two_layer_net

February 11, 2020

1 Implementing a Neural Network

In this exercise we will develop a neural network with fully-connected layers to perform classification, and test it out on the CIFAR-10 dataset.

```
In [1]: # A bit of setup

        import numpy as np
        import matplotlib.pyplot as plt

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

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

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

The neural network parameters will be stored in a dictionary (`model` below), where the keys are the parameter names and the values are numpy arrays. Below, we initialize toy data and a toy model that we will use to verify your implementations.

```
In [2]: # Create some toy data to check your implementations
        input_size = 4
        hidden_size = 10
        num_classes = 3
        num_inputs = 5

        def init_toy_model():
          model = {}
          model['W1'] = np.linspace(-0.2, 0.6, num=input_size*hidden_size).reshape(input_size,
```

```
    model['b1'] = np.linspace(-0.3, 0.7, num=hidden_size)
    model['W2'] = np.linspace(-0.4, 0.1, num=hidden_size*num_classes).reshape(hidden_size
    model['b2'] = np.linspace(-0.5, 0.9, num=num_classes)
    return model

  def init_toy_data():
    X = np.linspace(-0.2, 0.5, num=num_inputs*input_size).reshape(num_inputs, input_size)
    y = np.array([0, 1, 2, 2, 1])
    return X, y

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

2 Forward pass: compute scores

Open the file cs231n/classifiers/neural_net.py and look at the function two_layer_net. This function is very similar to the loss functions you have written for the Softmax exercise in HW0: It takes the data and weights and computes the class scores, the loss, and the gradients on the parameters.

Implement the first part of the forward pass which uses the weights and biases to compute the scores for all inputs.

```
In [3]: from cs231n.classifiers.neural_net import two_layer_net

        scores = two_layer_net(X, model)
        print(scores)
        correct_scores = [[-0.5328368, 0.20031504, 0.93346689],
         [-0.59412164, 0.15498488, 0.9040914 ],
         [-0.67658362, 0.08978957, 0.85616275],
         [-0.77092643, 0.01339997, 0.79772637],
         [-0.89110401, -0.08754544, 0.71601312]]

        # the difference should be very small. We get 3e-8
        print('Difference between your scores and correct scores:')
        print(np.sum(np.abs(scores - correct_scores)))
```

```
[[-0.5328368   0.20031504  0.93346689]
 [-0.59412164  0.15498488  0.9040914 ]
 [-0.67658362  0.08978957  0.85616275]
 [-0.77092643  0.01339997  0.79772637]
 [-0.89110401 -0.08754544  0.71601312]]
Difference between your scores and correct scores:
3.848682278081994e-08
```

3 Forward pass: compute loss

In the same function, implement the second part that computes the data and regularizaion loss.

```
In [4]: reg = 0.1
        loss, _ = two_layer_net(X, model, y, reg)
        correct_loss = 1.38191946092

        # should be very small, we get 5e-12
        print('Difference between your loss and correct loss:')
        print(np.sum(np.abs(loss - correct_loss)))
```

```
Difference between your loss and correct loss:
4.6769255135359344e-12
```

4 Backward pass

Implement the rest of the function. 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:

```
In [5]: from cs231n.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 = two_layer_net(X, model, y, reg)

        # these should all be less than 1e-8 or so
        for param_name in grads:
          param_grad_num = eval_numerical_gradient(lambda W: two_layer_net(X, model, y, reg)[0]
          print('%s max relative error: %e' % (param_name, rel_error(param_grad_num, grads[para
```

```
W2 max relative error: 8.023739e-10
b2 max relative error: 8.190173e-11
W1 max relative error: 4.426512e-09
b1 max relative error: 5.435432e-08
```

5 Train the network

To train the network we will use SGD with Momentum. Last assignment you implemented vanilla SGD. You will now implement the momentum update and the RMSProp update. Open the file `classifier_trainer.py` and familiarize yourself with the `ClassifierTrainer` class. It performs optimization given an arbitrary cost function data, and model. By default it uses vanilla SGD, which we have already implemented for you. First, run the optimization below using Vanilla SGD:

```
In [6]: from cs231n.classifier_trainer import ClassifierTrainer

        model = init_toy_model()
        trainer = ClassifierTrainer()
        # call the trainer to optimize the loss
        # Notice that we're using sample_batches=False, so we're performing Gradient Descent (
        best_model, loss_history, _, _ = trainer.train(X, y, X, y,
                                                     model, two_layer_net,
                                                     reg=0.001,
                                                     learning_rate=1e-1, momentum=0.0, learning
                                                     update='sgd', sample_batches=False,
                                                     num_epochs=100,
                                                     verbose=False)
        print('Final loss with vanilla SGD: %f' % (loss_history[-1], ))
```

```
starting iteration  0
starting iteration  10
starting iteration  20
starting iteration  30
starting iteration  40
starting iteration  50
starting iteration  60
starting iteration  70
starting iteration  80
starting iteration  90
Final loss with vanilla SGD: 0.940686
```

Now fill in the **momentum update** in the first missing code block inside the `train` function, and run the same optimization as above but with the momentum update. You should see a much better result in the final obtained loss:

```
In [7]: model = init_toy_model()
        trainer = ClassifierTrainer()
        # call the trainer to optimize the loss
        # Notice that we're using sample_batches=False, so we're performing Gradient Descent (
        best_model, loss_history, _, _ = trainer.train(X, y, X, y,
                                                     model, two_layer_net,
                                                     reg=0.001,
                                                     learning_rate=1e-1, momentum=0.9, learning
                                                     update='momentum', sample_batches=False,
                                                     num_epochs=100,
                                                     verbose=False)
        correct_loss = 0.494394
        print('Final loss with momentum SGD: %f. We get: %f' % (loss_history[-1], correct_loss
```

```
starting iteration  0
starting iteration  10
starting iteration  20
```

```
starting iteration  30
starting iteration  40
starting iteration  50
starting iteration  60
starting iteration  70
starting iteration  80
starting iteration  90
Final loss with momentum SGD: 0.494394. We get: 0.494394
```

The **RMSProp** update step is given as follows:

```
cache = decay_rate * cache + (1 - decay_rate) * dx**2
x += - learning_rate * dx / np.sqrt(cache + 1e-8)
```

Here, `decay_rate` is a hyperparameter and typical values are [0.9, 0.99, 0.999].

Implement the **RMSProp** update rule inside the `train` function and rerun the optimization:

```
In [8]: model = init_toy_model()
        trainer = ClassifierTrainer()
        # call the trainer to optimize the loss
        # Notice that we're using sample_batches=False, so we're performing Gradient Descent (
        best_model, loss_history, _, _ = trainer.train(X, y, X, y,
                                                      model, two_layer_net,
                                                      reg=0.001,
                                                      learning_rate=1e-1, momentum=0.9, learning
                                                      update='rmsprop', sample_batches=False,
                                                      num_epochs=100,
                                                      verbose=False)
        correct_loss = 0.439368
        print('Final loss with RMSProp: %f. We get: %f' % (loss_history[-1], correct_loss))
```

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

6 Load the data

Now that you have implemented a two-layer network that passes gradient checks, it's time to load up our favorite CIFAR-10 data so we can use it to train a classifier.

In [9]:
```
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.
    """
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'
    X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

    # Subsample the data
    mask = range(num_training, num_training + num_validation)
    X_val = X_train[mask]
    y_val = y_train[mask]
    mask = range(num_training)
    X_train = X_train[mask]
    y_train = y_train[mask]
    mask = 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,)
```

7 Train a network

To train our network we will use SGD with momentum. In addition, we will adjust the learning rate with an exponential learning rate schedule as optimization proceeds; after each epoch, we will reduce the learning rate by multiplying it by a decay rate.

```
In [10]: from cs231n.classifiers.neural_net import init_two_layer_model

         model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of cl
         trainer = ClassifierTrainer()
         best_model, loss_history, train_acc, val_acc = trainer.train(X_train, y_train, X_val,
                                                      model, two_layer_net,
                                                      num_epochs=5, reg=1.0,
                                                      momentum=0.9, learning_rate_decay = 0.95
                                                      learning_rate=1e-5, verbose=True)
```

```
starting iteration  0
Finished epoch 0 / 5: cost 2.302593, train: 0.101000, val 0.089000, lr 1.000000e-05
starting iteration  10
starting iteration  20
starting iteration  30
starting iteration  40
starting iteration  50
starting iteration  60
starting iteration  70
starting iteration  80
starting iteration  90
starting iteration  100
starting iteration  110
starting iteration  120
starting iteration  130
starting iteration  140
starting iteration  150
starting iteration  160
starting iteration  170
starting iteration  180
starting iteration  190
starting iteration  200
starting iteration  210
starting iteration  220
starting iteration  230
starting iteration  240
starting iteration  250
```

```
starting iteration  260
starting iteration  270
starting iteration  280
starting iteration  290
starting iteration  300
starting iteration  310
starting iteration  320
starting iteration  330
starting iteration  340
starting iteration  350
starting iteration  360
starting iteration  370
starting iteration  380
starting iteration  390
starting iteration  400
starting iteration  410
starting iteration  420
starting iteration  430
starting iteration  440
starting iteration  450
starting iteration  460
starting iteration  470
starting iteration  480
Finished epoch 1 / 5: cost 2.281436, train: 0.163000, val 0.151000, lr 9.500000e-06
starting iteration  490
starting iteration  500
starting iteration  510
starting iteration  520
starting iteration  530
starting iteration  540
starting iteration  550
starting iteration  560
starting iteration  570
starting iteration  580
starting iteration  590
starting iteration  600
starting iteration  610
starting iteration  620
starting iteration  630
starting iteration  640
starting iteration  650
starting iteration  660
starting iteration  670
starting iteration  680
starting iteration  690
starting iteration  700
starting iteration  710
starting iteration  720
```

```
starting iteration  730
starting iteration  740
starting iteration  750
starting iteration  760
starting iteration  770
starting iteration  780
starting iteration  790
starting iteration  800
starting iteration  810
starting iteration  820
starting iteration  830
starting iteration  840
starting iteration  850
starting iteration  860
starting iteration  870
starting iteration  880
starting iteration  890
starting iteration  900
starting iteration  910
starting iteration  920
starting iteration  930
starting iteration  940
starting iteration  950
starting iteration  960
starting iteration  970
Finished epoch 2 / 5: cost 1.982123, train: 0.242000, val 0.243000, lr 9.025000e-06
starting iteration  980
starting iteration  990
starting iteration  1000
starting iteration  1010
starting iteration  1020
starting iteration  1030
starting iteration  1040
starting iteration  1050
starting iteration  1060
starting iteration  1070
starting iteration  1080
starting iteration  1090
starting iteration  1100
starting iteration  1110
starting iteration  1120
starting iteration  1130
starting iteration  1140
starting iteration  1150
starting iteration  1160
starting iteration  1170
starting iteration  1180
starting iteration  1190
```

```
starting iteration  1200
starting iteration  1210
starting iteration  1220
starting iteration  1230
starting iteration  1240
starting iteration  1250
starting iteration  1260
starting iteration  1270
starting iteration  1280
starting iteration  1290
starting iteration  1300
starting iteration  1310
starting iteration  1320
starting iteration  1330
starting iteration  1340
starting iteration  1350
starting iteration  1360
starting iteration  1370
starting iteration  1380
starting iteration  1390
starting iteration  1400
starting iteration  1410
starting iteration  1420
starting iteration  1430
starting iteration  1440
starting iteration  1450
starting iteration  1460
Finished epoch 3 / 5: cost 1.833561, train: 0.315000, val 0.296000, lr 8.573750e-06
starting iteration  1470
starting iteration  1480
starting iteration  1490
starting iteration  1500
starting iteration  1510
starting iteration  1520
starting iteration  1530
starting iteration  1540
starting iteration  1550
starting iteration  1560
starting iteration  1570
starting iteration  1580
starting iteration  1590
starting iteration  1600
starting iteration  1610
starting iteration  1620
starting iteration  1630
starting iteration  1640
starting iteration  1650
starting iteration  1660
```

```
starting iteration  1670
starting iteration  1680
starting iteration  1690
starting iteration  1700
starting iteration  1710
starting iteration  1720
starting iteration  1730
starting iteration  1740
starting iteration  1750
starting iteration  1760
starting iteration  1770
starting iteration  1780
starting iteration  1790
starting iteration  1800
starting iteration  1810
starting iteration  1820
starting iteration  1830
starting iteration  1840
starting iteration  1850
starting iteration  1860
starting iteration  1870
starting iteration  1880
starting iteration  1890
starting iteration  1900
starting iteration  1910
starting iteration  1920
starting iteration  1930
starting iteration  1940
starting iteration  1950
Finished epoch 4 / 5: cost 1.836637, train: 0.324000, val 0.338000, lr 8.145063e-06
starting iteration  1960
starting iteration  1970
starting iteration  1980
starting iteration  1990
starting iteration  2000
starting iteration  2010
starting iteration  2020
starting iteration  2030
starting iteration  2040
starting iteration  2050
starting iteration  2060
starting iteration  2070
starting iteration  2080
starting iteration  2090
starting iteration  2100
starting iteration  2110
starting iteration  2120
starting iteration  2130
```

```
starting iteration  2140
starting iteration  2150
starting iteration  2160
starting iteration  2170
starting iteration  2180
starting iteration  2190
starting iteration  2200
starting iteration  2210
starting iteration  2220
starting iteration  2230
starting iteration  2240
starting iteration  2250
starting iteration  2260
starting iteration  2270
starting iteration  2280
starting iteration  2290
starting iteration  2300
starting iteration  2310
starting iteration  2320
starting iteration  2330
starting iteration  2340
starting iteration  2350
starting iteration  2360
starting iteration  2370
starting iteration  2380
starting iteration  2390
starting iteration  2400
starting iteration  2410
starting iteration  2420
starting iteration  2430
starting iteration  2440
Finished epoch 5 / 5: cost 1.810844, train: 0.371000, val 0.371000, lr 7.737809e-06
finished optimization. best validation accuracy: 0.371000
```

8 Debug the training

With the default parameters we provided above, you should get a validation accuracy of about 0.37 on the validation set. This isn't very good.

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.

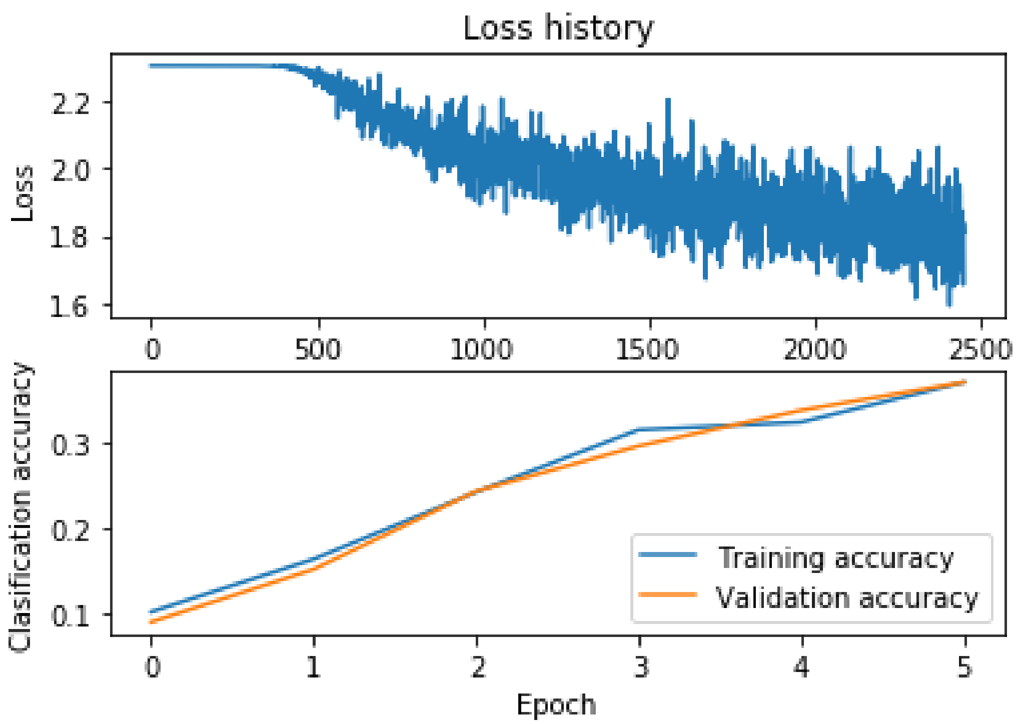
Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

In [11]:
```
# Plot the loss function and train / validation accuracies
plt.subplot(2, 1, 1)
```

```
plt.plot(loss_history)
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
plt.plot(train_acc)
plt.plot(val_acc)
plt.legend(['Training accuracy', 'Validation accuracy'], loc='lower right')
plt.xlabel('Epoch')
plt.ylabel('Clasification accuracy')
```

Out[11]: Text(0, 0.5, 'Clasification accuracy')

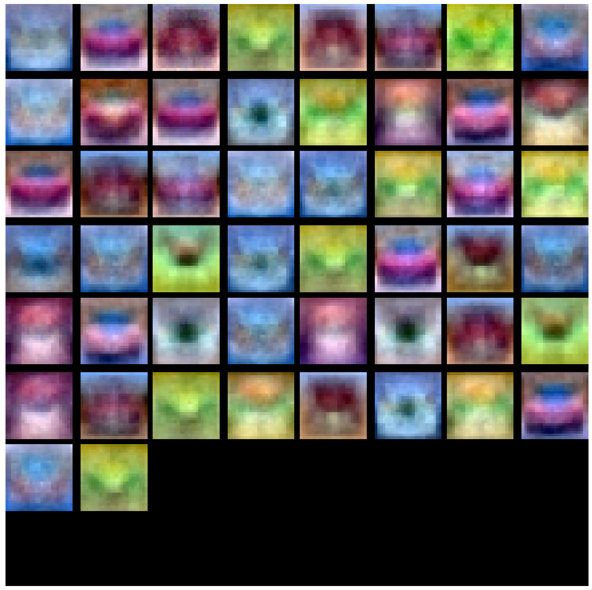


In [12]:
```
from cs231n.vis_utils import visualize_grid

# Visualize the weights of the network

def show_net_weights(model):
    plt.imshow(visualize_grid(model['W1'].T.reshape(-1, 32, 32, 3), padding=3).astype
    plt.gca().axis('off')
    plt.show()

show_net_weights(model)
```



9 Tune your hyperparameters

What's wrong?. Looking at the visualizations above, we see that the loss is decreasing more or less linearly, which seems to suggest that the learning rate may be too low. Moreover, there is no gap between the training and validation accuracy, suggesting that the model we used has low capacity, and that we should increase its size. On the other hand, with a very large model we would expect to see more overfitting, which would manifest itself as a very large gap between the training and validation accuracy.

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 momentum and learning rate decay parameters, but you should be able to get good performance using the default values.

Approximate results. You should be aim to achieve a classification accuracy of greater than 50% on the validation set. Our best network gets over 56% on the validation set.

Experiment: You goal in this exercise is to get as good of a result on CIFAR-10 as you can, with a fully-connected Neural Network. For every 1% above 56% on the Test set we will award you with one extra bonus point. Feel free implement your own techniques (e.g. PCA to reduce dimensionality, or adding dropout, or adding features to the solver, etc.).

```
In [20]: best_model = None # store the best model into this

         #################################################################################
         # TODO: Tune hyperparameters using the validation set. Store your best trained  #
         # model in best_model.                                                          #
```

```
#                                                                              #
# 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 assignment.                         #
################################################################################
# input size, hidden size, number of classes
model = init_two_layer_model(32*32*3, 1000, 10)
trainer = ClassifierTrainer()
best_model, loss_history, train_acc, val_acc = trainer.train(X_train, y_train,
                                             X_val, y_val,
                                             model, two_layer_net,
                                             num_epochs=10, reg=0.5,
                                             momentum=0.99, update= 'rmsprop',
                                             learning_rate_decay=0.95,
                                             learning_rate=1e-5, verbose=True)
################################################################################
#                              END OF YOUR CODE                                #
################################################################################
```

```
starting iteration  0
Finished epoch 0 / 10: cost 2.302663, train: 0.104000, val 0.084000, lr 1.000000e-05
starting iteration  10
starting iteration  20
starting iteration  30
starting iteration  40
starting iteration  50
starting iteration  60
starting iteration  70
starting iteration  80
starting iteration  90
starting iteration  100
starting iteration  110
starting iteration  120
starting iteration  130
starting iteration  140
starting iteration  150
starting iteration  160
starting iteration  170
starting iteration  180
starting iteration  190
starting iteration  200
starting iteration  210
starting iteration  220
starting iteration  230
```

```
starting iteration  240
starting iteration  250
starting iteration  260
starting iteration  270
starting iteration  280
starting iteration  290
starting iteration  300
starting iteration  310
starting iteration  320
starting iteration  330
starting iteration  340
starting iteration  350
starting iteration  360
starting iteration  370
starting iteration  380
starting iteration  390
starting iteration  400
starting iteration  410
starting iteration  420
starting iteration  430
starting iteration  440
starting iteration  450
starting iteration  460
starting iteration  470
starting iteration  480
Finished epoch 1 / 10: cost 1.733636, train: 0.413000, val 0.429000, lr 9.500000e-06
starting iteration  490
starting iteration  500
starting iteration  510
starting iteration  520
starting iteration  530
starting iteration  540
starting iteration  550
starting iteration  560
starting iteration  570
starting iteration  580
starting iteration  590
starting iteration  600
starting iteration  610
starting iteration  620
starting iteration  630
starting iteration  640
starting iteration  650
starting iteration  660
starting iteration  670
starting iteration  680
starting iteration  690
starting iteration  700
```

```
starting iteration  710
starting iteration  720
starting iteration  730
starting iteration  740
starting iteration  750
starting iteration  760
starting iteration  770
starting iteration  780
starting iteration  790
starting iteration  800
starting iteration  810
starting iteration  820
starting iteration  830
starting iteration  840
starting iteration  850
starting iteration  860
starting iteration  870
starting iteration  880
starting iteration  890
starting iteration  900
starting iteration  910
starting iteration  920
starting iteration  930
starting iteration  940
starting iteration  950
starting iteration  960
starting iteration  970
Finished epoch 2 / 10: cost 1.586378, train: 0.454000, val 0.461000, lr 9.025000e-06
starting iteration  980
starting iteration  990
starting iteration  1000
starting iteration  1010
starting iteration  1020
starting iteration  1030
starting iteration  1040
starting iteration  1050
starting iteration  1060
starting iteration  1070
starting iteration  1080
starting iteration  1090
starting iteration  1100
starting iteration  1110
starting iteration  1120
starting iteration  1130
starting iteration  1140
starting iteration  1150
starting iteration  1160
starting iteration  1170
```

```
starting iteration  1180
starting iteration  1190
starting iteration  1200
starting iteration  1210
starting iteration  1220
starting iteration  1230
starting iteration  1240
starting iteration  1250
starting iteration  1260
starting iteration  1270
starting iteration  1280
starting iteration  1290
starting iteration  1300
starting iteration  1310
starting iteration  1320
starting iteration  1330
starting iteration  1340
starting iteration  1350
starting iteration  1360
starting iteration  1370
starting iteration  1380
starting iteration  1390
starting iteration  1400
starting iteration  1410
starting iteration  1420
starting iteration  1430
starting iteration  1440
starting iteration  1450
starting iteration  1460
Finished epoch 3 / 10: cost 1.648804, train: 0.505000, val 0.481000, lr 8.573750e-06
starting iteration  1470
starting iteration  1480
starting iteration  1490
starting iteration  1500
starting iteration  1510
starting iteration  1520
starting iteration  1530
starting iteration  1540
starting iteration  1550
starting iteration  1560
starting iteration  1570
starting iteration  1580
starting iteration  1590
starting iteration  1600
starting iteration  1610
starting iteration  1620
starting iteration  1630
starting iteration  1640
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starting iteration  1650
starting iteration  1660
starting iteration  1670
starting iteration  1680
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starting iteration  1800
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starting iteration  1820
starting iteration  1830
starting iteration  1840
starting iteration  1850
starting iteration  1860
starting iteration  1870
starting iteration  1880
starting iteration  1890
starting iteration  1900
starting iteration  1910
starting iteration  1920
starting iteration  1930
starting iteration  1940
starting iteration  1950
Finished epoch 4 / 10: cost 1.363331, train: 0.497000, val 0.485000, lr 8.145063e-06
starting iteration  1960
starting iteration  1970
starting iteration  1980
starting iteration  1990
starting iteration  2000
starting iteration  2010
starting iteration  2020
starting iteration  2030
starting iteration  2040
starting iteration  2050
starting iteration  2060
starting iteration  2070
starting iteration  2080
starting iteration  2090
starting iteration  2100
starting iteration  2110
```

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starting iteration  2120
starting iteration  2130
starting iteration  2140
starting iteration  2150
starting iteration  2160
starting iteration  2170
starting iteration  2180
starting iteration  2190
starting iteration  2200
starting iteration  2210
starting iteration  2220
starting iteration  2230
starting iteration  2240
starting iteration  2250
starting iteration  2260
starting iteration  2270
starting iteration  2280
starting iteration  2290
starting iteration  2300
starting iteration  2310
starting iteration  2320
starting iteration  2330
starting iteration  2340
starting iteration  2350
starting iteration  2360
starting iteration  2370
starting iteration  2380
starting iteration  2390
starting iteration  2400
starting iteration  2410
starting iteration  2420
starting iteration  2430
starting iteration  2440
Finished epoch 5 / 10: cost 1.391698, train: 0.496000, val 0.485000, lr 7.737809e-06
starting iteration  2450
starting iteration  2460
starting iteration  2470
starting iteration  2480
starting iteration  2490
starting iteration  2500
starting iteration  2510
starting iteration  2520
starting iteration  2530
starting iteration  2540
starting iteration  2550
starting iteration  2560
starting iteration  2570
starting iteration  2580
```

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starting iteration  2590
starting iteration  2600
starting iteration  2610
starting iteration  2620
starting iteration  2630
starting iteration  2640
starting iteration  2650
starting iteration  2660
starting iteration  2670
starting iteration  2680
starting iteration  2690
starting iteration  2700
starting iteration  2710
starting iteration  2720
starting iteration  2730
starting iteration  2740
starting iteration  2750
starting iteration  2760
starting iteration  2770
starting iteration  2780
starting iteration  2790
starting iteration  2800
starting iteration  2810
starting iteration  2820
starting iteration  2830
starting iteration  2840
starting iteration  2850
starting iteration  2860
starting iteration  2870
starting iteration  2880
starting iteration  2890
starting iteration  2900
starting iteration  2910
starting iteration  2920
starting iteration  2930
Finished epoch 6 / 10: cost 1.431602, train: 0.541000, val 0.494000, lr 7.350919e-06
starting iteration  2940
starting iteration  2950
starting iteration  2960
starting iteration  2970
starting iteration  2980
starting iteration  2990
starting iteration  3000
starting iteration  3010
starting iteration  3020
starting iteration  3030
starting iteration  3040
starting iteration  3050
```

```
starting iteration  3060
starting iteration  3070
starting iteration  3080
starting iteration  3090
starting iteration  3100
starting iteration  3110
starting iteration  3120
starting iteration  3130
starting iteration  3140
starting iteration  3150
starting iteration  3160
starting iteration  3170
starting iteration  3180
starting iteration  3190
starting iteration  3200
starting iteration  3210
starting iteration  3220
starting iteration  3230
starting iteration  3240
starting iteration  3250
starting iteration  3260
starting iteration  3270
starting iteration  3280
starting iteration  3290
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starting iteration  3330
starting iteration  3340
starting iteration  3350
starting iteration  3360
starting iteration  3370
starting iteration  3380
starting iteration  3390
starting iteration  3400
starting iteration  3410
starting iteration  3420
Finished epoch 7 / 10: cost 1.455217, train: 0.544000, val 0.511000, lr 6.983373e-06
starting iteration  3430
starting iteration  3440
starting iteration  3450
starting iteration  3460
starting iteration  3470
starting iteration  3480
starting iteration  3490
starting iteration  3500
starting iteration  3510
starting iteration  3520
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starting iteration  3530
starting iteration  3540
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starting iteration  3560
starting iteration  3570
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starting iteration  3620
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starting iteration  3740
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starting iteration  3790
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starting iteration  3820
starting iteration  3830
starting iteration  3840
starting iteration  3850
starting iteration  3860
starting iteration  3870
starting iteration  3880
starting iteration  3890
starting iteration  3900
starting iteration  3910
Finished epoch 8 / 10: cost 1.475120, train: 0.561000, val 0.506000, lr 6.634204e-06
starting iteration  3920
starting iteration  3930
starting iteration  3940
starting iteration  3950
starting iteration  3960
starting iteration  3970
starting iteration  3980
starting iteration  3990
```

```
starting iteration  4000
starting iteration  4010
starting iteration  4020
starting iteration  4030
starting iteration  4040
starting iteration  4050
starting iteration  4060
starting iteration  4070
starting iteration  4080
starting iteration  4090
starting iteration  4100
starting iteration  4110
starting iteration  4120
starting iteration  4130
starting iteration  4140
starting iteration  4150
starting iteration  4160
starting iteration  4170
starting iteration  4180
starting iteration  4190
starting iteration  4200
starting iteration  4210
starting iteration  4220
starting iteration  4230
starting iteration  4240
starting iteration  4250
starting iteration  4260
starting iteration  4270
starting iteration  4280
starting iteration  4290
starting iteration  4300
starting iteration  4310
starting iteration  4320
starting iteration  4330
starting iteration  4340
starting iteration  4350
starting iteration  4360
starting iteration  4370
starting iteration  4380
starting iteration  4390
starting iteration  4400
Finished epoch 9 / 10: cost 1.453617, train: 0.552000, val 0.516000, lr 6.302494e-06
starting iteration  4410
starting iteration  4420
starting iteration  4430
starting iteration  4440
starting iteration  4450
starting iteration  4460
```

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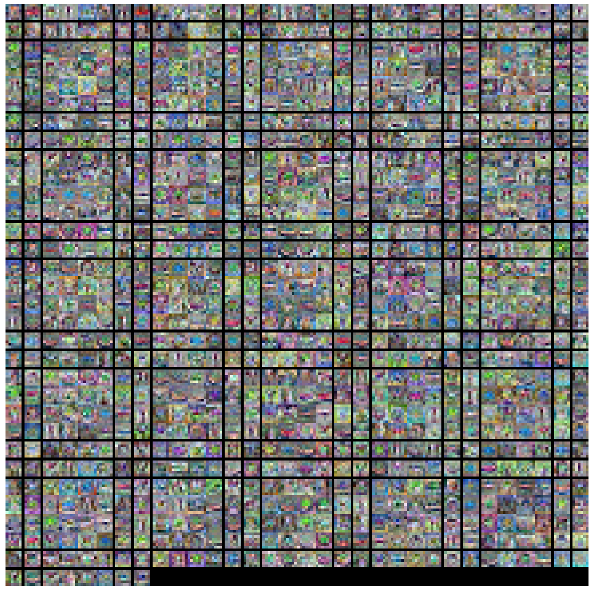
starting iteration  4470
starting iteration  4480
starting iteration  4490
starting iteration  4500
starting iteration  4510
starting iteration  4520
starting iteration  4530
starting iteration  4540
starting iteration  4550
starting iteration  4560
starting iteration  4570
starting iteration  4580
starting iteration  4590
starting iteration  4600
starting iteration  4610
starting iteration  4620
starting iteration  4630
starting iteration  4640
starting iteration  4650
starting iteration  4660
starting iteration  4670
starting iteration  4680
starting iteration  4690
starting iteration  4700
starting iteration  4710
starting iteration  4720
starting iteration  4730
starting iteration  4740
starting iteration  4750
starting iteration  4760
starting iteration  4770
starting iteration  4780
starting iteration  4790
starting iteration  4800
starting iteration  4810
starting iteration  4820
starting iteration  4830
starting iteration  4840
starting iteration  4850
starting iteration  4860
starting iteration  4870
starting iteration  4880
starting iteration  4890
Finished epoch 10 / 10: cost 1.628354, train: 0.551000, val 0.529000, lr 5.987369e-06
finished optimization. best validation accuracy: 0.529000
```

```
In [21]: # visualize the weights
```

```
show_net_weights(best_model)
```



10 Run on the test set

When you are done experimenting, you should evaluate your final trained network on the test set.

```
In [22]: scores_test = two_layer_net(X_test, best_model)
         print('Test accuracy: ', np.mean(np.argmax(scores_test, axis=1) == y_test))
```

```
Test accuracy:  0.527
```

```
In [ ]:
```