplot
train_acc3
val_acc3
legend'Training accuracy' 'Validation accuracy' 'lower right'
xlabel'Epoch'
ylabel'Clasification accuracy'
```

Out[62]:

```
<matplotlib.text.Text at 0x7fbb51d82a10>
```



RMS+Momentum Observations

Much better convergence and best performance. It peaks the validation accuracy almost at the 5th epoch and we see only a little improvement there after.

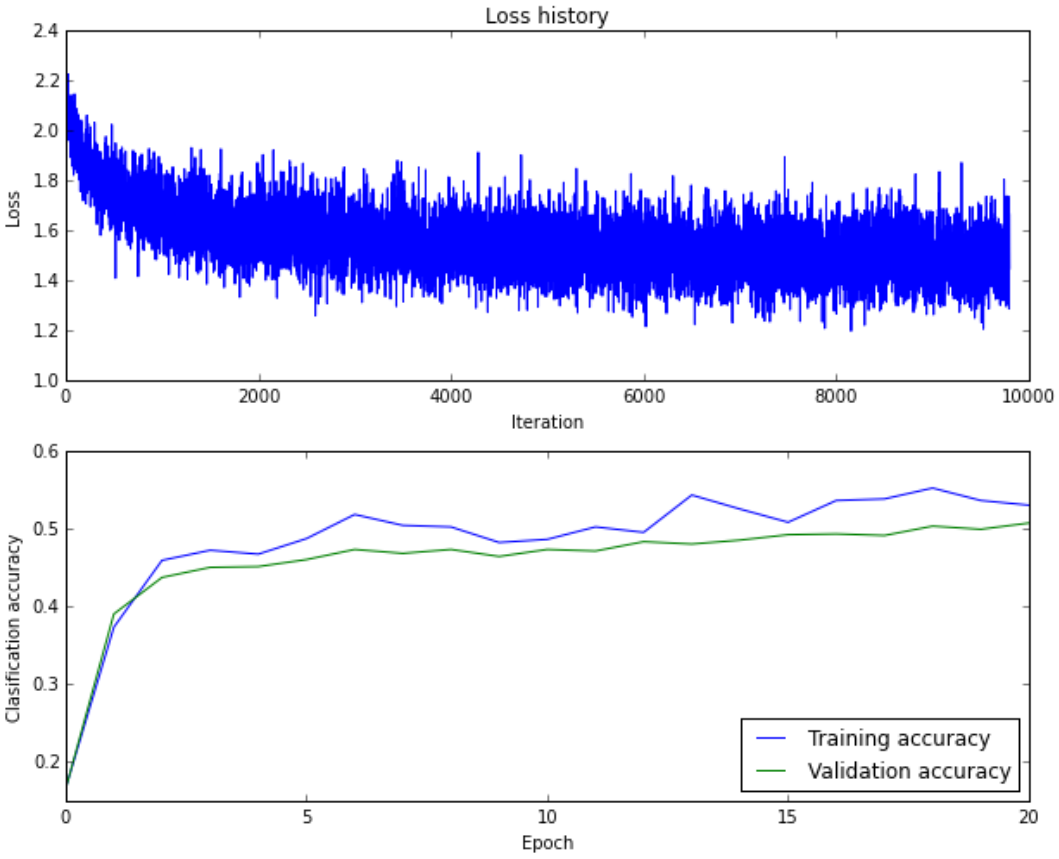
In [63]:

```
# Plot the loss function and train / validation accuracies
subplot
loss_history4
title'Loss history'
xlabel'Iteration'
ylabel'Loss'

subplot
train_acc4
val_acc4
legend'Training accuracy' 'Validation accuracy' 'lower right'
xlabel'Epoch'
ylabel'Clasification accuracy'
```

Out[63]:

```
<matplotlib.text.Text at 0x7fbb515bbb90>
```



AdaGrad Observations

AdaGrad is known as a optimization method that is robust to learning rate choice andeven you give a initial learning rate value, it finds a way to tune it to a optimal value in the couse of training, at least theoretically.

I used much greater learning rate for AdaGrad traning since it cannot improve the accuracy or the loss value otherwise.

One improtant behaviour of AdaGrad is , it needs a initial period to tune the learning to a good value. Therfore, we observe a non-decreasing even wildly increasing Loss value initially but it functions well at the end. It takes the second best accuracy as well after RMSprop+Momentum

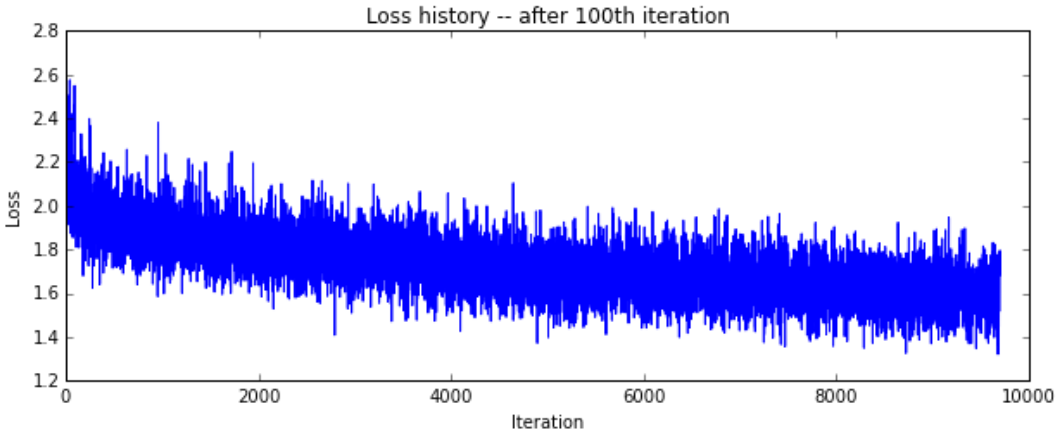
In [85]:

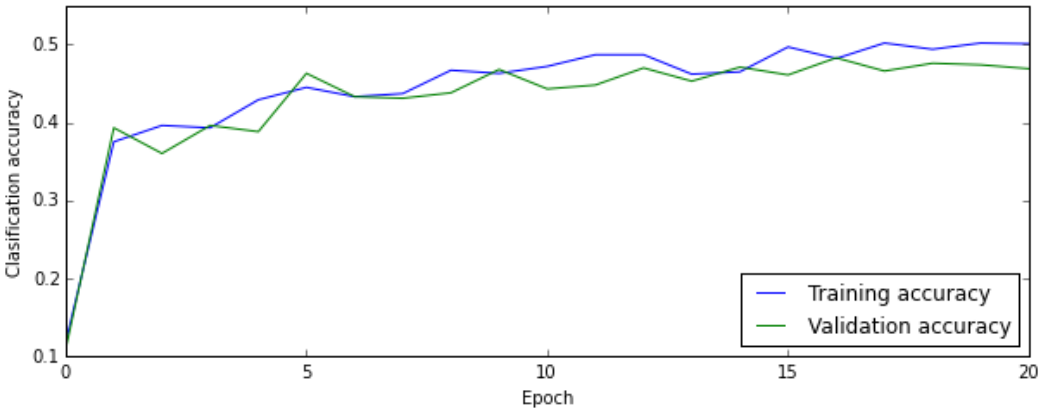
```
# Plot the loss function and train / validation accuracies
subplot
loss_history5
title'Loss history -- after 100th iteration'
xlabel'Iteration'
ylabel'Loss'

subplot
train_acc5
val_acc5
legend'Training accuracy' 'Validation accuracy' 'lower right'
xlabel'Epoch'
ylabel'Clasification accuracy'
```

Out[85]:

```
<matplotlib.text.Text at 0x7fbb51116290>
```





AdaGrad updates takes some epochs to tune learning rate. I printed loss values for first 50 epochs to see this effect.

In [68]:

```
loss_history5
```

Out[68]:

```
[2.3025928278904635,
 75.934736079622795,
 92.182474572629786,
 100.5019278755542,
 84.844181635490045,
 49.409391098629875,
 43.328290141355289,
 35.325688200166425,
 25.519854900507241,
 21.356402138599851,
 26.218600967478551,
 31.59622812204384,
 26.22040589643569,
 23.227517734307192,
 17.767912373878527,
 16.157541492684935,
 12.608468084163864,
 12.321226053503693,
 13.24122535188368,
 12.928515216653592,
 10.796928215446016,
 9.1984105449830302,
 11.298781826011448,
 10.804694477862794,
```

```
12.568968109093376,
10.56363563705977,
7.9977924016860049,
7.34338664646741,
6.6929796435282283,
7.1677274578861159,
7.2066434970512532,
6.7933009055358866,
6.7913307562240677,
6.6829018897838459,
7.0043970733245429,
7.3813129930707051,
6.4100443076342426,
5.7477095369608451,
7.3967044022923663,
5.8068102116770044,
6.1110745504385751,
5.4339376326257485,
5.3695441754045357,
4.6965492787415659,
5.7784881299439856,
5.4864936711432595,
4.4452802054476042,
4.7502021504025134,
5.2173199263390639,
3.9212560040704405]
```

Conclusion¶

Despite the simplicity of the both Momentum and RMSprop tricks, performance improvement is very high compared to naive SGD. Also from the above figures, you can see the problems that I've been told in my blog post http://bit.ly/1FGKb4K[1]. If we look at the loss changes of SGD it is very unstable and after we apply Momentum it is stabilized relatively. Then implication of RMSprop makes things better and modest.

Another fact is the convergence rates of the methods. As you can see RMSprop+Momentum reaches the very solid values after only the first epoch.

I add AdaGrad to experiments lately. As I stated above, if you like to see good values in a short time AdaGrad is not the choice but in some way or another it concludes a good model, if you are patient enough.

The accuracy values of train and validation are also more correlated as we improve the SGD with the additional tricks. Of course, I didn't suppose that this model is the best and you can see that we can increase the number of learning epochs or make the model larger since there is no gap between train and validation accuracies yet after 5th epoch.

As a side note, this notebook and the blog post is inspired as I was working on Stanford CS231n assignment2. Therefore I did not provide any replicable code for the sake of honor code.

Links

1. http://bit.ly/1FGKb4K

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