Chayut Archamonghol
6631309621

Homework 4 Neural Networks

Instructions

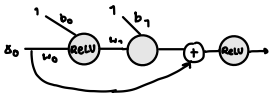
Answer the questions and upload your answers to courseville. Answers can be in Thai or English. Answers can be either typed or handwritten and scanned. the assignment is divided into several small tasks. Each task is weighted equally (marked with **T**). For this assignment, each task is awarded equally. There are also optional tasks (marked with **OT**) counts for half of the required task.

The Basics

In this section, we will review some of the basic materials taught in class. These are simple tasks and integral to the understanding of deep neural networks, but many students seem to misunderstand.

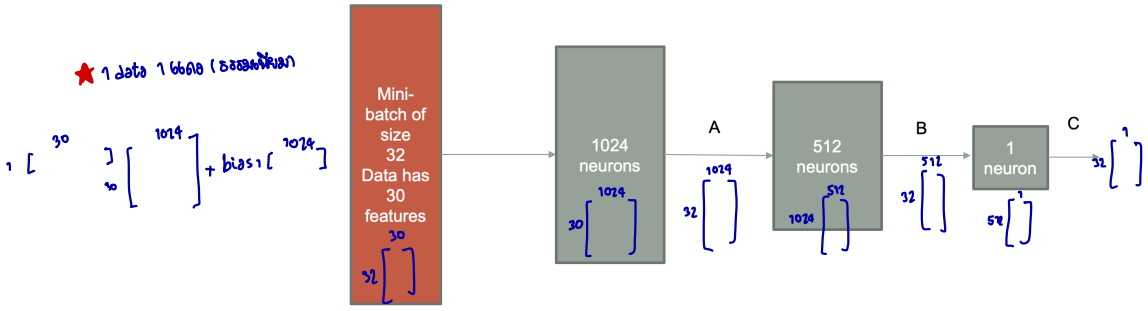
T1. Compute the forward and backward pass of the following computation. Note that this is a simplified residual connection.

$$x_1 = ReLU(x_0 * w_0 + b_0)$$
$$y_1 = x_1 * w_1 + b_1$$
$$z = ReLU(y_1 + x_0)$$



Let $x_0 = 1.0$, $w_0 = 0.3$, $w_1 = -0.2$, $b_0 = 0.1$, $b_1 = -0.3$. Find the gradient of z with respect to w_0, w_1, b_0, and b_1.

T2. Given the following network architecture specifications, determine the size of the output A, B, and C.



T3. What is the total number of learnable parameters in this network? (Don't forget the bias term)

Deep Learning from (almost) scratch

In this section we will code simple a neural network model from scratch (numpy). However, before we go into coding let's start with some loose ends, namely the gradient of the softmax layer.

Recall in class we define the softmax layer as:

$$P(y=j) = \frac{exp(h_j)}{\Sigma_k exp(h_k)} \tag{1}$$

where h_j is the output of the previous layer for class index j
The cross entropy loss is defined as:

$$L = -\Sigma_j y_j log P(y=j) \tag{2}$$

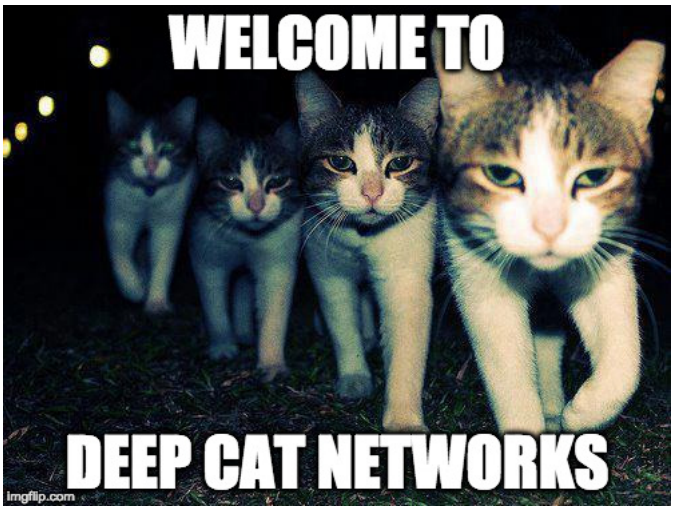
where y_j is 1 if y is class j, and 0 otherwise.

T4. Prove that the derivative of the loss with respect to h_i is $P(y=i) - y_i$. In other words, find $\frac{\partial L}{\partial h_i}$ for $i \in \{0, ..., N-1\}$ where N is the number of classes. Hint: first find $\frac{\partial P(y=j)}{\partial h_i}$ for the case where $j = i$, and the case where $j \neq i$. Then, use the results with chain rule to find the derivative of the loss.

Next, we will code a simple neural network using numpy. Use the starter code `hw4.zip` on github. There are 8 tasks you need to complete in the starter code.

Hints: In order to do this part of the assignment, you will need to find gradients of vectors over matrices. We have done gradients of scalars (Traces) over matrices before, which is a matrix (two-dimensional). However, gradients of vectors over matrices will be a tensor (three-dimensional), and the properties we learned will not work. I highly recommend you find the gradients in parts. In other words, compute the gradient for each element in the the matrix/vector separately. Then, combine the result back into matrices. For more information, you can read this simple guide `http://cs231n.stanford.edu/vecDerivs.pdf`

Happy coding.



04_Neural_Networks\cattern\neural_net.py

Choyut Archamonghol
6693307621

```python
from __future__ import print_function

import numpy as np
import matplotlib.pyplot as plt

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 (D, H)
    b1: First layer biases; has shape (H,)
    W2: Second layer weights; has shape (H, C)
    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(input_size, hidden_size)
    self.params['b1'] = np.zeros(hidden_size)
    self.params['W2'] = std * np.random.randn(hidden_size, output_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:
    - loss: Loss (data loss and regularization loss) for this batch of training
      samples.
    - grads: Dictionary mapping parameter names to gradients of those parameters
      with respect to the loss function; has the same keys as self.params.
    """
    # Unpack variables from the params dictionary
    W1, b1 = self.params['W1'], self.params['b1']
    W2, b2 = self.params['W2'], self.params['b2']
    N, D = X.shape

    # Compute the forward pass
    scores = None
    #############################################################################
    # T#5: Perform the forward pass, computing the class scores for the      #
    # input.                                                                    #
    # Store the result in the scores variable, which should be an array of      #
    # shape (N, C). Note that this does not include the softmax                 #
    # HINT: This is just a series of matrix multiplication.                     #
    #############################################################################
    h1 = X @ W1 + b1
    h1_relu = np.maximum(0, h1)
    scores = h1_relu @ W2 + b2
    #############################################################################
    #                              END OF T#5                                   #
    #############################################################################

    # If the targets are not given then jump out, we're done
    if y is None:
      return scores

    # Compute the loss
    loss = None
    #############################################################################
    # T#6: Finish the forward pass, and compute the loss. This should include#
    # both the data loss and L2 regularization for W1 and W2. Store the result  #
    # in the variable loss, which should be a scalar. Use the Softmax           #
    # classifier loss.                                                          #
    #############################################################################
```

```
    shift_scores = scores - np.max(scores, axis=1, keepdims=True) # prevent overflow
    softmax = np.exp(shift_scores)
    divider = np.sum(softmax, axis=1, keepdims=True)
    softmax = softmax / divider

    loss = -np.sum(np.log(softmax[np.arange(N), y]))

    # Average for each data
    loss /= y.shape[0]
    # Regularization 0.5 * lambda * sigma (every weight square)
    loss += 0.5 * reg * (np.sum(W1**2) + np.sum(W2**2))
    ############################################################################
    #                              END OF T#6                                  #
    ############################################################################

    # Backward pass: compute gradients
    grads = {}
    ############################################################################
    # T#7: Compute the backward pass, computing derivatives of the weights   #
    # and biases. Store the results in the grads dictionary. For example,       #
    # grads['W1'] should store the gradient on W1, and be a matrix of same size #
    # don't forget about the regularization term                                #
    ############################################################################

    # init with gradient of regularization term
    grads["W1"] = reg * self.params["W1"]
    grads["W2"] = reg * self.params["W2"]
    grads["b1"] = np.zeros(b1.shape)
    grads["b2"] = np.zeros(b2.shape)

    dscores = softmax.copy()
    dscores[np.arange(N), y] -= 1
    dscores /= N  # if not divide here then divide at the the last step of calculation which
doing it here is better

    grads["b2"] += 1 * np.sum(dscores, axis=0)

    grads["W2"] += h1_relu.T @ dscores

    dh1_relu = dscores @ W2.T
    dh1_relu[h1 <= 0] = 0
    grads["b1"] += np.sum(dh1_relu * 1, axis=0)

    grads["W1"] += X.T @ dh1_relu

    ############################################################################
    #                              END OF T#7                                  #
    ############################################################################

    return loss, grads
```

```
148
149   def train(self, X, y, X_val, y_val,
150             learning_rate=1e-3, learning_rate_decay=0.95,
151             reg=5e-6, num_iters=100,
152             batch_size=200, verbose=False):
153     """
154     Train this neural network using stochastic gradient descent.
155
156     Inputs:
157     - X: A numpy array of shape (N, D) giving training data.
158     - y: A numpy array f shape (N,) giving training labels; y[i] = c means that
159       X[i] has label c, where 0 <= c < C.
160     - X_val: A numpy array of shape (N_val, D) giving validation data.
161     - y_val: A numpy array of shape (N_val,) giving validation labels.
162     - learning_rate: Scalar giving learning rate for optimization.
163     - learning_rate_decay: Scalar giving factor used to decay the learning rate
164       after each epoch.
165     - reg: Scalar giving regularization strength.
166     - num_iters: Number of steps to take when optimizing.
167     - batch_size: Number of training examples to use per step.
168     - verbose: boolean; if true print progress during optimization.
169     """
170     num_train = X.shape[0]
171     iterations_per_epoch = max(num_train / batch_size, 1)
172
173     # Use SGD to optimize the parameters in self.model
174     loss_history = []
175     train_acc_history = []
176     val_acc_history = []
177
178     for it in range(num_iters):
179       X_batch = None
180       y_batch = None
181
182       #########################################################################
183       # T#8: Create a random minibatch of training data and labels, storing#
184       # them in X_batch and y_batch respectively.                             #
185       # You might find np.random.choice() helpful.                            #
186       #########################################################################
187       batch_index = np.random.choice(num_train, batch_size, replace=True)
188       X_batch = X[batch_index]
189       y_batch = y[batch_index]
190       #########################################################################
191       #                             END OF YOUR T#8                           #
192       #########################################################################
193
194       # Compute loss and gradients using the current minibatch
195       loss, grads = self.loss(X_batch, y=y_batch, reg=reg)
196       loss_history.append(loss)
197
```

```
      ###########################################################################
      # T#9: Use the gradients in the grads dictionary to update the       #
      # parameters of the network (stored in the dictionary self.params)      #
      # using stochastic gradient descent. You'll need to use the gradients   #
      # stored in the grads dictionary defined above.                         #
      ###########################################################################
      self.params['W1'] -= learning_rate * grads["W1"]
      self.params['W2'] -= learning_rate * grads["W2"]
      self.params['b1'] -= learning_rate * grads["b1"]
      self.params['b2'] -= learning_rate * grads["b2"]
      ###########################################################################
      #                             END OF YOUR T#9                             #
      ###########################################################################

      if verbose and it % 100 == 0:
        print('iteration %d / %d: loss %f' % (it, num_iters, loss))

      # Every epoch, check train and val accuracy and decay learning rate.
      if it % iterations_per_epoch == 0:
        # Check accuracy
        train_acc = (self.predict(X_batch) == y_batch).mean()
        val_acc = (self.predict(X_val) == y_val).mean()
        train_acc_history.append(train_acc)
        val_acc_history.append(val_acc)

        # Decay learning rate
        ###########################################################################
        # T#10: Decay learning rate (exponentially) after each epoch        #
        ###########################################################################
        learning_rate *= learning_rate_decay
        ###########################################################################
        #                             END OF YOUR T#10                            #
        ###########################################################################


    return {
      'loss_history': loss_history,
      'train_acc_history': train_acc_history,
      'val_acc_history': val_acc_history,
    }

  def predict(self, X):
    """
    Use the trained weights of this two-layer network to predict labels for
    data points. For each data point we predict scores for each of the C
    classes, and assign each data point to the class with the highest score.

    Inputs:
    - X: A numpy array of shape (N, D) giving N D-dimensional data points to
      classify.
```

```
248
249     Returns:
250     - y_pred: A numpy array of shape (N,) giving predicted labels for each of
251       the elements of X. For all i, y_pred[i] = c means that X[i] is predicted
252       to have class c, where 0 <= c < C.
253     """
254     y_pred = None
255
256     ###########################################################################
257     # T#11: Implement this function; it should be VERY simple!                #
258     ###########################################################################
259     h1_relu = np.maximum(0, X @ self.params['W1'] + self.params['b1'])
260     scores = h1_relu @ self.params['W2'] + self.params['b2']
261     y_pred = np.argmax(scores, axis=1)
262     ###########################################################################
263     #                              END OF YOUR T#11                           #
264     ###########################################################################
265
266     return y_pred
267
268
269
```

Simple_Neural_Network_Lab

February 7, 2026

1 Two-Layer Neural Networks

In this part of the homework, we will work on building a simple Neural Network to classify digits using MNIST dataset. There are many powerful neural network frameworks nowadays that are relatively straightforward to use. However, we believe that in order to understand the theory behind neural networks, and to have the right intuitions in order to build, use, and debug more complex architectures, one must first start from the basics.

Your task is to complete the missing codes needed for training and testing of a simple fully-connected neural network.

The missing parts will be marked with T#N, where #N represents the task number.

Many parts in this homework are modified from Stanford's cs231n assignments.

[1]:
```
import numpy as np
import matplotlib.pyplot as plt

from __future__ import print_function

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

from cattern.neural_net import TwoLayerNet

%load_ext autoreload
%autoreload 2
```

[2]:
```
# Just a function that verifies if your answers are correct

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))))
```

We will use the class `TwoLayerNet` in the file `cattern/neural_net.py` to represent instances of our network. The network parameters (weights and biases) are stored in the instance variable `self.params` where the keys are parameter names and values are numpy arrays. Below, we initialize some toy data and a toy model that will guide you with your implementation.

[3]:
```
# 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()
```

2 Forward pass: compute scores

Open the file `cattern/neural_net.py` and look at the method `TwoLayerNet.loss`. This function takes the data and weights and computes the class scores, the loss, and the gradients on the parameters.

Complete T#5 in `TwoLayerNet.loss`, by implementing the first part of the forward pass which uses the weights and biases to compute the scores for all inputs. The scores refer to the output of the network just before the softmax layer.

[4]:
```
scores = net.loss(X)
print('Your scores:')
print(scores)
print()
print('correct scores:')
correct_scores = np.asarray([
  [-0.81233741, -1.27654624, -0.70335995],
  [-0.17129677, -1.18803311, -0.47310444],
  [-0.51590475, -1.01354314, -0.8504215 ],
  [-0.15419291, -0.48629638, -0.52901952],
  [-0.00618733, -0.12435261, -0.15226949]])
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:
[[-0.81233741 -1.27654624 -0.70335995]
 [-0.17129677 -1.18803311 -0.47310444]
 [-0.51590475 -1.01354314 -0.8504215 ]
 [-0.15419291 -0.48629638 -0.52901952]
 [-0.00618733 -0.12435261 -0.15226949]]

correct scores:
[[-0.81233741 -1.27654624 -0.70335995]
 [-0.17129677 -1.18803311 -0.47310444]
 [-0.51590475 -1.01354314 -0.8504215 ]
 [-0.15419291 -0.48629638 -0.52901952]
 [-0.00618733 -0.12435261 -0.15226949]]

Difference between your scores and correct scores:
3.6802720745909845e-08
```

3 Forward pass: compute loss

In the same function, complete T6 by implementing the second part that computes the data and regularizaion loss.

[5]:
```
loss, _ = net.loss(X, y, reg=0.1)
correct_loss = 1.30378789133

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

```
Difference between your loss and correct loss:
1.7985612998927536e-13
1.3037878913298202 1.30378789133
```

4 Backward pass

Implement the rest of the function by completing T#7. This will compute the gradient of the loss with respect to the variables `W1`, `b1`, `W2`, and `b2`. Now that you (hopefully!) have a correctly implemented forward pass, you can debug your backward pass using a numeric gradient check:

[6]:
```
from cattern.gradient_check import eval_numerical_gradient

# Use numeric gradient checking to check your implementation of the backward␣
 ↪pass.
# If your implementation is correct, the difference between the numeric 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('%s max relative error: %e' % (param_name, rel_error(param_grad_num,␣
 ↪grads[param_name])))
```

```
W1 max relative error: 3.561318e-09
W2 max relative error: 3.440708e-09
b1 max relative error: 2.738421e-09
b2 max relative error: 4.447625e-11
```

5 Train the network

To train the network we will use stochastic gradient descent (SGD). Look at the function `TwoLayerNet.train` and fill in the missing sections to implement the training procedure (T#8-10). You will also have to implement `TwoLayerNet.predict` (T#11), as the training process periodically performs prediction to keep track of accuracy over time while the network trains.

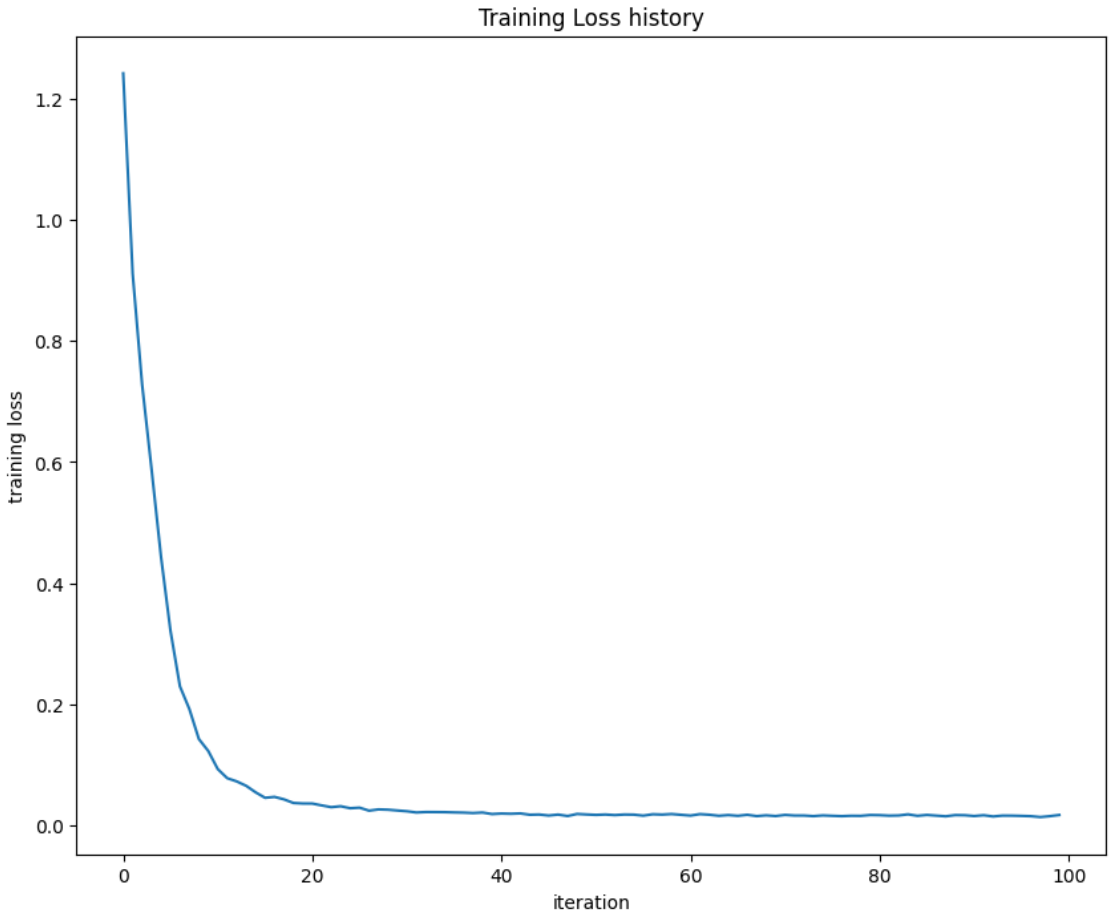
Once you have implemented the method, run the code below to train a two-layer network on toy data. You should achieve a training loss less than 0.05.

[7]:
```
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:  0.01714364353292376
```



6 Load the data

Now that you have implemented a two-layer network that passes gradient checks and works on toy data, it's time to load up MNIST data so we can use it to train a classifier on a real dataset.

[8]:
```
from mnist_data import load_mnist


def get_mnist_data(num_training=55000, num_validation=5000, num_test=10000):
    """
    Load the MNIST dataset from disk and perform preprocessing to prepare
    it for the two-layer neural net classifier.
    """
    # Load the raw MNIST data
    X_train, y_train, X_val, y_val, X_test, y_test = load_mnist.
 ↪read_data_sets('mnist_data')

    # Normalize the data: subtract the mean image
```

```
    mean_image = np.mean(X_train, axis=0)
    X_train = X_train - mean_image
    X_val = X_val - mean_image
    X_test = 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

X_train, y_train, X_val, y_val, X_test, y_test = get_mnist_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)
```

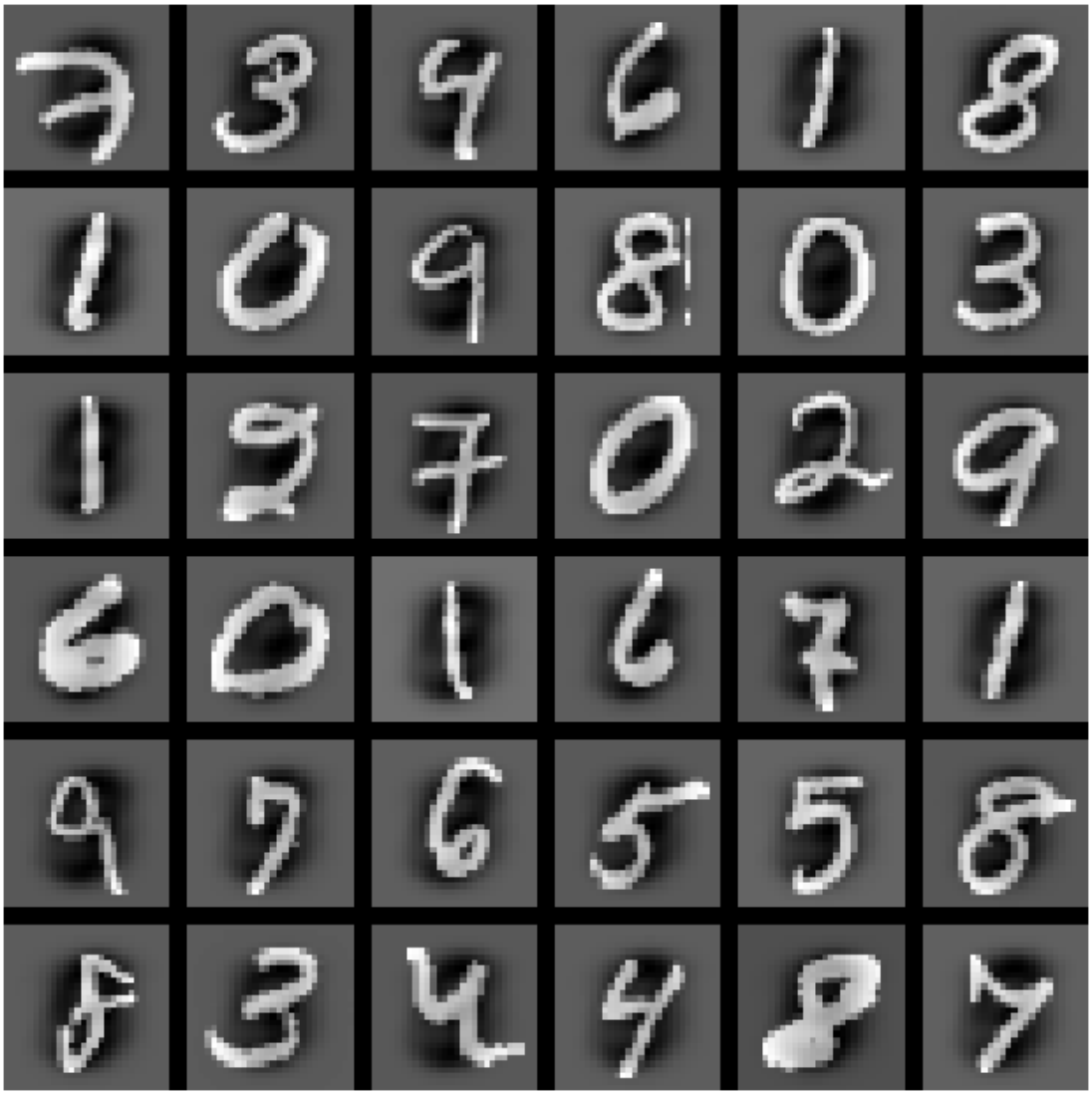
```
Extracting mnist_data/train-images-idx3-ubyte.gz
Extracting mnist_data/train-labels-idx1-ubyte.gz
Extracting mnist_data/t10k-images-idx3-ubyte.gz
Extracting mnist_data/t10k-labels-idx1-ubyte.gz
Train data shape:  (55000, 784)
Train labels shape:  (55000,)
Validation data shape:  (5000, 784)
Validation labels shape:  (5000,)
Test data shape:  (10000, 784)
Test labels shape:  (10000,)
```

[9]:
```
from mnist_data.vis_utils import visualize_grid

# Visualize mnist data

def show_mnist_image(data):
  data = data.reshape(-1, 28, 28, 1)
  plt.imshow(visualize_grid(data, padding=3).astype('uint8').squeeze(axis=2))
  plt.gca().axis('off')
  plt.show()

show_mnist_image(X_train[:36])
```



7 Train a network

To train our network we will use SGD with momentum. We will use fixed learning rate to train this model.

[10]:
```
input_size = 28 * 28 * 1
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=2000, batch_size=200,
            learning_rate=1e-4, learning_rate_decay=1,
            reg=0, verbose=True)

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

```
iteration 0 / 2000: loss 2.302592
iteration 100 / 2000: loss 2.302232
iteration 200 / 2000: loss 2.300876
iteration 300 / 2000: loss 2.291126
iteration 400 / 2000: loss 2.239348
iteration 500 / 2000: loss 2.008828
iteration 600 / 2000: loss 1.814898
iteration 700 / 2000: loss 1.425479
iteration 800 / 2000: loss 1.268225
iteration 900 / 2000: loss 0.994899
iteration 1000 / 2000: loss 0.847616
iteration 1100 / 2000: loss 0.758159
iteration 1200 / 2000: loss 0.633341
iteration 1300 / 2000: loss 0.536447
iteration 1400 / 2000: loss 0.478063
iteration 1500 / 2000: loss 0.397137
iteration 1600 / 2000: loss 0.415201
iteration 1700 / 2000: loss 0.385851
iteration 1800 / 2000: loss 0.517132
iteration 1900 / 2000: loss 0.425830
Validation accuracy:  0.8922
```

8 Learning Rate Decay

In the previous run, we used the same learning rate during the whole training process. This fix-sized learning rate disregards the benefit of larger learning rate at the beginning of the training, and it might suffer from overshooting around the minima.

Add learning rate decay to the train function, run the model again with larger starting learning rate and learning rate decay, then compare the losses.

[11]:
```
net = TwoLayerNet(input_size, hidden_size, num_classes)
stats_LRDecay = net.train(X_train, y_train, X_val, y_val,
                    num_iters=2000, batch_size=200,
                    learning_rate=5e-4, learning_rate_decay=0.95,
                    reg=0, verbose=True)

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

```
iteration 0 / 2000: loss 2.302581
iteration 100 / 2000: loss 2.119326
iteration 200 / 2000: loss 0.804760
iteration 300 / 2000: loss 0.492363
iteration 400 / 2000: loss 0.407158
iteration 500 / 2000: loss 0.286767
iteration 600 / 2000: loss 0.318665
iteration 700 / 2000: loss 0.363674
iteration 800 / 2000: loss 0.273462
iteration 900 / 2000: loss 0.278906
iteration 1000 / 2000: loss 0.263698
iteration 1100 / 2000: loss 0.181063
iteration 1200 / 2000: loss 0.257531
iteration 1300 / 2000: loss 0.353448
iteration 1400 / 2000: loss 0.188915
iteration 1500 / 2000: loss 0.165813
iteration 1600 / 2000: loss 0.248227
iteration 1700 / 2000: loss 0.259703
iteration 1800 / 2000: loss 0.292172
iteration 1900 / 2000: loss 0.196248
Validation accuracy:  0.9432
```

9 Debug the training

With the default parameters we provided above, you should get a validation accuracy of about 0.94 on the validation set. This isn't very good for MNIST data which has reports of up to 0.99 accuracy.

One strategy for getting insight into what's wrong is to plot the loss function and the accuracies on the training and validation sets during optimization.

Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

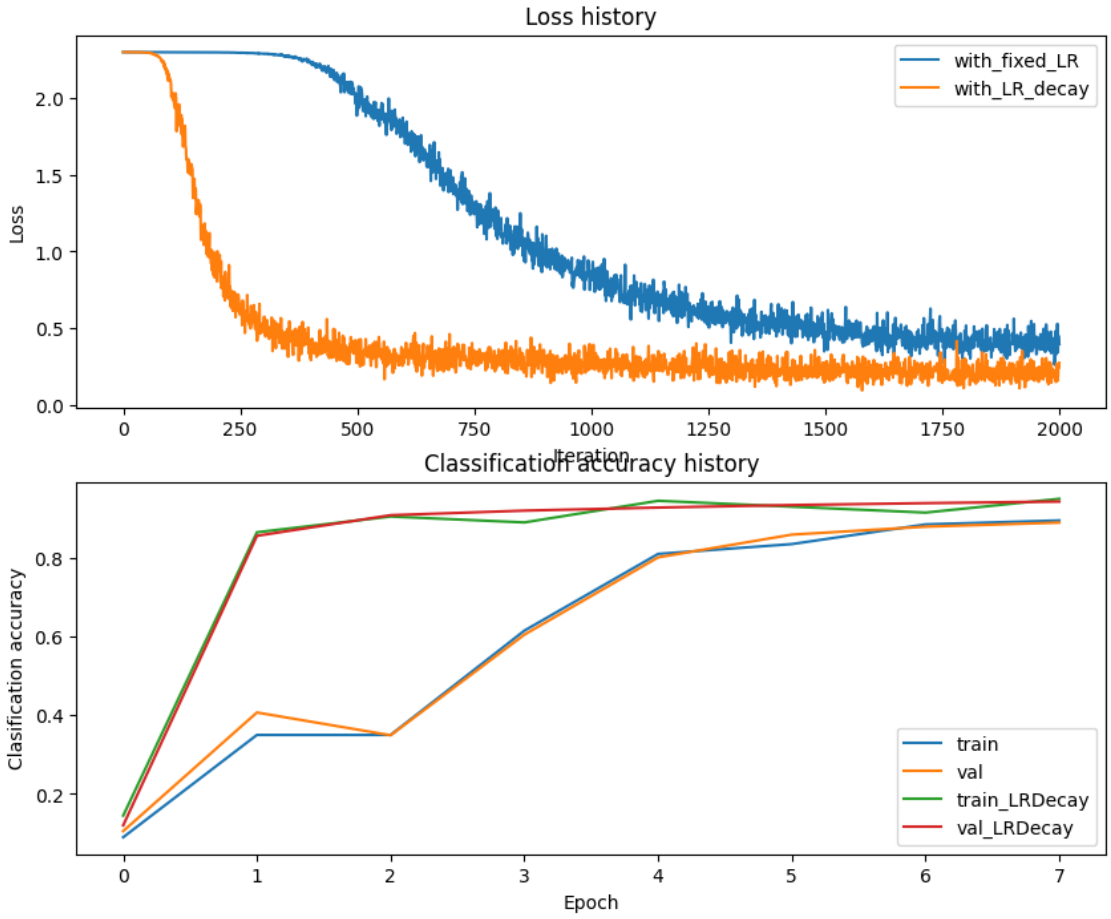
(You can think of the first layer weights as a projection W^TX. This is very similar to how we project our training data using PCA projection in our previous homework. Just like how we visualize the eigenfaces. We can also visualize the weights of the neural network in the same manner.)

Below, we will also show you lossed between two models we trained above. Do you notice the difference between the two?

[12]:
```
# Plot the loss function and train / validation accuracies
plt.subplot(2, 1, 1)
plt.plot(stats['loss_history'], label='with_fixed_LR')
plt.plot(stats_LRDecay['loss_history'], label='with_LR_decay')
plt.title('Loss history')
plt.legend()
plt.xlabel('Iteration')
```

```
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
plt.plot(stats['train_acc_history'], label='train')
plt.plot(stats['val_acc_history'], label='val')
plt.plot(stats_LRDecay['train_acc_history'], label='train_LRDecay')
plt.plot(stats_LRDecay['val_acc_history'], label='val_LRDecay')
plt.title('Classification accuracy history')
plt.legend()
plt.xlabel('Epoch')
plt.ylabel('Clasification accuracy')
plt.show()
```

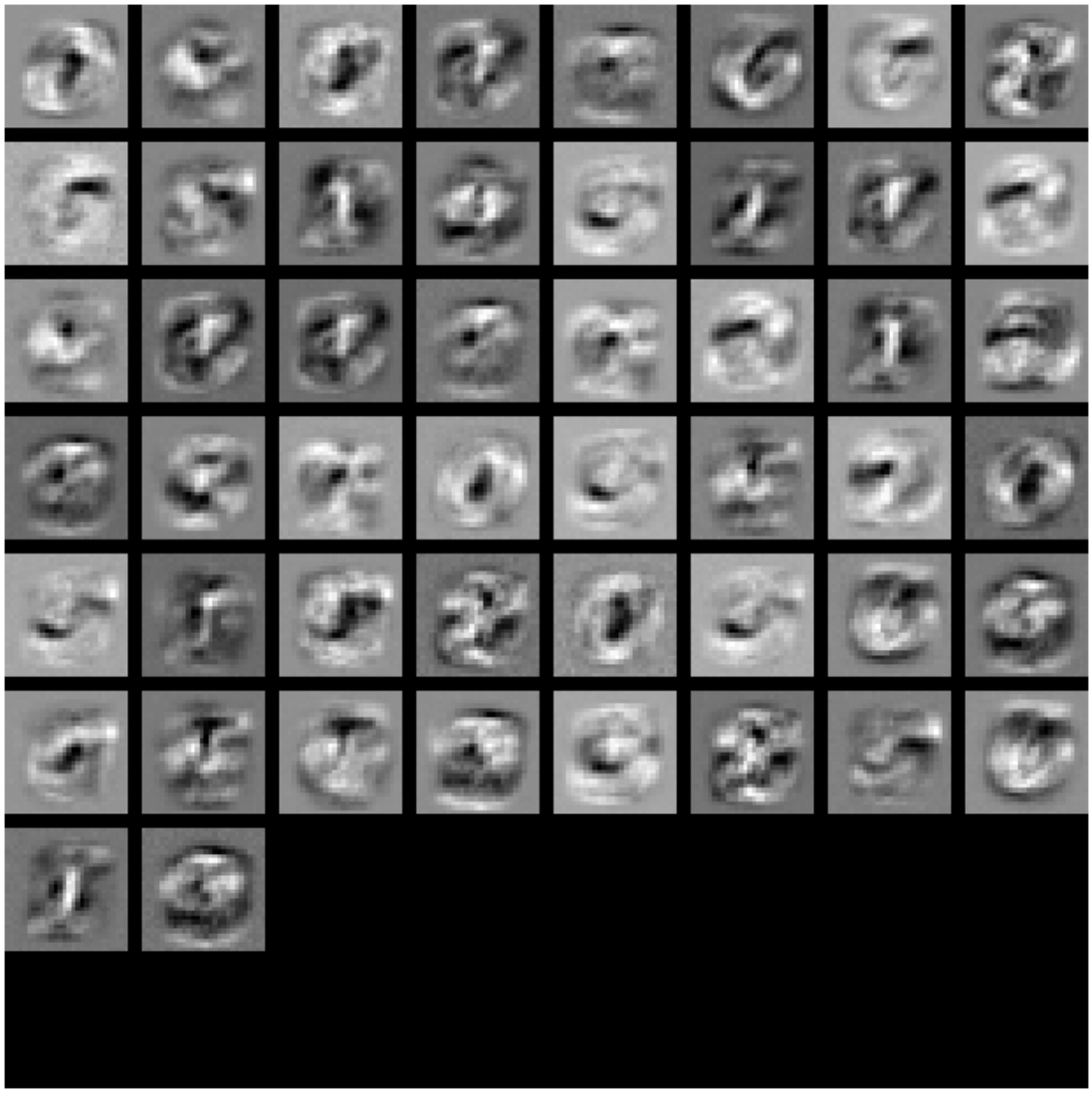


[13]:
```
# Visualize the weights of the network

def show_net_weights(net):
    W1 = net.params['W1']
    W1 = W1.reshape(28, 28, 1, -1).transpose(3, 0, 1, 2)
```

```
    plt.imshow(visualize_grid(W1, padding=3).astype('uint8').squeeze(axis=2))
    plt.gca().axis('off')
    plt.show()

show_net_weights(net)
```



10 Tune your hyperparameters

Tuning. Tuning the hyperparameters and developing intuition for how they affect the final performance is a large part of using Neural Networks, so we want you to get a lot of practice. Below, you should experiment with different values of the various hyperparameters, including hidden layer size, learning rate, numer of training epochs, and regularization strength. You might also consider

tuning the learning rate decay, but you should be able to get good performance using the default value.

Approximate results. You should be aim to achieve a classification accuracy of greater than 97.4% on the validation set.

Experiment: You goal in this exercise is to get as good of a result on MNIST as you can, with a fully-connected Neural Network. Feel free implement your own techniques (e.g. PCA to reduce dimensionality, or adding dropout, or adding features to the solver, etc.).

[14]:
```
best_net = None # store the best model into this

################################################################################
# T#12: Tune hyperparameters using the validation set. Store your best trained#
# model in best_net.                                                           ␣
 ↪#
#                                                                              ␣
 ↪#
# To help debug your network, it may help to use visualizations similar to the ␣
 ↪#
# ones we used above; these visualizations will have significant qualitative   ␣
 ↪#
# differences from the ones we saw above for the poorly tuned network.         ␣
 ↪#
#                                                                              ␣
 ↪#
# Tweaking hyperparameters by hand can be fun, but you might find it useful to ␣
 ↪#
# write code to sweep through possible combinations of hyperparameters         ␣
 ↪#
# automatically like we did on the previous exercises.                         ␣
 ↪#
################################################################################
input_size = 28 * 28 * 1
num_classes = 10

hidden_sizes = [50, 150]
learing_rates = [0.0001, 0.001, 0.01]
regs = [1e-1, 1e-2, 1e-3]
learning_rate_decay = [0.95, 0.82]

best_val = -1
results = {}

# Try PCA, dropout, adding features

for hs in hidden_sizes:
    for lr in learing_rates:
```

```
        for reg in regs:
            for decay in learning_rate_decay:
                net = TwoLayerNet(input_size, hs, num_classes)

                stats = net.train(X_train, y_train, X_val, y_val,
                            num_iters=6000,
                            batch_size=1024,
                            learning_rate=lr,
                            learning_rate_decay=decay,
                            reg=reg,
                            verbose=False
                        )

                val_acc = (net.predict(X_val) == y_val).mean()
                print(f"Training: Hidden:{hs}, LR:{lr}, Reg:{reg}, Decay:
 ↪{decay}, Val Acc: {val_acc:.4f}")

                key = (hs, lr, reg, decay)
                results[key] = val_acc

                if val_acc > best_val:
                    best_val = val_acc
                    best_net = net

print("-" * 20)
print(f"Best Validation Accuracy: {best_val}")
################################################################################
#                               END OF T#12                                    #
################################################################################
```

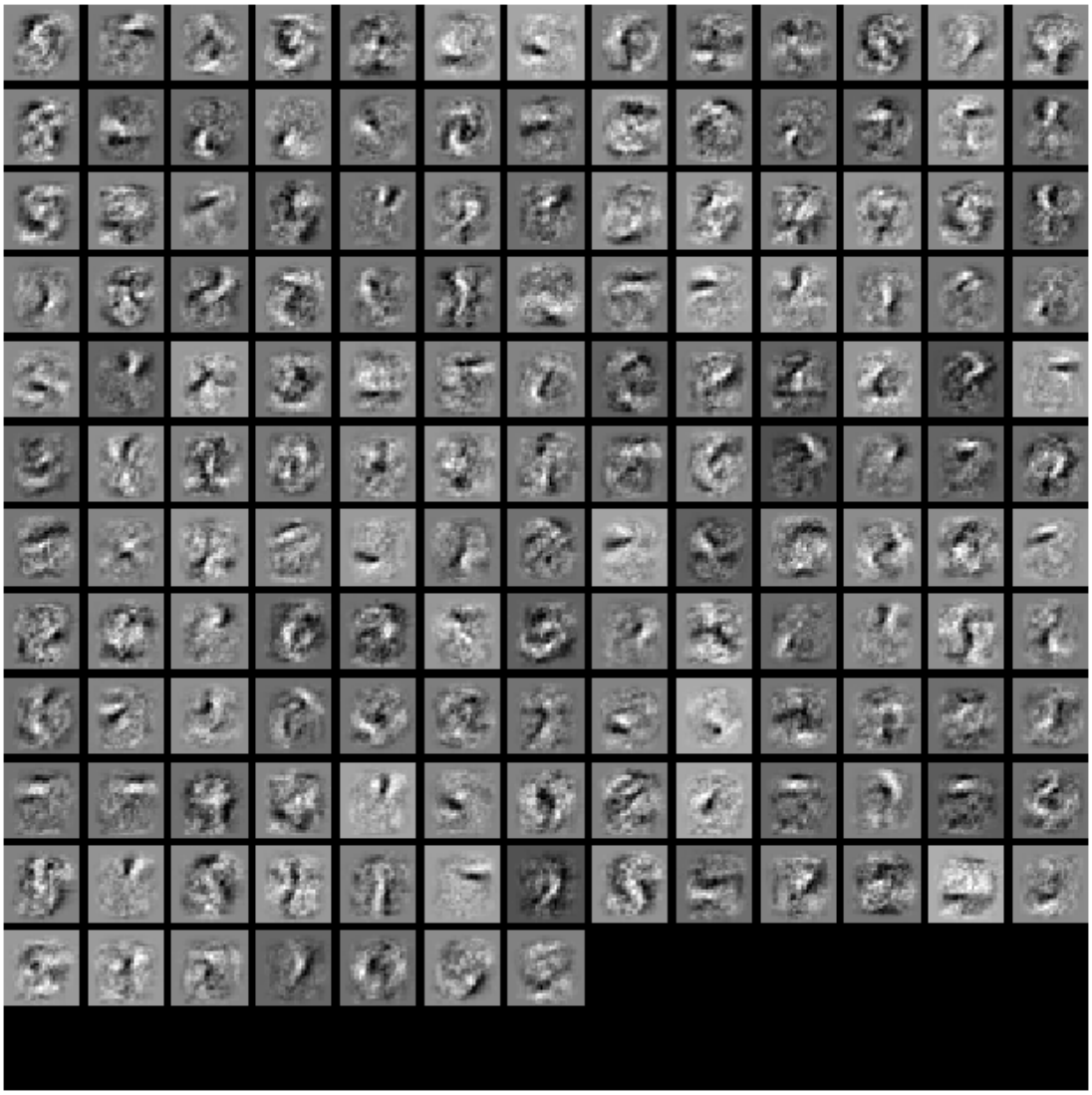
```
Training: Hidden:50, LR:0.0001, Reg:0.1, Decay:0.95, Val Acc: 0.9346
Training: Hidden:50, LR:0.0001, Reg:0.1, Decay:0.82, Val Acc: 0.9290
Training: Hidden:50, LR:0.0001, Reg:0.01, Decay:0.95, Val Acc: 0.9326
Training: Hidden:50, LR:0.0001, Reg:0.01, Decay:0.82, Val Acc: 0.9270
Training: Hidden:50, LR:0.0001, Reg:0.001, Decay:0.95, Val Acc: 0.9344
Training: Hidden:50, LR:0.0001, Reg:0.001, Decay:0.82, Val Acc: 0.9288
Training: Hidden:50, LR:0.001, Reg:0.1, Decay:0.95, Val Acc: 0.9734
Training: Hidden:50, LR:0.001, Reg:0.1, Decay:0.82, Val Acc: 0.9744
Training: Hidden:50, LR:0.001, Reg:0.01, Decay:0.95, Val Acc: 0.9736
Training: Hidden:50, LR:0.001, Reg:0.01, Decay:0.82, Val Acc: 0.9714
Training: Hidden:50, LR:0.001, Reg:0.001, Decay:0.95, Val Acc: 0.9732
Training: Hidden:50, LR:0.001, Reg:0.001, Decay:0.82, Val Acc: 0.9704
Training: Hidden:50, LR:0.01, Reg:0.1, Decay:0.95, Val Acc: 0.9796
Training: Hidden:50, LR:0.01, Reg:0.1, Decay:0.82, Val Acc: 0.9774
Training: Hidden:50, LR:0.01, Reg:0.01, Decay:0.95, Val Acc: 0.9750
Training: Hidden:50, LR:0.01, Reg:0.01, Decay:0.82, Val Acc: 0.9768
Training: Hidden:50, LR:0.01, Reg:0.001, Decay:0.95, Val Acc: 0.9744
Training: Hidden:50, LR:0.01, Reg:0.001, Decay:0.82, Val Acc: 0.9764
```

```
Training: Hidden:150, LR:0.0001, Reg:0.1, Decay:0.95, Val Acc: 0.9350
Training: Hidden:150, LR:0.0001, Reg:0.1, Decay:0.82, Val Acc: 0.9314
Training: Hidden:150, LR:0.0001, Reg:0.01, Decay:0.95, Val Acc: 0.9346
Training: Hidden:150, LR:0.0001, Reg:0.01, Decay:0.82, Val Acc: 0.9318
Training: Hidden:150, LR:0.0001, Reg:0.001, Decay:0.95, Val Acc: 0.9354
Training: Hidden:150, LR:0.0001, Reg:0.001, Decay:0.82, Val Acc: 0.9324
Training: Hidden:150, LR:0.001, Reg:0.1, Decay:0.95, Val Acc: 0.9760
Training: Hidden:150, LR:0.001, Reg:0.1, Decay:0.82, Val Acc: 0.9770
Training: Hidden:150, LR:0.001, Reg:0.01, Decay:0.95, Val Acc: 0.9774
Training: Hidden:150, LR:0.001, Reg:0.01, Decay:0.82, Val Acc: 0.9770
Training: Hidden:150, LR:0.001, Reg:0.001, Decay:0.95, Val Acc: 0.9768
Training: Hidden:150, LR:0.001, Reg:0.001, Decay:0.82, Val Acc: 0.9770
Training: Hidden:150, LR:0.01, Reg:0.1, Decay:0.95, Val Acc: 0.9814
Training: Hidden:150, LR:0.01, Reg:0.1, Decay:0.82, Val Acc: 0.9828
Training: Hidden:150, LR:0.01, Reg:0.01, Decay:0.95, Val Acc: 0.9812
Training: Hidden:150, LR:0.01, Reg:0.01, Decay:0.82, Val Acc: 0.9814
Training: Hidden:150, LR:0.01, Reg:0.001, Decay:0.95, Val Acc: 0.9820
Training: Hidden:150, LR:0.01, Reg:0.001, Decay:0.82, Val Acc: 0.9814
--------------------
Best Validation Accuracy: 0.9828
```

[17]:
```python
import pickle

with open("best_net.pkl", 'wb') as f:
    pickle.dump(best_net, f)
```

[15]:
```python
# visualize the weights of the best network
show_net_weights(best_net)
```



11 Run on the test set

When you are done experimenting, you should evaluate your final trained network on the test set; you should get above 96.3%.

[18]:
```
test_acc = (best_net.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

```
Test accuracy:  0.9791
```