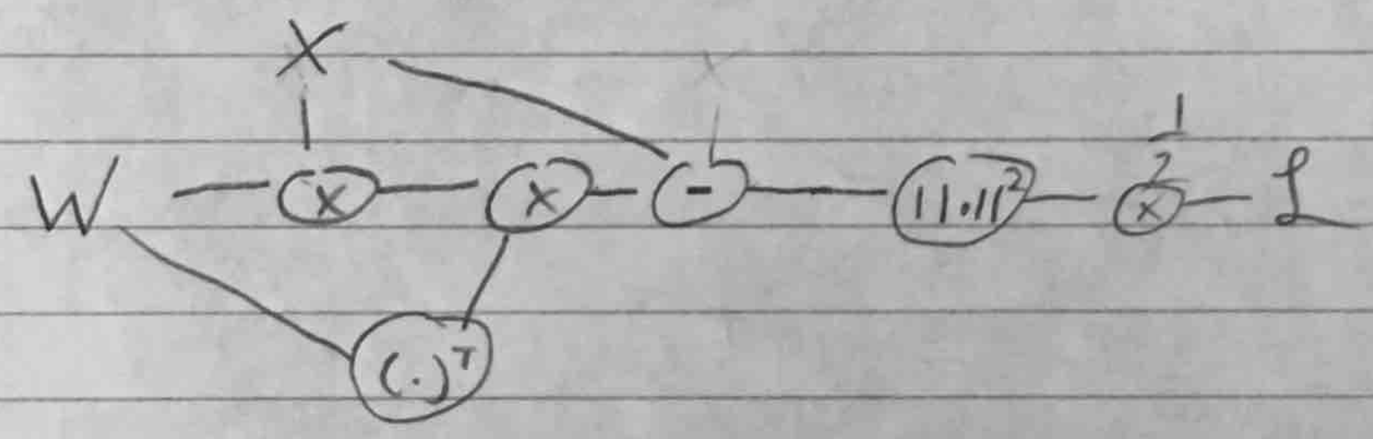
ECE 239AS HW #3

1. $\mathcal{L} = \frac{1}{2}||W^TWx - x||^2$

a.) If $W \in R^{m \times n}$, then $W^TW \in R^{n \times n}$. Wx represents the dimensionally reduced input data. W^TWx then represents the reconstructed data. Minimizing the difference between this term and the original vector will result in a matrix W that retains information within W.

b.)



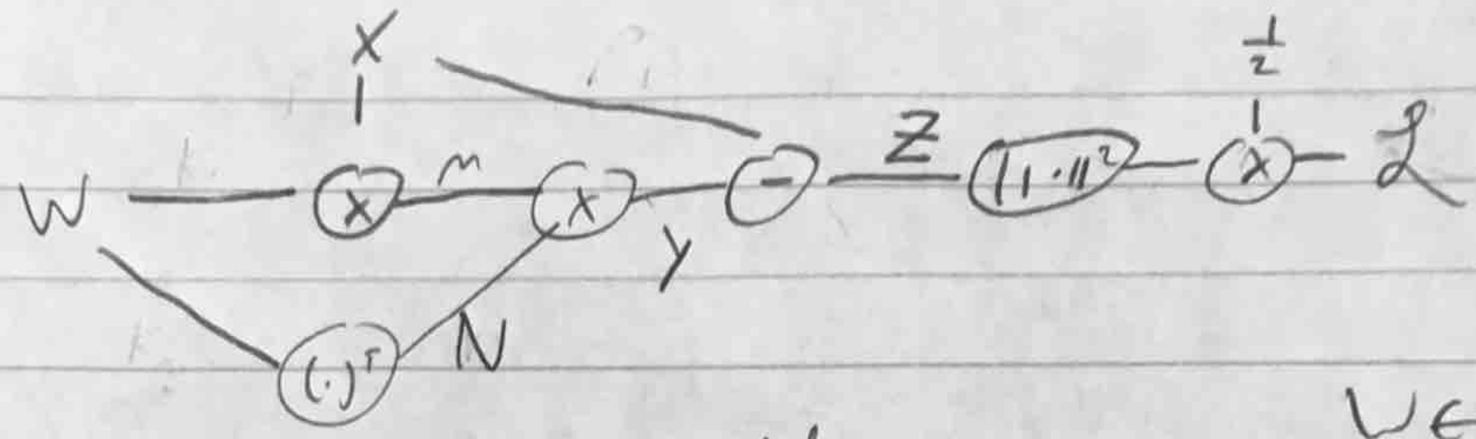
c.) The gradient of $\mathcal{L}$ w.r.t. W must be a summation of all paths leading from W. This is shown by the definition of a "total derivative" which is defined as:

$$\frac{df}{dt} = \frac{\partial f}{\partial t} + \frac{\partial f}{\partial x}\frac{dx}{dt} + \frac{\partial f}{\partial y}\frac{dy}{dt}$$

where x and y are variables dependent on t.

In this case, the derivative of $\mathcal{L}$ w.r.t W must include all 'back propagation paths' leading to it.

d.



$\mathcal{L} = \frac{1}{2}\|z\|^2$

$z = y - x$

$y = Nm$

$m = Wx$

$N = W^T$

$\frac{\partial \mathcal{L}}{\partial z} = z$

$\frac{\partial z}{\partial y} = 1$

$\frac{\partial y}{\partial m} = N^T$, $\frac{\partial y}{\partial N} = *x^T$

$\frac{\partial m}{\partial w} = *x^T$

$\frac{\partial N}{\partial w} = (\cdot)^T$

$W \in \mathbb{R}^{m \times n}$

$x \in \mathbb{R}^n$

$N = W^T \in \mathbb{R}^{n \times m}$

$z \in \mathbb{R}^n$

$y \in \mathbb{R}^n$

$m \in \mathbb{R}^m$

$\frac{\partial \mathcal{L}}{\partial z} = z$

$\frac{\partial \mathcal{L}}{\partial y} = \frac{\partial z}{\partial y}\frac{\partial \mathcal{L}}{\partial z} = z$

$\frac{\partial \mathcal{L}}{\partial m} = \frac{\partial y}{\partial m} \cdot \frac{\partial \mathcal{L}}{\partial y} = N^T z$

$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial m}{\partial w_1} \cdot \frac{\partial \mathcal{L}}{\partial m} = N^T z \cdot x^T$

$\frac{\partial \mathcal{L}}{\partial N} = \frac{\partial y}{\partial N} \cdot \frac{\partial \mathcal{L}}{\partial y} = z \cdot m^T$

$\frac{\partial \mathcal{L}}{\partial w_2} = \frac{\partial N}{\partial w}\frac{\partial \mathcal{L}}{\partial N} = (z m^T)^T = m z^T$

$\frac{\partial \mathcal{L}}{\partial w} = \frac{\partial \mathcal{L}}{\partial w_1} + \frac{\partial \mathcal{L}}{\partial w_2} = N^T z \cdot x^T + m z^T$

$= W(y-x)x^T + Wx(y-x)^T$

$= W(Nm-x)x^T + Wx(Nm-x)^T$

$\boxed{\nabla_W \mathcal{L} = W(W^T W x - x)x^T + Wx(W^T W x - x)^T}$

This is the 2-layer neural network workbook for ECE 239AS Assignment #3

Please follow the notebook linearly to implement a two layer neural network.

Please print out the workbook entirely when completed.

We thank Serena Yeung & Justin Johnson for permission to use code written for the CS 231n class (cs231n.stanford.edu). These are the functions in the cs231n folders and code in the jupyer notebook to preprocess and show the images. The classifiers used are based off of code prepared for CS 231n as well.

The goal of this workbook is to give you experience with training a two layer neural network.

In [126]:
```
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

%matplotlib inline
%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.ab
s(y))))
```

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

Toy example

Before loading CIFAR-10, there will be a toy example to test your implementation of the forward and backward pass

In [127]:
```
from nndl.neural_net import TwoLayerNet
```

In [158]:
```
# Create a small net and some toy data to check your implementations.
# Note that we set the random seed for repeatable experiments.

input_size = 4
hidden_size = 10
num_classes = 3
num_inputs = 5

def init_toy_model():
    np.random.seed(0)
    return TwoLayerNet(input_size, hidden_size, num_classes, std=1e-
1)

def init_toy_data():
    np.random.seed(1)
    X = 10 * np.random.randn(num_inputs, input_size)
    y = np.array([0, 1, 2, 2, 1])
    return X, y

net = init_toy_model()
X, y = init_toy_data()
```

Compute forward pass scores

In [159]:
```
## Implement the forward pass of the neural network.

# Note, there is a statement if y is None: return scores, which is wh
y
# the following call will calculate the scores.
scores = net.loss(X)
print('Your scores:')
print(scores)
print()
print('correct scores:')
correct_scores = np.asarray([
    [-1.07260209,  0.05083871, -0.87253915],
    [-2.02778743, -0.10832494, -1.52641362],
    [-0.74225908,  0.15259725, -0.39578548],
    [-0.38172726,  0.10835902, -0.17328274],
    [-0.64417314, -0.18886813, -0.41106892]])
print(correct_scores)
print()

# The difference should be very small. We get < 1e-7
print('Difference between your scores and correct scores:')
print(np.sum(np.abs(scores - correct_scores)))
```

```
Your scores:
[[-1.07260209  0.05083871 -0.87253915]
 [-2.02778743 -0.10832494 -1.52641362]
 [-0.74225908  0.15259725 -0.39578548]
 [-0.38172726  0.10835902 -0.17328274]
 [-0.64417314 -0.18886813 -0.41106892]]
()
correct scores:
[[-1.07260209  0.05083871 -0.87253915]
 [-2.02778743 -0.10832494 -1.52641362]
 [-0.74225908  0.15259725 -0.39578548]
 [-0.38172726  0.10835902 -0.17328274]
 [-0.64417314 -0.18886813 -0.41106892]]
()
Difference between your scores and correct scores:
3.381231222787662e-08
```

Forward pass loss

In [160]:
```
loss, _ = net.loss(X, y, reg=0.05)
correct_loss = 1.071696123862817

# should be very small, we get < 1e-12
print('Difference between your loss and correct loss:')
print(np.sum(np.abs(loss - correct_loss)))
```

```
Difference between your loss and correct loss:
0.0
```

In [161]:
```
print(loss)
```

```
1.071696123862817
```

Backward pass

Implements the backwards pass of the neural network. Check your gradients with the gradient check utilities provided.

In [162]:
```
from cs231n.gradient_check import eval_numerical_gradient

# Use numeric gradient checking to check your implementation of the b
ackward pass.
# If your implementation is correct, the difference between the numer
ic and
# analytic gradients should be less than 1e-8 for each of W1, W2, b1,
 and b2.

loss, grads = net.loss(X, y, reg=0.05)

# these should all be less than 1e-8 or so
for param_name in grads:
    f = lambda W: net.loss(X, y, reg=0.05)[0]
    param_grad_num = eval_numerical_gradient(f,
net.params[param_name], verbose=False)
    print('{} max relative error: {}'.format(param_name, rel_error(pa
ram_grad_num, grads[param_name])))
```

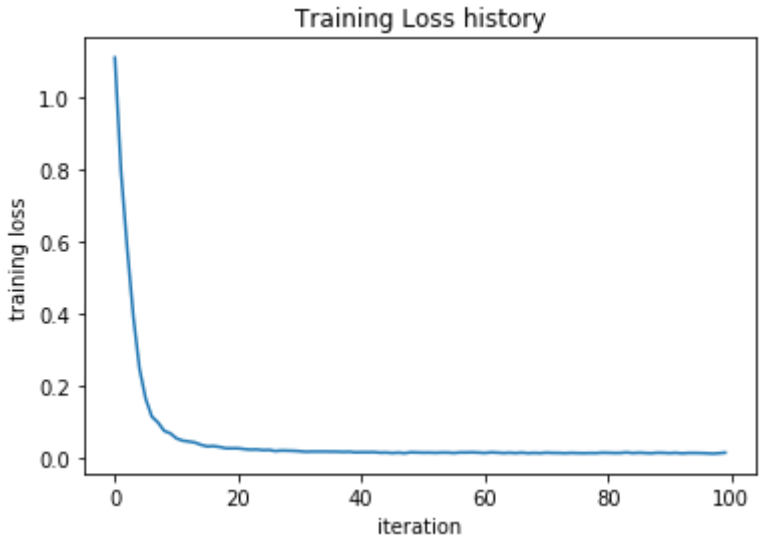
```
b2 max relative error: 1.83913010442e-10
b1 max relative error: 3.1726800927e-09
W1 max relative error: 1.28328233376e-09
W2 max relative error: 2.9632227682e-10
```

Training the network

Implement neural_net.train() to train the network via stochastic gradient descent, much like the softmax and SVM.

In [163]:
```
net = init_toy_model()
stats = net.train(X, y, X, y,
            learning_rate=1e-1, reg=5e-6,
            num_iters=100, verbose=False)

print('Final training loss: ', stats['loss_history'][-1])

# plot the loss history
plt.plot(stats['loss_history'])
plt.xlabel('iteration')
plt.ylabel('training loss')
plt.title('Training Loss history')
plt.show()
```

```
('Final training loss: ', 0.014497864587765875)
```



Classify CIFAR-10

Do classification on the CIFAR-10 dataset.

In [164]:
```
from cs231n.data_utils import load_CIFAR10

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    """
    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 = 'cifar-10-batches-py'
    X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

    # Subsample the data
    mask = list(range(num_training, num_training + num_validation))
    X_val = X_train[mask]
    y_val = y_train[mask]
    mask = list(range(num_training))
    X_train = X_train[mask]
    y_train = y_train[mask]
    mask = list(range(num_test))
    X_test = X_test[mask]
    y_test = y_test[mask]

    # Normalize the data: subtract the mean image
    mean_image = np.mean(X_train, axis=0)
    X_train -= mean_image
    X_val -= mean_image
    X_test -= mean_image

    # Reshape data to rows
    X_train = X_train.reshape(num_training, -1)
    X_val = X_val.reshape(num_validation, -1)
    X_test = X_test.reshape(num_test, -1)

    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_train.shape)
print('Train labels shape: ', y_train.shape)
print('Validation data shape: ', X_val.shape)
print('Validation labels shape: ', y_val.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

```
('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,))
```

Running SGD

If your implementation is correct, you should see a validation accuracy of around 28-29%.

In [165]:
```
input_size = 32 * 32 * 3
hidden_size = 50
num_classes = 10
net = TwoLayerNet(input_size, hidden_size, num_classes)

# Train the network
stats = net.train(X_train, y_train, X_val, y_val,
            num_iters=1000, batch_size=200,
            learning_rate=1e-4, learning_rate_decay=0.95,
            reg=0.25, verbose=True)

# Predict on the validation set
val_acc = (net.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)

# Save this net as the variable subopt_net for later comparison.
subopt_net = net
```

```
iteration 0 / 1000: loss 2.30275751861
iteration 100 / 1000: loss 2.30212015921
iteration 200 / 1000: loss 2.29561360074
iteration 300 / 1000: loss 2.25182590432
iteration 400 / 1000: loss 2.18899523505
iteration 500 / 1000: loss 2.11625277919
iteration 600 / 1000: loss 2.0646708277
iteration 700 / 1000: loss 1.99016886231
iteration 800 / 1000: loss 2.00282764012
iteration 900 / 1000: loss 1.94651768179
('Validation accuracy: ', 0.283)
```

Questions:

The training accuracy isn't great.

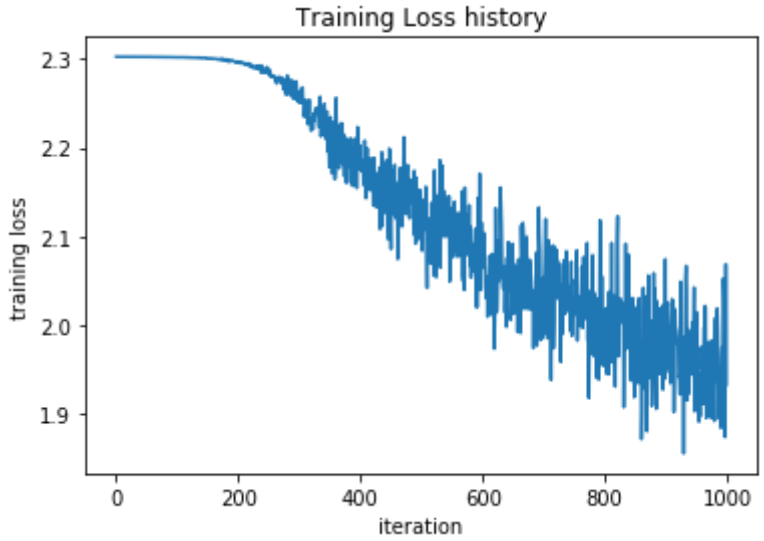
(1) What are some of the reasons why this is the case? Take the following cell to do some analyses and then report your answers in the cell following the one below.

(2) How should you fix the problems you identified in (1)?

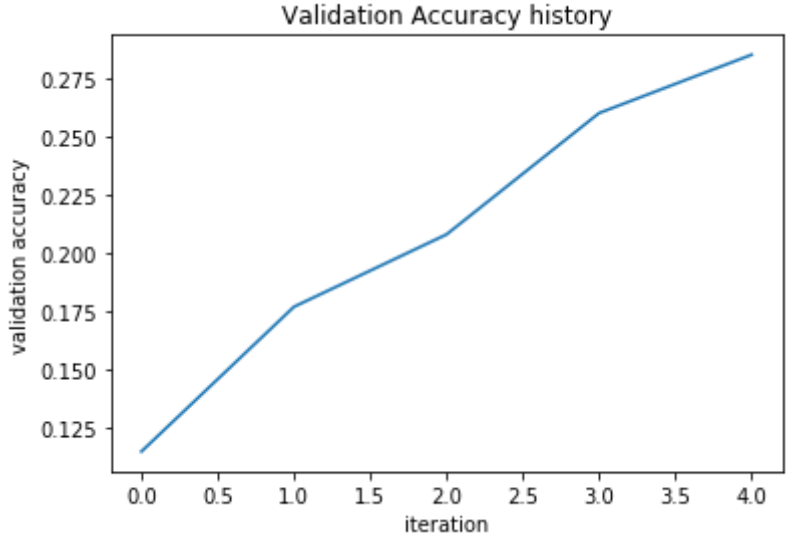
In [166]:
```
stats['train_acc_history']
```

Out[166]: [0.095, 0.15, 0.25, 0.25, 0.315]

In [167]:
```
# ================================================================ #
# YOUR CODE HERE:
#   Do some debugging to gain some insight into why the optimization
#   isn't great.
# ================================================================ #

# Plot the loss function and train / validation accuracies
plt.plot(stats['loss_history'])
plt.xlabel('iteration')
plt.ylabel('training loss')
plt.title('Training Loss history')
plt.show()
plt.plot(stats['train_acc_history'])
plt.xlabel('iteration')
plt.ylabel('training accuracy')
plt.title('Training Accuracy history')
plt.show()
plt.plot(stats['val_acc_history'])
plt.xlabel('iteration')
plt.ylabel('validation accuracy')
plt.title('Validation Accuracy history')
plt.show()


# ================================================================ #
# END YOUR CODE HERE
# ================================================================ #
```


Training Loss history
training loss
iteration
2.3
2.2
2.1
2.0
1.9
0
200
400
600
800
1000


Training Accuracy history
training accuracy
iteration
0.30
0.25
0.20
0.15
0.10
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0


Validation Accuracy history
validation accuracy
iteration
0.275
0.250
0.225
0.200
0.175
0.150
0.125
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

Answers:

(1) All of the histories still have a slope to them, so it seems that additional accuracy could be gained with additional training. The validation accuracy and training accuracy are more or less in step, which suggest that the model is underfitting or not at full capacity.

(2) The NN needs to be trained further, which can be accomplished by either increasing the learning rates or increasing the number of iterations. The capacity could also be increased by increasing the model complexity. Since by the instructions of the HW we cannot do the third, increasing the learning rate and number of iterations will be a good first step.

Optimize the neural network

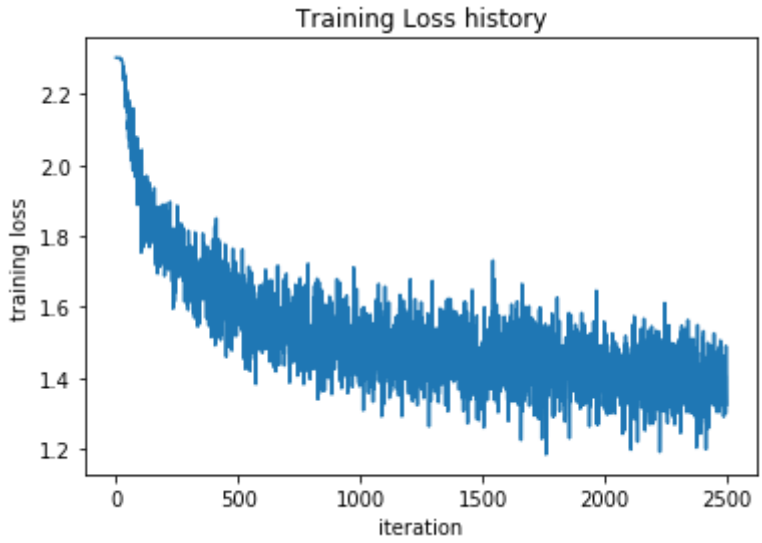
Use the following part of the Jupyter notebook to optimize your hyperparameters on the validation set. Store your nets as best_net.

In [154]:
```
best_net = None # store the best model into this

# ================================================================ #
# YOUR CODE HERE:
#   Optimize over your hyperparameters to arrive at the best neural
#   network.  You should be able to get over 50% validation accuracy.
#   For this part of the notebook, we will give credit based on the
#   accuracy you get.  Your score on this question will be multiplied
 by:
#      min(floor((X - 28%)) / %22, 1)
#   where if you get 50% or higher validation accuracy, you get full
#   points.
#
#   Note, you need to use the same network structure (keep hidden_siz
e = 50)!
# ================================================================ #

#learning_rates = [1e-1, 5e-2, 1e-2, 5e-3, 1e-3]
learning_rates = [1e-3]
regularization_strengths = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6]
best_score = -1
best_stats = None
accuracies = {}
iters = 2500

for rate in learning_rates:
    for strength in regularization_strengths:

        net = TwoLayerNet(input_size, hidden_size, num_classes)

        stats = net.train(X_train, y_train, X_val, y_val,
            num_iters=iters, batch_size=200,
            learning_rate=rate, learning_rate_decay=0.95,
            reg=strength, verbose=False)
```

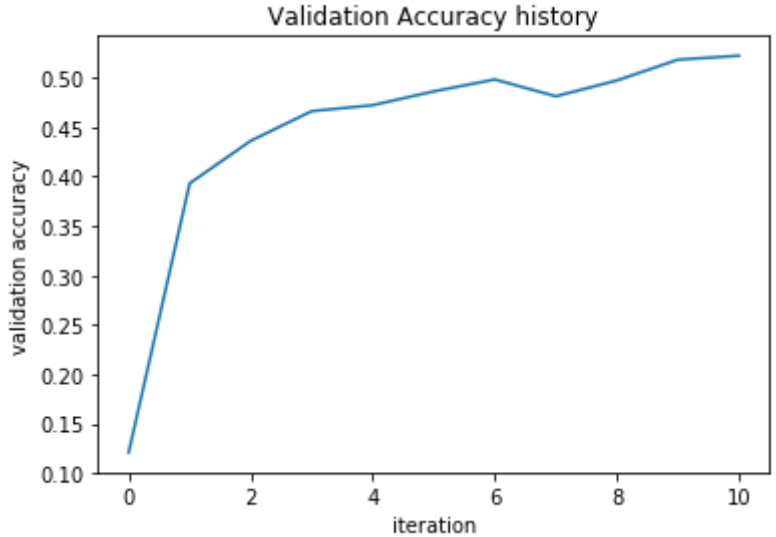
```
        train_acc = (net.predict(X_train) == y_train).mean()
        val_acc = (net.predict(X_val) == y_val).mean()

        accuracies[(rate,strength)] = (train_acc, val_acc)

        if val_acc >  best_score:
            best_stats = stats
            best_score = val_acc
            best_net = net









# ================================================================ #
# END YOUR CODE HERE
# ================================================================ #
```

In [168]:
```
print best_score

plt.plot(best_stats['loss_history'])
plt.xlabel('iteration')
plt.ylabel('training loss')
plt.title('Training Loss history')
plt.show()
plt.plot(best_stats['train_acc_history'])
plt.xlabel('iteration')
plt.ylabel('training accuracy')
plt.title('Training Accuracy history')
plt.show()
plt.plot(best_stats['val_acc_history'])
plt.xlabel('iteration')
plt.ylabel('validation accuracy')
plt.title('Validation Accuracy history')
plt.show()
```

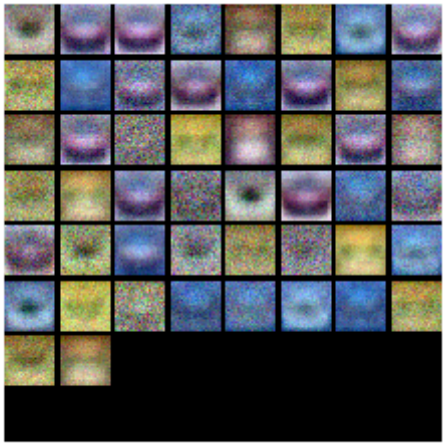
```
0.512
```

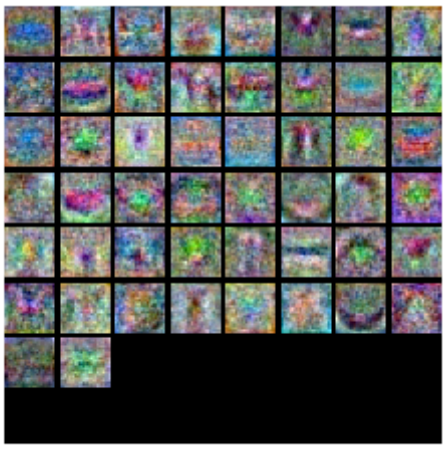

Training Loss history
training loss
iteration
2.2
2.0
1.8
1.6
1.4
1.2
0
500
1000
1500
2000
2500


Training Accuracy history
training accuracy
iteration
0.6
0.5
0.4
0.3
0.2
0
2
4
6
8
10


Validation Accuracy history
validation accuracy
iteration
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0
2
4
6
8
10

In [156]:
```
from cs231n.vis_utils import visualize_grid

# Visualize the weights of the network

def show_net_weights(net):
    W1 = net.params['W1']
    W1 = W1.T.reshape(32, 32, 3, -1).transpose(3, 0, 1, 2)
    plt.imshow(visualize_grid(W1, padding=3).astype('uint8'))
    plt.gca().axis('off')
    plt.show()

show_net_weights(subopt_net)
show_net_weights(best_net)
```





Question:

(1) What differences do you see in the weights between the suboptimal net and the best net you arrived at?

Answer:

(1) The weights in the suboptimized one are taking more vague approximations of the objects in the pictures. You can see in the best net that certain features are being emphasized, and these can be assumed to be unique to the classes.

Evaluate on test set

In [157]:
```
test_acc = (best_net.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

```
('Test accuracy: ', 0.5)
```

```python
import numpy as np
import matplotlib.pyplot as plt

"""
This code was originally written for CS 231n at Stanford University
(cs231n.stanford.edu).  It has been modified in various areas for use in the
ECE 239AS class at UCLA.  This includes the descriptions of what code to
implement as well as some slight potential changes in variable names to be
consistent with class nomenclature.  We thank Justin Johnson & Serena Yeung for
permission to use this code.  To see the original version, please visit
cs231n.stanford.edu.
"""

class TwoLayerNet(object):
  """
  A two-layer fully-connected neural network. The net has an input dimension of
  N, a hidden layer dimension of H, and performs classification over C classes.
  We train the network with a softmax loss function and L2 regularization on the
  weight matrices. The network uses a ReLU nonlinearity after the first fully
  connected layer.

  In other words, the network has the following architecture:

  input - fully connected layer - ReLU - fully connected layer - softmax

  The outputs of the second fully-connected layer are the scores for each class.
  """

  def __init__(self, input_size, hidden_size, output_size, std=1e-4):
    """
    Initialize the model. Weights are initialized to small random values and
    biases are initialized to zero. Weights and biases are stored in the
    variable self.params, which is a dictionary with the following keys:

    W1: First layer weights; has shape (H, D)
    b1: First layer biases; has shape (H,)
    W2: Second layer weights; has shape (C, H)
    b2: Second layer biases; has shape (C,)

    Inputs:
    - input_size: The dimension D of the input data.
    - hidden_size: The number of neurons H in the hidden layer.
    - output_size: The number of classes C.
    """
    self.params = {}
    self.params['W1'] = std * np.random.randn(hidden_size, input_size)
    self.params['b1'] = np.zeros(hidden_size)
    self.params['W2'] = std * np.random.randn(output_size, hidden_size)
    self.params['b2'] = np.zeros(output_size)


  def loss(self, X, y=None, reg=0.0):
    """
    Compute the loss and gradients for a two layer fully connected neural
    network.

    Inputs:
    - X: Input data of shape (N, D). Each X[i] is a training sample.
    - y: Vector of training labels. y[i] is the label for X[i], and each y[i] is
      an integer in the range 0 <= y[i] < C. This parameter is optional; if it
      is not passed then we only return scores, and if it is passed then we
      instead return the loss and gradients.
    - reg: Regularization strength.

    Returns:
    If y is None, return a matrix scores of shape (N, C) where scores[i, c] is
    the score for class c on input X[i].

    If y is not None, instead return a tuple of:
```

```
70      - loss: Loss (data loss and regularization loss) for this batch of training
71        samples.
72      - grads: Dictionary mapping parameter names to gradients of those parameters
73        with respect to the loss function; has the same keys as self.params.
74      """
75      # Unpack variables from the params dictionary
76      W1, b1 = self.params['W1'], self.params['b1']
77      W2, b2 = self.params['W2'], self.params['b2']
78      N, D = X.shape
79
80      # Compute the forward pass
81      scores = None
82
83      # ============================================================================ #
84      # YOUR CODE HERE:
85      #   Calculate the output scores of the neural network.  The result
86      #   should be (C, N). As stated in the description for this class,
87      #   there should not be a ReLU layer after the second FC layer.
88      #   The output of the second FC layer is the output scores. Do not
89      #   use a for loop in your implementation.
90      # ============================================================================ #
91
92      H1 = W1.dot(X.T) + b1[:, np.newaxis]
93      H1[H1<0] = 0
94      scores = W2.dot(H1) + b2[:,np.newaxis]
95      scores = scores.T
96
97      # ============================================================================ #
98      # END YOUR CODE HERE
99      # ============================================================================ #
100
101
102     # If the targets are not given then jump out, we're done
103     if y is None:
104       return scores
105
106     # Compute the loss
107     loss = None
108
109     # ============================================================================ #
110     # YOUR CODE HERE:
111     #   Calculate the loss of the neural network.  This includes the
112     #   softmax loss and the L2 regularization for W1 and W2. Store the
113     #   total loss in the variable loss.  Multiply the regularization
114     #   loss by 0.5 (in addition to the factor reg).
115     # ============================================================================ #
116
117     # scores is num_examples by num_classes
118     num_examples = scores.shape[0]
119
120     max_score = np.amax(scores, axis=1)
121     scores -= max_score[:, np.newaxis]
122
123     e_scores = np.exp(scores)
124     sums = np.sum(e_scores, axis=1)
125     log_sums = np.log(sums)
126     y_terms = scores[np.arange(num_examples), y]
127     loss = np.sum(log_sums - y_terms)/num_examples + .5*reg*np.sum(W1*W1) + .5*reg*np.sum(W2*W2)
128     # ============================================================================ #
129     # END YOUR CODE HERE
130     # ============================================================================ #
131
132     grads = {}
133
134     # ============================================================================ #
135     # YOUR CODE HERE:
136     #   Implement the backward pass.  Compute the derivatives of the
137     #   weights and the biases.  Store the results in the grads
138     #   dictionary.  e.g., grads['W1'] should store the gradient for
```

```
139     #   W1, and be of the same size as W1.
140     # ============================================================ #
141
142     #print W1.shape
143     #print H1.shape
144     #print scores.shape
145
146     d_scores = e_scores/sums[:,np.newaxis]
147     d_scores[np.arange(num_examples),y] -= 1
148     d_scores = d_scores.T/num_examples
149
150     b2_grad = np.sum(d_scores,axis=1)
151     W2_grad = d_scores.dot(H1.T)
152
153     r_grad = W2.T.dot(d_scores)
154     r_grad[H1<=0] = 0
155
156     b1_grad = np.sum(r_grad,axis=1)
157     W1_grad = r_grad.dot(X)
158
159     grads['b1'] = b1_grad
160     grads['W1'] = W1_grad + reg*W1
161
162     grads['b2'] = b2_grad
163     grads['W2'] = W2_grad + reg*W2
164
165     # ============================================================ #
166     # END YOUR CODE HERE
167     # ============================================================ #
168
169     return loss, grads
170
171   def train(self, X, y, X_val, y_val,
172             learning_rate=1e-3, learning_rate_decay=0.95,
173             reg=1e-5, num_iters=100,
174             batch_size=200, verbose=False):
175     """
176     Train this neural network using stochastic gradient descent.
177
178     Inputs:
179     - X: A numpy array of shape (N, D) giving training data.
180     - y: A numpy array f shape (N,) giving training labels; y[i] = c means that
181       X[i] has label c, where 0 <= c < C.
182     - X_val: A numpy array of shape (N_val, D) giving validation data.
183     - y_val: A numpy array of shape (N_val,) giving validation labels.
184     - learning_rate: Scalar giving learning rate for optimization.
185     - learning_rate_decay: Scalar giving factor used to decay the learning rate
186       after each epoch.
187     - reg: Scalar giving regularization strength.
188     - num_iters: Number of steps to take when optimizing.
189     - batch_size: Number of training examples to use per step.
190     - verbose: boolean; if true print progress during optimization.
191     """
192     num_train = X.shape[0]
193     iterations_per_epoch = max(num_train / batch_size, 1)
194
195     # Use SGD to optimize the parameters in self.model
196     loss_history = []
197     train_acc_history = []
198     val_acc_history = []
199
200     for it in np.arange(num_iters):
201       X_batch = None
202       y_batch = None
203
204       # ============================================================ #
205       # YOUR CODE HERE:
206       #   Create a minibatch by sampling batch_size samples randomly.
207       # ============================================================ #
```

```
208       mask = np.random.choice(np.arange(X.shape[0]), batch_size)
209       X_batch = X[mask]
210       y_batch = y[mask]
211
212       # ========================================================== #
213       # END YOUR CODE HERE
214       # ========================================================== #
215
216        # Compute loss and gradients using the current minibatch
217       loss, grads = self.loss(X_batch, y=y_batch, reg=reg)
218       loss_history.append(loss)
219
220       # ========================================================== #
221       # YOUR CODE HERE:
222       #   Perform a gradient descent step using the minibatch to update
223       #   all parameters (i.e., W1, W2, b1, and b2).
224       # ========================================================== #
225
226       self.params['W1'] -= learning_rate*grads['W1']
227       self.params['b1'] -= learning_rate*grads['b1']
228       self.params['W2'] -= learning_rate*grads['W2']
229       self.params['b2'] -= learning_rate*grads['b2']
230
231
232       # ========================================================== #
233       # END YOUR CODE HERE
234       # ========================================================== #
235
236       if verbose and it % 100 == 0:
237         print('iteration {} / {}: loss {}' .format(it, num_iters, loss))
238
239       # Every epoch, check train and val accuracy and decay learning rate.
240       if it % iterations_per_epoch  == 0:
241         # Check accuracy
242         train_acc = (self.predict(X_batch) == y_batch).mean()
243         val_acc = (self.predict(X_val) == y_val).mean()
244         train_acc_history.append(train_acc)
245         val_acc_history.append(val_acc)
246
247         # Decay learning rate
248         learning_rate *= learning_rate_decay
249
250     return {
251       'loss_history': loss_history,
252       'train_acc_history': train_acc_history,
253       'val_acc_history': val_acc_history,
254     }
255
256   def predict(self, X):
257     """
258     Use the trained weights of this two-layer network to predict labels for
259     data points. For each data point we predict scores for each of the C
260     classes, and assign each data point to the class with the highest score.
261
262     Inputs:
263     - X: A numpy array of shape (N, D) giving N D-dimensional data points to
264       classify.
265
266     Returns:
267     - y_pred: A numpy array of shape (N,) giving predicted labels for each of
268       the elements of X. For all i, y_pred[i] = c means that X[i] is predicted
269       to have class c, where 0 <= c < C.
270     """
271     y_pred = None
272
273     # ========================================================== #
274     # YOUR CODE HERE:
275     #   Predict the class given the input data.
276     # ========================================================== #
```

```
277     W1, b1 = self.params['W1'], self.params['b1']
278     W2, b2 = self.params['W2'], self.params['b2']
279
280     N, D = X.shape
281     H1 = W1.dot(X.T) + b1[:, np.newaxis]
282     H1[H1<0] = 0
283     scores = W2.dot(H1) + b2[:,np.newaxis]
284
285     y_pred = np.argmax(scores,axis=0)
286
287
288     # ================================================================ #
289     # END YOUR CODE HERE
290     # ================================================================ #
291
292     return y_pred
```

Fully connected networks

In the previous notebook, you implemented a simple two-layer neural network class. However, this class is not modular. If you wanted to change the number of layers, you would need to write a new loss and gradient function. If you wanted to optimize the network with different optimizers, you'd need to write new training functions. If you wanted to incorporate regularizations, you'd have to modify the loss and gradient function.

Instead of having to modify functions each time, for the rest of the class, we'll work in a more modular framework where we define forward and backward layers that calculate losses and gradients respectively. Since the forward and backward layers share intermediate values that are useful for calculating both the loss and the gradient, we'll also have these function return "caches" which store useful intermediate values.

The goal is that through this modular design, we can build different sized neural networks for various applications.

In this HW #3, we'll define the basic architecture, and in HW #4, we'll build on this framework to implement different optimizers and regularizations (like BatchNorm and Dropout).

CS231n has built a solid API for building these modular frameworks and training them, and we will use their very well implemented framework as opposed to "reinventing the wheel." This includes using their Solver, various utility functions, and their layer structure. This also includes nndl.fc_net, nndl.layers, and nndl.layer_utils. As in prior assignments, we thank Serena Yeung & Justin Johnson for permission to use code written for the CS 231n class (cs231n.stanford.edu).

Modular layers

This notebook will build modular layers in the following manner. First, there will be a forward pass for a given layer with inputs (`x`) and return the output of that layer (`out`) as well as cached variables (`cache`) that will be used to calculate the gradient in the backward pass.

```
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 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
```

In [107]:
```
## Import and setups

import time
import numpy as np
import matplotlib.pyplot as plt
from nndl.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient, eval_numer
ical_gradient_array
from cs231n.solver import Solver

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

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/autoreload-of-module
s-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))))
```

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

In [108]:
```
# Load the (preprocessed) CIFAR10 data.

data = get_CIFAR10_data()
for k in data.keys():
  print('{}: {} '.format(k, data[k].shape))
```

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

Linear layers

In this section, we'll implement the forward and backward pass for the linear layers.

The linear layer forward pass is the function `affine_forward` in `nndl/layers.py` and the backward pass is `affine_backward`.

After you have implemented these, test your implementation by running the cell below.

Affine layer forward pass

Implement `affine_forward` and then test your code by running the following cell.

In [109]:
```
# 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_sha
pe), 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 1e-9.
print('Testing affine_forward function:')
print('difference: {}'.format(rel_error(out, correct_out)))
```

```
Testing affine_forward function:
difference: 9.76984946819e-10
```

Affine layer backward pass

Implement `affine_backward` and then test your code by running the following cell.

In [110]:
```
# Test the affine_backward function

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 1e-10
print('Testing affine_backward function:')
print('dx error: {}'.format(rel_error(dx_num, dx)))
print('dw error: {}'.format(rel_error(dw_num, dw)))
print('db error: {}'.format(rel_error(db_num, db)))
```

```
Testing affine_backward function:
dx error: 8.60871575069e-11
dw error: 5.16849626491e-11
db error: 6.21942801469e-11
```

Activation layers

In this section you'll implement the ReLU activation.

ReLU forward pass

Implement the `relu_forward` function in `nndl/layers.py` and then test your code by running the following cell.

In [111]:
```
# 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,  0.13
636364,],
                        [ 0.22727273,  0.31818182,  0.40909091,  0.5,
       ]])


# Compare your output with ours. The error should be around 1e-8
print('Testing relu_forward function:')
print('difference: {}'.format(rel_error(out, correct_out)))
```

```
Testing relu_forward function:
difference: 4.99999979802e-08
```

ReLU backward pass

Implement the `relu_backward` function in `nndl/layers.py` and then test your code by running the following cell.

In [112]:
```
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 around 1e-12
print('Testing relu_backward function:')
print('dx error: {}'.format(rel_error(dx_num, dx)))
```

```
Testing relu_backward function:
dx error: 3.27561396362e-12
```

Combining the affine and ReLU layers

Often times, an affine layer will be followed by a ReLU layer. So let's make one that puts them together. Layers that are combined are stored in `nndl/layer_utils.py`.

Affine-ReLU layers

We've implemented `affine_relu_forward()` and `affine_relu_backward` in `nndl/layer_utils.py`. Take a look at them to make sure you understand what's going on. Then run the following cell to ensure its implemented correctly.

In [113]:
```
from nndl.layer_utils import affine_relu_forward, affine_relu_backwar
d

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)

print('Testing affine_relu_forward and affine_relu_backward:')
print('dx error: {}'.format(rel_error(dx_num, dx)))
print('dw error: {}'.format(rel_error(dw_num, dw)))
print('db error: {}'.format(rel_error(db_num, db)))
```

```
Testing affine_relu_forward and affine_relu_backward:
dx error: 1.47423906121e-08
dw error: 9.4703746119e-10
db error: 1.35072953084e-11
```

Softmax and SVM losses

You've already implemented these, so we have written these in `layers.py`. The following code will ensure they are working correctly.

In [114]:
```
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, verb
ose=False)
loss, dx = svm_loss(x, y)

# Test svm_loss function. Loss should be around 9 and dx error should
 be 1e-9
print('Testing svm_loss:')
print('loss: {}'.format(loss))
print('dx error: {}'.format(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 2.3 and dx error should
 be 1e-8
print('\nTesting softmax_loss:')
print('loss: {}'.format(loss))
print('dx error: {}'.format(rel_error(dx_num, dx)))
```

```
Testing svm_loss:
loss: 9.00013162042
dx error: 3.0387355051e-09

Testing softmax_loss:
loss: 2.30259872626
dx error: 1.0323036143e-08
```

Implementation of a two-layer NN

In `nndl/fc_net.py`, implement the class `TwoLayerNet` which uses the layers you made here. When you have finished, the following cell will test your implementation.

In [115]:
```
N, D, H, C = 3, 5, 50, 7
X = np.random.randn(N, D)
y = np.random.randint(C, size=N)

std = 1e-2
model = TwoLayerNet(input_dim=D, hidden_dims=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,  14.571984
34, 15.33206765,  16.09215096],
   [12.05769098,  12.74614105,  13.43459113,  14.1230412,   14.811491
28, 15.49994135,  16.18839143],
   [12.58373087,  13.20054771,  13.81736455,  14.43418138,  15.050998
22, 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'

for reg in [0.0, 0.7]:
  print('Running numeric gradient check with reg = {}'.format(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('{} relative error: {}'.format(name, rel_error(grad_num, gr
ads[name])))
```

```
Testing initialization ...
Testing test-time forward pass ...
Testing training loss (no regularization)
Running numeric gradient check with reg = 0.0
W1 relative error: 1.83365627867e-08
W2 relative error: 3.11807423476e-10
b1 relative error: 9.82831520464e-09
b2 relative error: 4.32913495457e-10
Running numeric gradient check with reg = 0.7
W1 relative error: 2.52791523102e-07
W2 relative error: 7.97665280616e-08
b1 relative error: 1.34676189626e-08
b2 relative error: 7.75909428384e-10
```

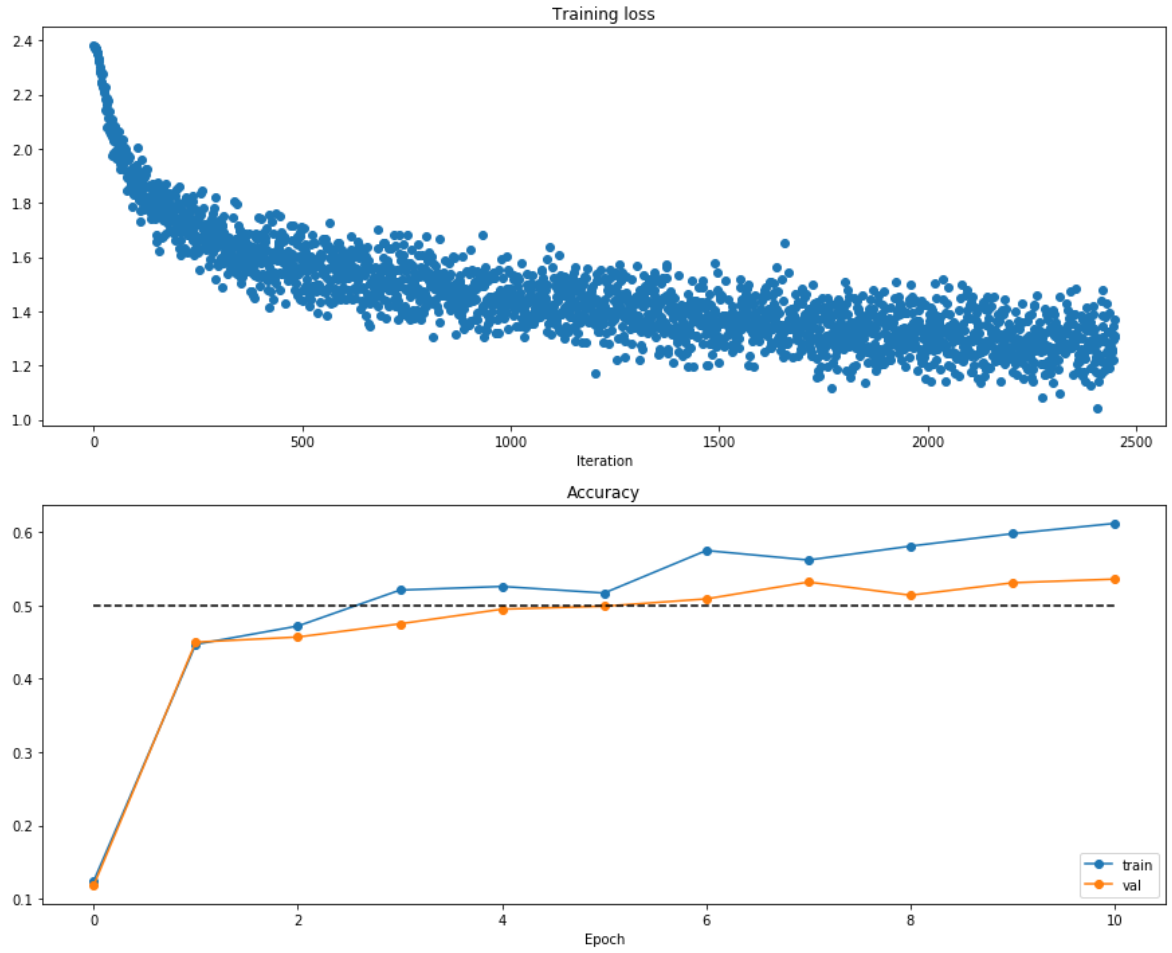
Solver

We will now use the cs231n Solver class to train these networks. Familiarize yourself with the API in `cs231n/solver.py`. After you have done so, declare an instance of a TwoLayerNet with 200 units and then train it with the Solver. Choose parameters so that your validation accuracy is at least 50%.

In [117]:
```
model = TwoLayerNet()
solver = None

# ============================================================ #
# YOUR CODE HERE:
#   Declare an instance of a TwoLayerNet and then train
#   it with the Solver. Choose hyperparameters so that your validatio
n
#   accuracy is at least 40%.  We won't have you optimize this furthe
r
#   since you did it in the previous notebook.
# ============================================================ #

model = TwoLayerNet(hidden_dims=200, reg=.25)

solver = Solver(model, data, print_every=490,
                batch_size=200,
                lr_decay=.95,
                optim_config = {
                    'learning_rate' : 1e-3,
                })

solver.train()




# ============================================================ #
# END YOUR CODE HERE
# ============================================================ #
```

```
(Iteration 1 / 2450) loss: 2.381478
(Epoch 0 / 10) train acc: 0.124000; val_acc: 0.118000
(Epoch 1 / 10) train acc: 0.447000; val_acc: 0.450000
(Epoch 2 / 10) train acc: 0.472000; val_acc: 0.457000
(Iteration 491 / 2450) loss: 1.457798
(Epoch 3 / 10) train acc: 0.521000; val_acc: 0.475000
(Epoch 4 / 10) train acc: 0.526000; val_acc: 0.495000
(Iteration 981 / 2450) loss: 1.523241
(Epoch 5 / 10) train acc: 0.517000; val_acc: 0.499000
(Epoch 6 / 10) train acc: 0.575000; val_acc: 0.509000
(Iteration 1471 / 2450) loss: 1.432054
(Epoch 7 / 10) train acc: 0.562000; val_acc: 0.532000
(Epoch 8 / 10) train acc: 0.581000; val_acc: 0.514000
(Iteration 1961 / 2450) loss: 1.343220
(Epoch 9 / 10) train acc: 0.598000; val_acc: 0.531000
(Epoch 10 / 10) train acc: 0.612000; val_acc: 0.536000
```

In [118]:
```
# Run this cell to visualize training loss and train / val accuracy

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

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



Multilayer Neural Network

Now, we implement a multi-layer neural network.

Read through the `FullyConnectedNet` class in the file `nndl/fc_net.py`.

Implement the initialization, the forward pass, and the backward pass. There will be lines for batchnorm and dropout layers and caches; ignore these all for now. That'll be in assignment #4.

In [148]:
```
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 = {}'.format(reg))
  model = FullyConnectedNet([H1, H2], input_dim=D, num_classes=C,
                            reg=reg, weight_scale=5e-2, dtype=np.floa
t64)

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

  for name in sorted(grads):
    f = lambda _: model.loss(X, y)[0]
    grad_num = eval_numerical_gradient(f, model.params[name],
verbose=False, h=1e-5)
    print('{} relative error: {}'.format(name, rel_error(grad_num, gr
ads[name])))
```

```
Running check with reg = 0
Initial loss: 2.3013653843
W1 relative error: 1.35064716142e-06
W2 relative error: 4.01073941783e-07
W3 relative error: 1.04377988289e-07
b1 relative error: 8.39454578961e-08
b2 relative error: 7.1797379996e-09
b3 relative error: 8.52298577931e-11
Running check with reg = 3.14
Initial loss: 7.31589155688
W1 relative error: 6.28609875144e-09
W2 relative error: 1.44438461983e-08
W3 relative error: 1.28177508603e-08
b1 relative error: 2.11059960475e-07
b2 relative error: 5.58921132425e-09
b3 relative error: 1.99575793561e-10
```

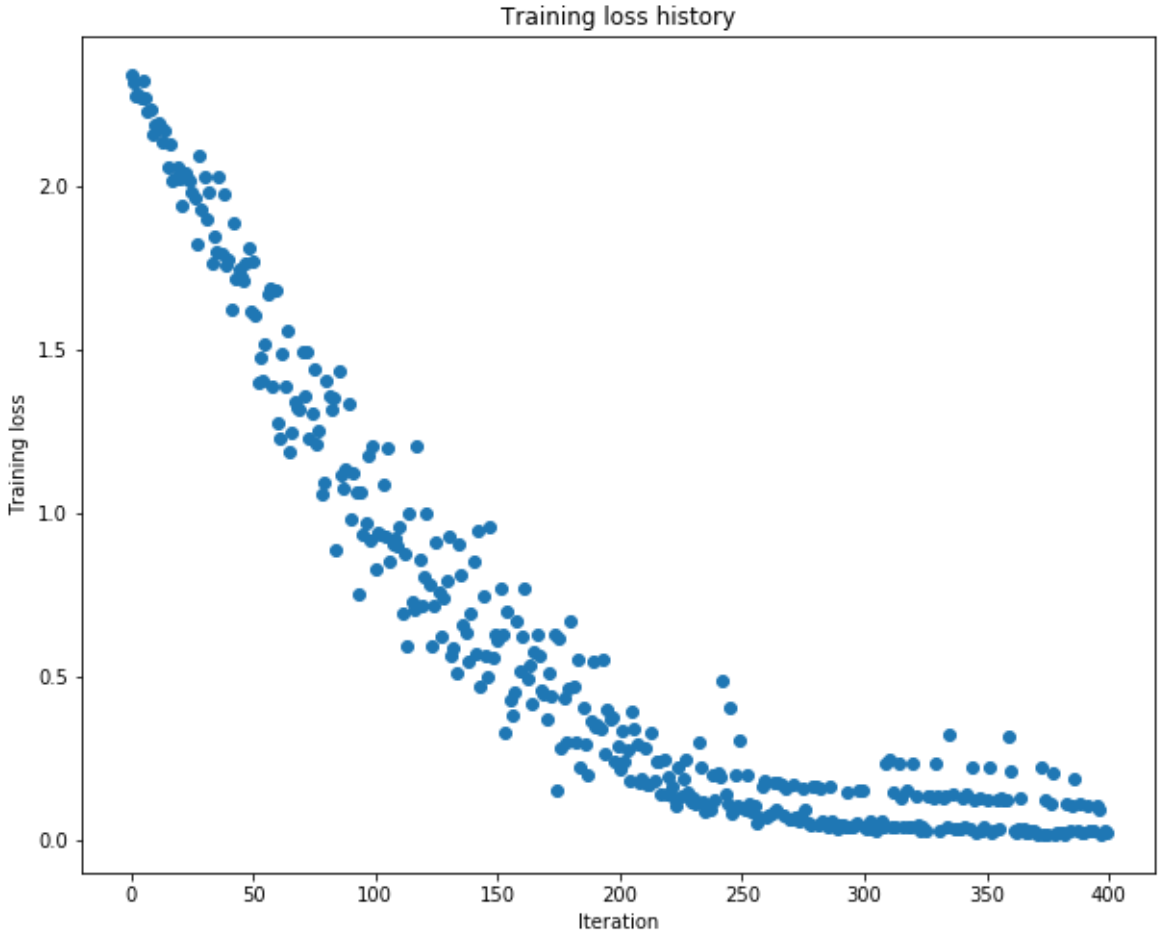
In [163]:
```
# Use the three layer neural network to overfit a small dataset.

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'],
}


#### !!!!!!
# Play around with the weight_scale and learning_rate so that you can
 overfit a small dataset.
# Your training accuracy should be 1.0 to receive full credit on this
 part.
weight_scale = 1e-2
learning_rate = 1e-3

model = FullyConnectedNet([100, 100],
              weight_scale=weight_scale, dtype=np.float64)
solver = Solver(model, small_data,
                print_every=400, num_epochs=200, 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 / 400) loss: 2.340599
(Epoch 0 / 200) train acc: 0.100000; val_acc: 0.102000
(Epoch 1 / 200) train acc: 0.120000; val_acc: 0.100000
(Epoch 2 / 200) train acc: 0.140000; val_acc: 0.107000
(Epoch 3 / 200) train acc: 0.180000; val_acc: 0.116000
(Epoch 4 / 200) train acc: 0.160000; val_acc: 0.115000
(Epoch 5 / 200) train acc: 0.200000; val_acc: 0.119000
(Epoch 6 / 200) train acc: 0.240000; val_acc: 0.125000
(Epoch 7 / 200) train acc: 0.280000; val_acc: 0.128000
(Epoch 8 / 200) train acc: 0.380000; val_acc: 0.128000
(Epoch 9 / 200) train acc: 0.360000; val_acc: 0.127000
(Epoch 10 / 200) train acc: 0.480000; val_acc: 0.131000
(Epoch 11 / 200) train acc: 0.440000; val_acc: 0.126000
(Epoch 12 / 200) train acc: 0.420000; val_acc: 0.130000
(Epoch 13 / 200) train acc: 0.460000; val_acc: 0.136000
(Epoch 14 / 200) train acc: 0.500000; val_acc: 0.147000
(Epoch 15 / 200) train acc: 0.520000; val_acc: 0.159000
(Epoch 16 / 200) train acc: 0.520000; val_acc: 0.158000
(Epoch 17 / 200) train acc: 0.540000; val_acc: 0.165000
(Epoch 18 / 200) train acc: 0.560000; val_acc: 0.157000
(Epoch 19 / 200) train acc: 0.540000; val_acc: 0.161000
(Epoch 20 / 200) train acc: 0.540000; val_acc: 0.162000
(Epoch 21 / 200) train acc: 0.560000; val_acc: 0.164000
(Epoch 22 / 200) train acc: 0.560000; val_acc: 0.161000
(Epoch 23 / 200) train acc: 0.560000; val_acc: 0.166000
(Epoch 24 / 200) train acc: 0.580000; val_acc: 0.163000
(Epoch 25 / 200) train acc: 0.600000; val_acc: 0.177000
(Epoch 26 / 200) train acc: 0.600000; val_acc: 0.175000
(Epoch 27 / 200) train acc: 0.600000; val_acc: 0.173000
(Epoch 28 / 200) train acc: 0.580000; val_acc: 0.169000
(Epoch 29 / 200) train acc: 0.580000; val_acc: 0.169000
(Epoch 30 / 200) train acc: 0.580000; val_acc: 0.165000
(Epoch 31 / 200) train acc: 0.620000; val_acc: 0.176000
(Epoch 32 / 200) train acc: 0.600000; val_acc: 0.183000
(Epoch 33 / 200) train acc: 0.620000; val_acc: 0.184000
(Epoch 34 / 200) train acc: 0.620000; val_acc: 0.176000
(Epoch 35 / 200) train acc: 0.620000; val_acc: 0.178000
(Epoch 36 / 200) train acc: 0.620000; val_acc: 0.175000
(Epoch 37 / 200) train acc: 0.620000; val_acc: 0.174000
(Epoch 38 / 200) train acc: 0.700000; val_acc: 0.188000
(Epoch 39 / 200) train acc: 0.680000; val_acc: 0.172000
(Epoch 40 / 200) train acc: 0.700000; val_acc: 0.176000
(Epoch 41 / 200) train acc: 0.700000; val_acc: 0.175000
(Epoch 42 / 200) train acc: 0.700000; val_acc: 0.173000
(Epoch 43 / 200) train acc: 0.700000; val_acc: 0.167000
(Epoch 44 / 200) train acc: 0.740000; val_acc: 0.175000
(Epoch 45 / 200) train acc: 0.740000; val_acc: 0.176000
(Epoch 46 / 200) train acc: 0.700000; val_acc: 0.178000
(Epoch 47 / 200) train acc: 0.760000; val_acc: 0.183000
(Epoch 48 / 200) train acc: 0.760000; val_acc: 0.178000
(Epoch 49 / 200) train acc: 0.780000; val_acc: 0.192000
(Epoch 50 / 200) train acc: 0.800000; val_acc: 0.193000
(Epoch 51 / 200) train acc: 0.800000; val_acc: 0.190000
(Epoch 52 / 200) train acc: 0.820000; val_acc: 0.193000
(Epoch 53 / 200) train acc: 0.820000; val_acc: 0.190000
(Epoch 54 / 200) train acc: 0.800000; val_acc: 0.189000
(Epoch 55 / 200) train acc: 0.820000; val_acc: 0.197000
```

```
(Epoch 56 / 200) train acc: 0.840000; val_acc: 0.191000
(Epoch 57 / 200) train acc: 0.840000; val_acc: 0.196000
(Epoch 58 / 200) train acc: 0.840000; val_acc: 0.188000
(Epoch 59 / 200) train acc: 0.860000; val_acc: 0.187000
(Epoch 60 / 200) train acc: 0.840000; val_acc: 0.184000
(Epoch 61 / 200) train acc: 0.820000; val_acc: 0.183000
(Epoch 62 / 200) train acc: 0.860000; val_acc: 0.189000
(Epoch 63 / 200) train acc: 0.860000; val_acc: 0.189000
(Epoch 64 / 200) train acc: 0.860000; val_acc: 0.195000
(Epoch 65 / 200) train acc: 0.840000; val_acc: 0.199000
(Epoch 66 / 200) train acc: 0.840000; val_acc: 0.195000
(Epoch 67 / 200) train acc: 0.860000; val_acc: 0.191000
(Epoch 68 / 200) train acc: 0.880000; val_acc: 0.190000
(Epoch 69 / 200) train acc: 0.880000; val_acc: 0.188000
(Epoch 70 / 200) train acc: 0.880000; val_acc: 0.192000
(Epoch 71 / 200) train acc: 0.880000; val_acc: 0.182000
(Epoch 72 / 200) train acc: 0.880000; val_acc: 0.179000
(Epoch 73 / 200) train acc: 0.880000; val_acc: 0.191000
(Epoch 74 / 200) train acc: 0.880000; val_acc: 0.196000
(Epoch 75 / 200) train acc: 0.880000; val_acc: 0.186000
(Epoch 76 / 200) train acc: 0.880000; val_acc: 0.193000
(Epoch 77 / 200) train acc: 0.880000; val_acc: 0.189000
(Epoch 78 / 200) train acc: 0.880000; val_acc: 0.186000
(Epoch 79 / 200) train acc: 0.880000; val_acc: 0.182000
(Epoch 80 / 200) train acc: 0.880000; val_acc: 0.188000
(Epoch 81 / 200) train acc: 0.880000; val_acc: 0.183000
(Epoch 82 / 200) train acc: 0.880000; val_acc: 0.187000
(Epoch 83 / 200) train acc: 0.880000; val_acc: 0.189000
(Epoch 84 / 200) train acc: 0.900000; val_acc: 0.183000
(Epoch 85 / 200) train acc: 0.900000; val_acc: 0.186000
(Epoch 86 / 200) train acc: 0.900000; val_acc: 0.184000
(Epoch 87 / 200) train acc: 0.900000; val_acc: 0.186000
(Epoch 88 / 200) train acc: 0.940000; val_acc: 0.187000
(Epoch 89 / 200) train acc: 0.920000; val_acc: 0.190000
(Epoch 90 / 200) train acc: 0.940000; val_acc: 0.177000
(Epoch 91 / 200) train acc: 0.960000; val_acc: 0.184000
(Epoch 92 / 200) train acc: 0.960000; val_acc: 0.182000
(Epoch 93 / 200) train acc: 0.960000; val_acc: 0.181000
(Epoch 94 / 200) train acc: 0.980000; val_acc: 0.183000
(Epoch 95 / 200) train acc: 0.980000; val_acc: 0.187000
(Epoch 96 / 200) train acc: 0.980000; val_acc: 0.188000
(Epoch 97 / 200) train acc: 0.980000; val_acc: 0.189000
(Epoch 98 / 200) train acc: 0.980000; val_acc: 0.188000
(Epoch 99 / 200) train acc: 0.980000; val_acc: 0.185000
(Epoch 100 / 200) train acc: 0.980000; val_acc: 0.188000
(Epoch 101 / 200) train acc: 0.980000; val_acc: 0.187000
(Epoch 102 / 200) train acc: 0.980000; val_acc: 0.187000
(Epoch 103 / 200) train acc: 0.980000; val_acc: 0.187000
(Epoch 104 / 200) train acc: 0.980000; val_acc: 0.192000
(Epoch 105 / 200) train acc: 0.980000; val_acc: 0.190000
(Epoch 106 / 200) train acc: 0.980000; val_acc: 0.190000
(Epoch 107 / 200) train acc: 0.980000; val_acc: 0.189000
(Epoch 108 / 200) train acc: 0.980000; val_acc: 0.188000
(Epoch 109 / 200) train acc: 0.980000; val_acc: 0.183000
(Epoch 110 / 200) train acc: 0.980000; val_acc: 0.188000
(Epoch 111 / 200) train acc: 0.980000; val_acc: 0.187000
(Epoch 112 / 200) train acc: 0.980000; val_acc: 0.190000
```

```
(Epoch 113 / 200) train acc: 0.980000; val_acc: 0.186000
(Epoch 114 / 200) train acc: 0.980000; val_acc: 0.190000
(Epoch 115 / 200) train acc: 0.980000; val_acc: 0.200000
(Epoch 116 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 117 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 118 / 200) train acc: 0.980000; val_acc: 0.190000
(Epoch 119 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 120 / 200) train acc: 0.980000; val_acc: 0.191000
(Epoch 121 / 200) train acc: 0.980000; val_acc: 0.198000
(Epoch 122 / 200) train acc: 0.980000; val_acc: 0.191000
(Epoch 123 / 200) train acc: 0.980000; val_acc: 0.193000
(Epoch 124 / 200) train acc: 0.980000; val_acc: 0.193000
(Epoch 125 / 200) train acc: 0.980000; val_acc: 0.197000
(Epoch 126 / 200) train acc: 0.980000; val_acc: 0.192000
(Epoch 127 / 200) train acc: 0.980000; val_acc: 0.188000
(Epoch 128 / 200) train acc: 0.980000; val_acc: 0.191000
(Epoch 129 / 200) train acc: 0.980000; val_acc: 0.190000
(Epoch 130 / 200) train acc: 0.980000; val_acc: 0.190000
(Epoch 131 / 200) train acc: 0.980000; val_acc: 0.191000
(Epoch 132 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 133 / 200) train acc: 0.980000; val_acc: 0.191000
(Epoch 134 / 200) train acc: 0.980000; val_acc: 0.192000
(Epoch 135 / 200) train acc: 0.980000; val_acc: 0.191000
(Epoch 136 / 200) train acc: 0.980000; val_acc: 0.191000
(Epoch 137 / 200) train acc: 0.980000; val_acc: 0.191000
(Epoch 138 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 139 / 200) train acc: 0.980000; val_acc: 0.193000
(Epoch 140 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 141 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 142 / 200) train acc: 0.980000; val_acc: 0.193000
(Epoch 143 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 144 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 145 / 200) train acc: 0.980000; val_acc: 0.192000
(Epoch 146 / 200) train acc: 0.980000; val_acc: 0.192000
(Epoch 147 / 200) train acc: 0.980000; val_acc: 0.192000
(Epoch 148 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 149 / 200) train acc: 0.980000; val_acc: 0.193000
(Epoch 150 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 151 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 152 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 153 / 200) train acc: 0.980000; val_acc: 0.197000
(Epoch 154 / 200) train acc: 0.980000; val_acc: 0.197000
(Epoch 155 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 156 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 157 / 200) train acc: 0.980000; val_acc: 0.197000
(Epoch 158 / 200) train acc: 0.980000; val_acc: 0.198000
(Epoch 159 / 200) train acc: 0.980000; val_acc: 0.199000
(Epoch 160 / 200) train acc: 0.980000; val_acc: 0.198000
(Epoch 161 / 200) train acc: 0.980000; val_acc: 0.198000
(Epoch 162 / 200) train acc: 0.980000; val_acc: 0.197000
(Epoch 163 / 200) train acc: 0.980000; val_acc: 0.197000
(Epoch 164 / 200) train acc: 0.980000; val_acc: 0.198000
(Epoch 165 / 200) train acc: 0.980000; val_acc: 0.197000
(Epoch 166 / 200) train acc: 0.980000; val_acc: 0.198000
(Epoch 167 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 168 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 169 / 200) train acc: 0.980000; val_acc: 0.196000
```

```
(Epoch 170 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 171 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 172 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 173 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 174 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 175 / 200) train acc: 0.980000; val_acc: 0.193000
(Epoch 176 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 177 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 178 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 179 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 180 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 181 / 200) train acc: 0.980000; val_acc: 0.194000
(Epoch 182 / 200) train acc: 0.980000; val_acc: 0.193000
(Epoch 183 / 200) train acc: 0.980000; val_acc: 0.198000
(Epoch 184 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 185 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 186 / 200) train acc: 0.980000; val_acc: 0.197000
(Epoch 187 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 188 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 189 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 190 / 200) train acc: 0.980000; val_acc: 0.198000
(Epoch 191 / 200) train acc: 0.980000; val_acc: 0.198000
(Epoch 192 / 200) train acc: 0.980000; val_acc: 0.195000
(Epoch 193 / 200) train acc: 0.980000; val_acc: 0.196000
(Epoch 194 / 200) train acc: 1.000000; val_acc: 0.192000
(Epoch 195 / 200) train acc: 1.000000; val_acc: 0.192000
(Epoch 196 / 200) train acc: 1.000000; val_acc: 0.192000
(Epoch 197 / 200) train acc: 1.000000; val_acc: 0.194000
(Epoch 198 / 200) train acc: 1.000000; val_acc: 0.198000
(Epoch 199 / 200) train acc: 1.000000; val_acc: 0.198000
(Epoch 200 / 200) train acc: 1.000000; val_acc: 0.196000
```



In [167]:
```
print solver.train_acc_history[-1]
```

```
1.0
```

```python
import numpy as np
import pdb

"""
This code was originally written for CS 231n at Stanford University
(cs231n.stanford.edu).  It has been modified in various areas for use in the
ECE 239AS class at UCLA.  This includes the descriptions of what code to
implement as well as some slight potential changes in variable names to be
consistent with class nomenclature.  We thank Justin Johnson & Serena Yeung for
permission to use this code.  To see the original version, please visit
cs231n.stanford.edu.
"""


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

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

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

  Returns a tuple of:
  - out: output, of shape (N, M)
  - cache: (x, w, b)
  """

  # ============================================================ #
  # YOUR CODE HERE:
  #   Calculate the output of the forward pass.  Notice the dimensions
  #   of w are D x M, which is the transpose of what we did in earlier
  #   assignments.
  # ============================================================ #
  shape = x.shape
  N = shape[0]
  D = np.prod(shape[1:])
  reshaped_x = np.reshape(x, (N,D))

  out = reshaped_x.dot(w) + b[:, np.newaxis].T

  # ============================================================ #
  # END YOUR CODE HERE
  # ============================================================ #

  cache = (x, w, b)
  return out, cache


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

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

  Returns a tuple of:
  - dx: Gradient with respect to x, of shape (N, d1, ..., d_k)
  - dw: Gradient with respect to w, of shape (D, M)
  - db: Gradient with respect to b, of shape (M,)
  """
```

```
  x, w, b = cache
  dx, dw, db = None, None, None

  # ============================================================== #
  # YOUR CODE HERE:
  #   Calculate the gradients for the backward pass.
  # ============================================================== #
  N, M = dout.shape
  D = w.shape[0]

  reshaped_x = np.reshape(x, (N,D))

  db = np.sum(dout, axis=0)
  dw = reshaped_x.T.dot(dout)
  dx = np.reshape(dout.dot(w.T), x.shape)


  # ============================================================== #
  # END YOUR CODE HERE
  # ============================================================== #

  return dx, dw, db

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

  Input:
  - x: Inputs, of any shape

  Returns a tuple of:
  - out: Output, of the same shape as x
  - cache: x
  """
  # ============================================================== #
  # YOUR CODE HERE:
  #   Implement the ReLU forward pass.
  # ============================================================== #
  out = np.empty_like(x)
  out[:] = x
  out[out<0] = 0
  # ============================================================== #
  # END YOUR CODE HERE
  # ============================================================== #

  cache = x
  return out, cache


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

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

  Returns:
  - dx: Gradient with respect to x
  """
  x = cache

  # ============================================================== #
  # YOUR CODE HERE:
  #   Implement the ReLU backward pass
  # ============================================================== #
  dx = np.empty_like(dout)
  dx[:] = dout
  dx[x<0] = 0
```

```
139
140   # ================================================================ #
141   # END YOUR CODE HERE
142   # ================================================================ #
143
144   return dx
145
146 def svm_loss(x, y):
147   """
148   Computes the loss and gradient using for multiclass SVM classification.
149
150   Inputs:
151   - x: Input data, of shape (N, C) where x[i, j] is the score for the jth class
152     for the ith input.
153   - y: Vector of labels, of shape (N,) where y[i] is the label for x[i] and
154     0 <= y[i] < C
155
156   Returns a tuple of:
157   - loss: Scalar giving the loss
158   - dx: Gradient of the loss with respect to x
159   """
160   N = x.shape[0]
161   correct_class_scores = x[np.arange(N), y]
162   margins = np.maximum(0, x - correct_class_scores[:, np.newaxis] + 1.0)
163   margins[np.arange(N), y] = 0
164   loss = np.sum(margins) / N
165   num_pos = np.sum(margins > 0, axis=1)
166   dx = np.zeros_like(x)
167   dx[margins > 0] = 1
168   dx[np.arange(N), y] -= num_pos
169   dx /= N
170   return loss, dx
171
172
173 def softmax_loss(x, y):
174   """
175   Computes the loss and gradient for softmax classification.
176
177   Inputs:
178   - x: Input data, of shape (N, C) where x[i, j] is the score for the jth class
179     for the ith input.
180   - y: Vector of labels, of shape (N,) where y[i] is the label for x[i] and
181     0 <= y[i] < C
182
183   Returns a tuple of:
184   - loss: Scalar giving the loss
185   - dx: Gradient of the loss with respect to x
186   """
187
188   probs = np.exp(x - np.max(x, axis=1, keepdims=True))
189   probs /= np.sum(probs, axis=1, keepdims=True)
190   N = x.shape[0]
191   loss = -np.sum(np.log(probs[np.arange(N), y])) / N
192   dx = probs.copy()
193   dx[np.arange(N), y] -= 1
194   dx /= N
195   return loss, dx
```

```python
import numpy as np

from .layers import *
from .layer_utils import *

"""
This code was originally written for CS 231n at Stanford University
(cs231n.stanford.edu).  It has been modified in various areas for use in the
ECE 239AS class at UCLA.  This includes the descriptions of what code to
implement as well as some slight potential changes in variable names to be
consistent with class nomenclature.  We thank Justin Johnson & Serena Yeung for
permission to use this code.  To see the original version, please visit
cs231n.stanford.edu.
"""

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

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

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

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

  def __init__(self, input_dim=3*32*32, hidden_dims=100, num_classes=10,
               dropout=0, weight_scale=1e-3, reg=0.0):
    """
    Initialize a new network.

    Inputs:
    - input_dim: An integer giving the size of the input
    - hidden_dims: An integer giving the size of the hidden layer
    - num_classes: An integer giving the number of classes to classify
    - dropout: Scalar between 0 and 1 giving dropout strength.
    - weight_scale: Scalar giving the standard deviation for random
      initialization of the weights.
    - reg: Scalar giving L2 regularization strength.
    """
    self.params = {}
    self.reg = reg

    # ============================================================ #
    # YOUR CODE HERE:
    #   Initialize W1, W2, b1, and b2.  Store these as self.params['W1'],
    #   self.params['W2'], self.params['b1'] and self.params['b2']. The
    #   biases are initialized to zero and the weights are initialized
    #   so that each parameter has mean 0 and standard deviation weight_scale.
    #   The dimensions of W1 should be (input_dim, hidden_dim) and the
    #   dimensions of W2 should be (hidden_dims, num_classes)
    # ============================================================ #

    self.params['W1'] = weight_scale * np.random.randn(input_dim, hidden_dims)
    self.params['b1'] = np.zeros(hidden_dims)
    self.params['W2'] = weight_scale * np.random.randn(hidden_dims, num_classes)
    self.params['b2'] = np.zeros(num_classes)

    # ============================================================ #
    # END YOUR CODE HERE
    # ============================================================ #

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

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

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

    If y is not None, then run a training-time forward and backward pass and
    return a tuple of:
    - loss: Scalar value giving the loss
    - grads: Dictionary with the same keys as self.params, mapping parameter
      names to gradients of the loss with respect to those parameters.
    """
    scores = None

    # ============================================================ #
    # YOUR CODE HERE:
    #   Implement the forward pass of the two-layer neural network. Store
    #   the class scores as the variable 'scores'.  Be sure to use the layers
```

```
93      #   you prior implemented.
94      # ================================================================ #
95
96      h1, cache1 = affine_relu_forward(X, self.params['W1'], self.params['b1'])
97      scores, cache2 = affine_relu_forward(h1, self.params['W2'], self.params['b2'])
98      # ================================================================ #
99      # END YOUR CODE HERE
100     # ================================================================ #
101
102     # If y is None then we are in test mode so just return scores
103     if y is None:
104       return scores
105
106     loss, grads = 0, {}
107     # ================================================================ #
108     # YOUR CODE HERE:
109     #   Implement the backward pass of the two-layer neural net.  Store
110     #   the loss as the variable 'loss' and store the gradients in the
111     #   'grads' dictionary.  For the grads dictionary, grads['W1'] holds
112     #   the gradient for W1, grads['b1'] holds the gradient for b1, etc.
113     #   i.e., grads[k] holds the gradient for self.params[k].
114     #
115     #   Add L2 regularization, where there is an added cost 0.5*self.reg*W^2
116     #   for each W.  Be sure to include the 0.5 multiplying factor to
117     #   match our implementation.
118     #
119     #   And be sure to use the layers you prior implemented.
120     # ================================================================ #
121     W1 = self.params['W1']
122     W2 = self.params['W2']
123
124     num_examples = scores.shape[0]
125
126     max_score = np.amax(scores, axis=1)
127     scores -= max_score[:, np.newaxis]
128
129     e_scores = np.exp(scores)
130     sums = np.sum(e_scores, axis=1)
131     log_sums = np.log(sums)
132     y_terms = scores[np.arange(num_examples), y]
133     loss = np.sum(log_sums - y_terms)/num_examples + .5*self.reg*np.sum(W1*W1) + .5*self.reg*np.sum(W2*W2)
134
135     d_scores = e_scores/sums[:,np.newaxis]
136     d_scores[np.arange(num_examples),y] -= 1
137     d_scores = d_scores.T/num_examples
138
139     dx2, dw2, db2 = affine_relu_backward(d_scores.T, cache2)
140     dx1, dw1, db1 = affine_relu_backward(dx2, cache1)
141
142
143     grads['W1'] = dw1 + self.reg*W1
144     grads['b1'] = db1
145     grads['W2'] = dw2 + self.reg*W2
146     grads['b2'] = db2
147
148
149
150
151
152
153     # ================================================================ #
154     # END YOUR CODE HERE
155     # ================================================================ #
156
157     return loss, grads
158
159
160 class FullyConnectedNet(object):
161   """
162   A fully-connected neural network with an arbitrary number of hidden layers,
163   ReLU nonlinearities, and a softmax loss function. This will also implement
164   dropout and batch normalization as options. For a network with L layers,
165   the architecture will be
166
167   {affine - [batch norm] - relu - [dropout]} x (L - 1) - affine - softmax
168
169   where batch normalization and dropout are optional, and the {...} block is
170   repeated L - 1 times.
171
172   Similar to the TwoLayerNet above, learnable parameters are stored in the
173   self.params dictionary and will be learned using the Solver class.
174   """
175
176   def __init__(self, hidden_dims, input_dim=3*32*32, num_classes=10,
177                dropout=0, use_batchnorm=False, reg=0.0,
178                weight_scale=1e-2, dtype=np.float32, seed=None):
179     """
180     Initialize a new FullyConnectedNet.
181
182     Inputs:
183     - hidden_dims: A list of integers giving the size of each hidden layer.
184     - input_dim: An integer giving the size of the input.
```

```
    - num_classes: An integer giving the number of classes to classify.
    - dropout: Scalar between 0 and 1 giving dropout strength. If dropout=0 then
      the network should not use dropout at all.
    - use_batchnorm: Whether or not the network should use batch normalization.
    - reg: Scalar giving L2 regularization strength.
    - weight_scale: Scalar giving the standard deviation for random
      initialization of the weights.
    - dtype: A numpy datatype object; all computations will be performed using
      this datatype. float32 is faster but less accurate, so you should use
      float64 for numeric gradient checking.
    - seed: If not None, then pass this random seed to the dropout layers. This
      will make the dropout layers deteriminstic so we can gradient check the
      model.
    """
    self.use_batchnorm = use_batchnorm
    self.use_dropout = dropout > 0
    self.reg = reg
    self.num_layers = 1 + len(hidden_dims)
    self.dtype = dtype
    self.params = {}

    # ============================================================ #
    # YOUR CODE HERE:
    #   Initialize all parameters of the network in the self.params dictionary.
    #   The weights and biases of layer 1 are W1 and b1; and in general the
    #   weights and biases of layer i are Wi and bi. The
    #   biases are initialized to zero and the weights are initialized
    #   so that each parameter has mean 0 and standard deviation weight_scale.
    # ============================================================ #

    dimensions = [input_dim] + hidden_dims + [num_classes]

    for i in np.arange(self.num_layers):
      self.params['W{}'.format(i+1)] = weight_scale * np.random.randn(dimensions[i], dimensions[i+1])
      self.params['b{}'.format(i+1)] = np.zeros(dimensions[i+1])



    # ============================================================ #
    # END YOUR CODE HERE
    # ============================================================ #

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

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

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


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

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

    # Set train/test mode for batchnorm params and dropout param since they
    # behave differently during training and testing.
    if self.dropout_param is not None:
      self.dropout_param['mode'] = mode
    if self.use_batchnorm:
      for bn_param in self.bn_params:
        bn_param[mode] = mode

    scores = None

    # ============================================================ #
    # YOUR CODE HERE:
    #   Implement the forward pass of the FC net and store the output
    #   scores as the variable "scores".
    # ============================================================ #
    caches = []
    layer_scores = []

```

```
277     layer_scores.append(X)
278
279     for i in np.arange(self.num_layers):
280       temp_score, temp_cache = affine_relu_forward(layer_scores[i], self.params['W{}'.format(i+1)], self.params['b{}'.format(i+1)])
281       caches.append(temp_cache)
282       layer_scores.append(temp_score)
283
284     scores = layer_scores[-1]
285
286     # ============================================================ #
287     # END YOUR CODE HERE
288     # ============================================================ #
289
290     # If test mode return early
291     if mode == 'test':
292       return scores
293
294     loss, grads = 0.0, {}
295     # ============================================================ #
296     # YOUR CODE HERE:
297     #   Implement the backwards pass of the FC net and store the gradients
298     #   in the grads dict, so that grads[k] is the gradient of self.params[k]
299     #   Be sure your L2 regularization includes a 0.5 factor.
300     # ============================================================ #
301     num_examples = scores.shape[0]
302
303     max_score = np.amax(scores, axis=1)
304     scores -= max_score[:, np.newaxis]
305
306     e_scores = np.exp(scores)
307     sums = np.sum(e_scores, axis=1)
308     log_sums = np.log(sums)
309     y_terms = scores[np.arange(num_examples), y]
310
311     reg_loss = 0
312     for i in np.arange(self.num_layers):
313       W = self.params['W{}'.format(i+1)]
314       reg_loss += .5*self.reg*np.sum(W*W)
315
316     loss = np.sum(log_sums - y_terms)/num_examples + reg_loss
317
318
319
320     d_scores = e_scores/sums[:,np.newaxis]
321     d_scores[np.arange(num_examples),y] -= 1
322     d_scores = d_scores/num_examples
323
324     #print len(caches)
325     #print self.num_layers
326
327     for i in np.arange(self.num_layers-1, -1,-1):
328       dx, dw, db = affine_relu_backward(d_scores, caches[i])
329       grads['W{}'.format(i+1)] = dw + self.reg*self.params['W{}'.format(i+1)]
330       grads['b{}'.format(i+1)] = db
331       d_scores = dx
332
333     #dx2, dw2, db2 = affine_relu_backward(d_scores, cache[i])
334    # dx1, dw1, db1 = affine_relu_backward(dx2, cache1)
335
336
337     # ============================================================ #
338     # END YOUR CODE HERE
339     # ============================================================ #
340     return loss, grads
```