two_layer_net

February 22, 2019

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 tensorflow as tf
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))))
```

We will use the class `TwoLayerNet` in the file `implementations/b_neural_net.py` to represent instances of our network. The network parameters are stored in the instance variable `self.params` where keys are string parameter names and values are numpy arrays. Below, we initialize toy data and a toy model that we will use to develop your implementation.

In [2]:
```
from implementations.b_neural_net import TwoLayerNet

# 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 = np.float32(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 `implementations/neural_net.py` and look at the method `TwoLayerNet.compute_scores`.

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

```
In [3]: nclasses = 3
        session = tf.Session()
        session.run(tf.global_variables_initializer())
        scores,_ = session.run(net.compute_scores(X))

        print('Your scores:')
        print(scores)
        print()
        print('correct scores:')
        correct_scores = np.array([[-0.8048996, -1.2701722,  -0.69626933],
         [-0.16263291, -1.1806408,  -0.4659379, ],
         [-0.50724095, -1.006151,   -0.843255,  ],
         [-0.14552905, -0.4789041,  -0.5218529, ],
         [ 0.00391591, -0.11607306, -0.14394382]])
        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:
[[-0.8123374  -1.2765464  -0.7033599 ]
 [-0.17129679 -1.1880331  -0.4731045 ]
 [-0.5159048  -1.0135431  -0.8504215 ]
```

```
 [-0.1541929  -0.4862964  -0.52901953]
 [-0.00618732 -0.12435262 -0.15226948]]

correct scores:
[[-0.8048996  -1.2701722  -0.69626933]
 [-0.16263291 -1.1806408  -0.4659379 ]
 [-0.50724095 -1.006151   -0.843255  ]
 [-0.14552905 -0.4789041  -0.5218529 ]
 [ 0.00391591 -0.11607306 -0.14394382]]

Difference between your scores and correct scores:
0.1172789880991364
```

3 Forward pass: compute loss

Implement the function `softmax_loss` that computes the data loss.

```
In [4]: objective = net.compute_objective(X, y, reg=0.05)
        np_obj = session.run(objective)

        print(np_obj)

        correct_objective = 6.3694286

        # should be very small, we get < 1e-7
        print('Difference between your loss and correct loss:')
        print(np.sum(np.abs(np_obj - correct_objective)))
```

```
WARNING:tensorflow:From /Users/alanzhou/Documents/comp150/comp150a1/implementations/b_neural_n
Instructions for updating:

Future major versions of TensorFlow will allow gradients to flow
into the labels input on backprop by default.

See @{tf.nn.softmax_cross_entropy_with_logits_v2}.

6.3672156
Difference between your loss and correct loss:
0.0022129666076660115
```

4 Backward pass

Tensorflow takes care of the backpropagation, so we are ready to train the neural network!

5 Train the network

To train the network we will use stochastic gradient descent (SGD), similar to the SVM and Softmax classifiers. Look at the function `TwoLayerNet.train` and fill in the missing sections to implement the training procedure. This should be very similar to the training procedure you used for the SVM and Softmax classifiers. You will also have to implement `TwoLayerNet.predict`, as the training process periodically performs prediction to keep track of accuracy over time while the network trains.

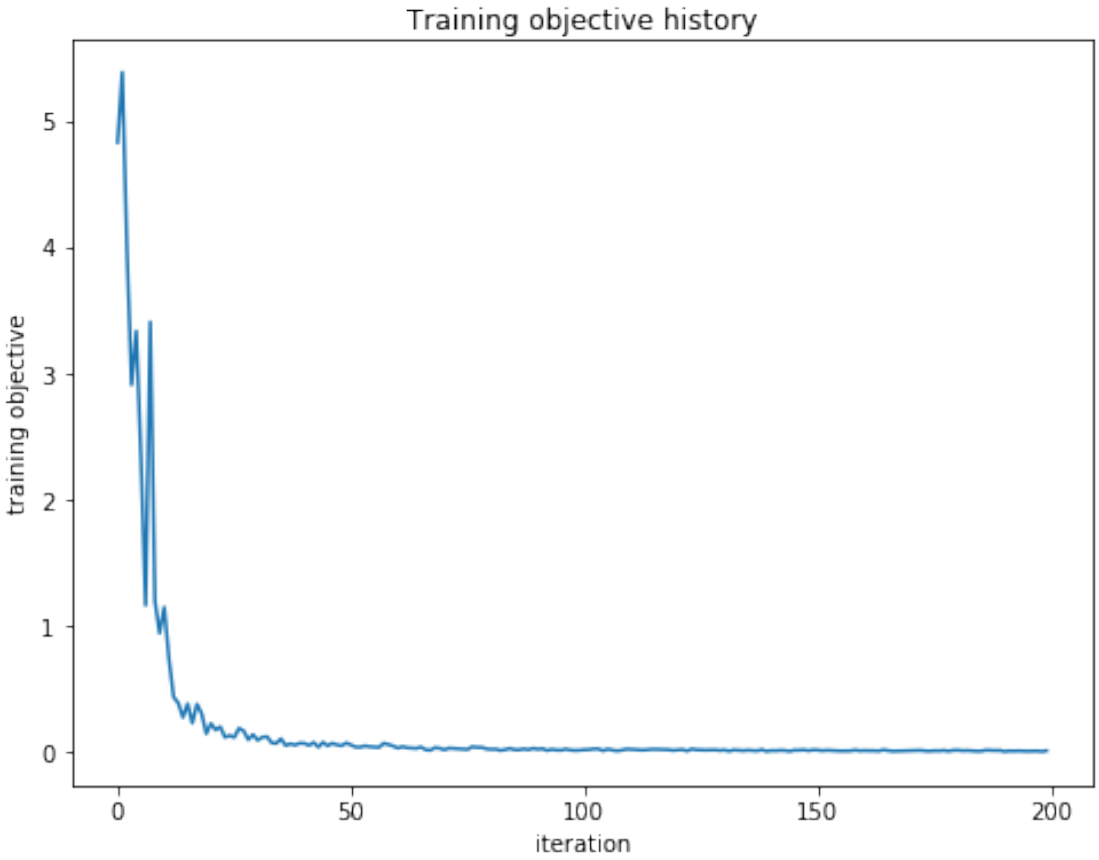
Once you have implemented the method, run the code below to train a two-layer network on toy data. You should achieve a training loss less than 0.2.

```
In [8]: net = init_toy_model()
        stats = net.train(X, y, X, y,
                    learning_rate=1e-2, reg=5e-6,
                    num_iters=200, verbose=True,
                    batch_size = 5)

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

        # plot the loss history
        plt.figure(figsize = (8,6))
        plt.plot(stats['loss_history'],)
        plt.xlabel('iteration')
        plt.ylabel('training objective')
        plt.title('Training objective history')
        plt.show()

iteration 0 / 200
iteration 50 / 200
iteration 100 / 200
iteration 150 / 200
Final training loss:  0.009404805
```



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 our favorite CIFAR-10 data so we can use it to train a classifier on a real dataset.

```
In [10]: from 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 = 'datasets/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


# Cleaning up variables to prevent loading data multiple times (which may cause memor
try:
   del X_train, y_train
   del X_test, y_test
   print('Clear previously loaded data.')
except:
   pass

# Invoke the above function to get our data.
X_train, y_train, X_val, y_val, X_test, y_test = get_CIFAR10_data()

X_train = np.float32(X_train)
X_val = np.float32(X_val)
X_test = np.float32(X_test)

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)
```

```
Clear previously loaded data.
```

```
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. 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 [35]: if net:
             del net

         input_size = 32 * 32 * 3
         hidden_size = 256
         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=5000, batch_size=200,
                     learning_rate=1e-6, learning_rate_decay=0.95,
                     reg=0.5, verbose=True)

         # Predict on the validation set
         print(X_val.shape)
         val_acc = np.float32(np.equal(net.predict(X_val), y_val)).mean()
         print('Validation accuracy: ', val_acc)
```

```
iteration 0 / 5000
iteration 50 / 5000
iteration 100 / 5000
iteration 150 / 5000
iteration 200 / 5000
iteration 250 / 5000
iteration 300 / 5000
iteration 350 / 5000
iteration 400 / 5000
iteration 450 / 5000
iteration 500 / 5000
iteration 550 / 5000
iteration 600 / 5000
iteration 650 / 5000
iteration 700 / 5000
```

```
iteration 750 / 5000
iteration 800 / 5000
iteration 850 / 5000
iteration 900 / 5000
iteration 950 / 5000
iteration 1000 / 5000
iteration 1050 / 5000
iteration 1100 / 5000
iteration 1150 / 5000
iteration 1200 / 5000
iteration 1250 / 5000
iteration 1300 / 5000
iteration 1350 / 5000
iteration 1400 / 5000
iteration 1450 / 5000
iteration 1500 / 5000
iteration 1550 / 5000
iteration 1600 / 5000
iteration 1650 / 5000
iteration 1700 / 5000
iteration 1750 / 5000
iteration 1800 / 5000
iteration 1850 / 5000
iteration 1900 / 5000
iteration 1950 / 5000
iteration 2000 / 5000
iteration 2050 / 5000
iteration 2100 / 5000
iteration 2150 / 5000
iteration 2200 / 5000
iteration 2250 / 5000
iteration 2300 / 5000
iteration 2350 / 5000
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iteration 2750 / 5000
iteration 2800 / 5000
iteration 2850 / 5000
iteration 2900 / 5000
iteration 2950 / 5000
iteration 3000 / 5000
iteration 3050 / 5000
iteration 3100 / 5000
```

```
iteration 3150 / 5000
iteration 3200 / 5000
iteration 3250 / 5000
iteration 3300 / 5000
iteration 3350 / 5000
iteration 3400 / 5000
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iteration 4650 / 5000
iteration 4700 / 5000
iteration 4750 / 5000
iteration 4800 / 5000
iteration 4850 / 5000
iteration 4900 / 5000
iteration 4950 / 5000
(1000, 3072)
Validation accuracy:  0.521
```
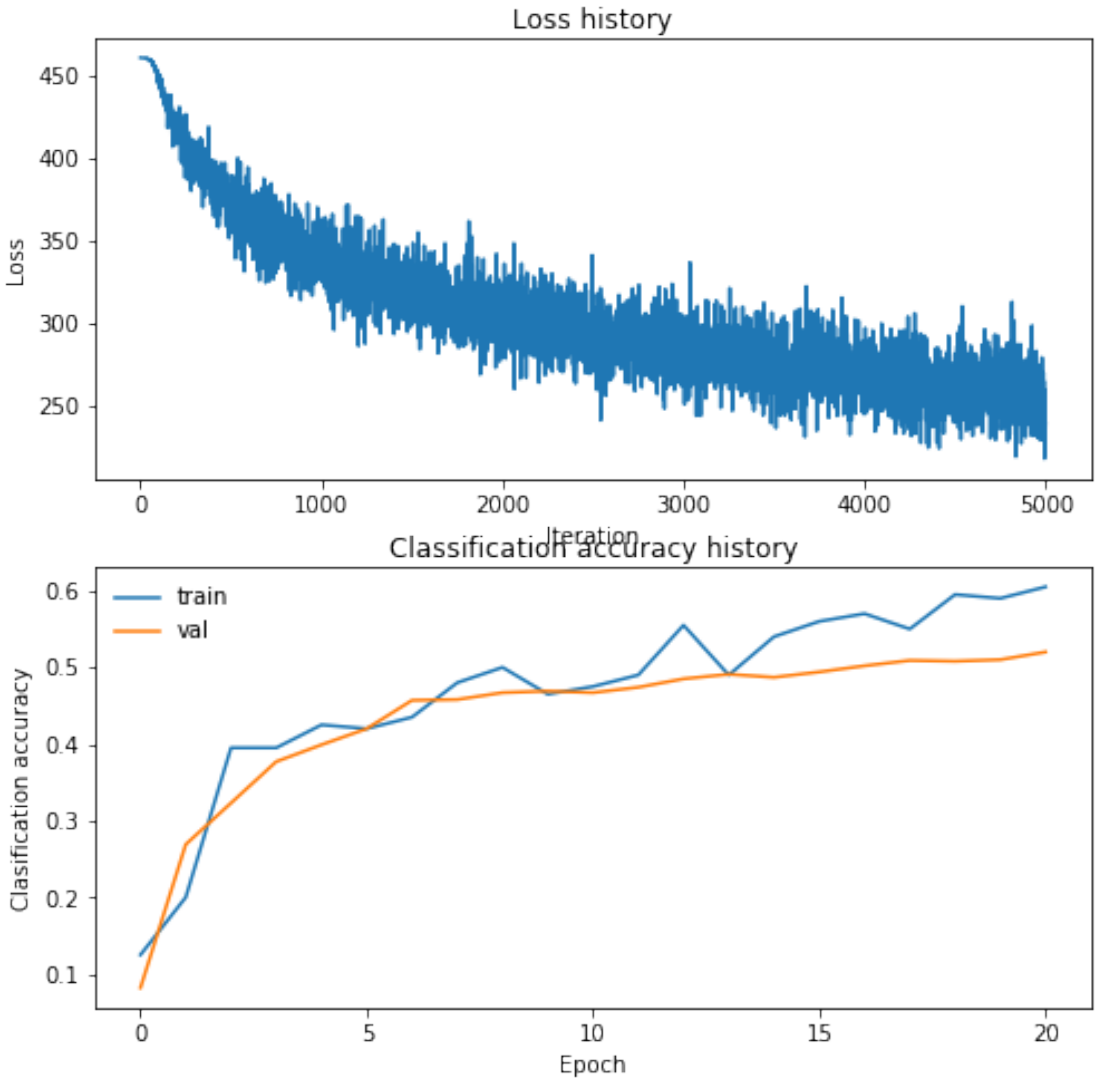

8 Debug the training

With the default parameters we provided above, you should get a validation accuracy of about 0.4 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.

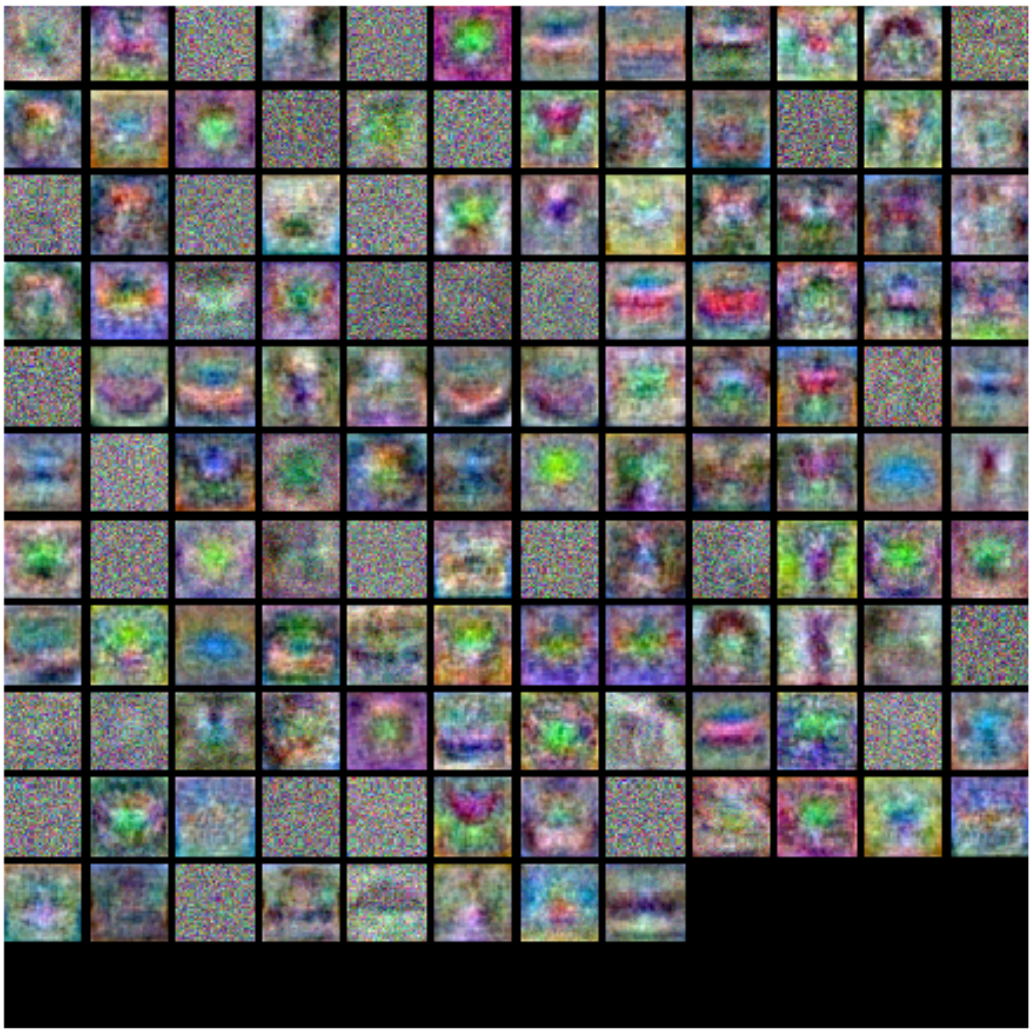
Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

In [36]:
```
# Plot the loss function and train / validation accuracies
plt.figure(figsize = (8,8))
plt.subplot(2, 1, 1)
plt.plot(stats['loss_history'])
plt.title('Loss history')
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.title('Classification accuracy history')
plt.xlabel('Epoch')
plt.ylabel('Clasification accuracy')
plt.legend()
plt.show()
```




```
In [28]: from vis_utils import visualize_grid

         # Visualize the weights of the network

         def show_net_weights(learned_params):

             W1 = learned_params['W1']

             W1 = W1.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()

         plt.figure(figsize = (8,8))
```

```
learned_params = net.get_learned_parameters()
show_net_weights(learned_params)
```



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

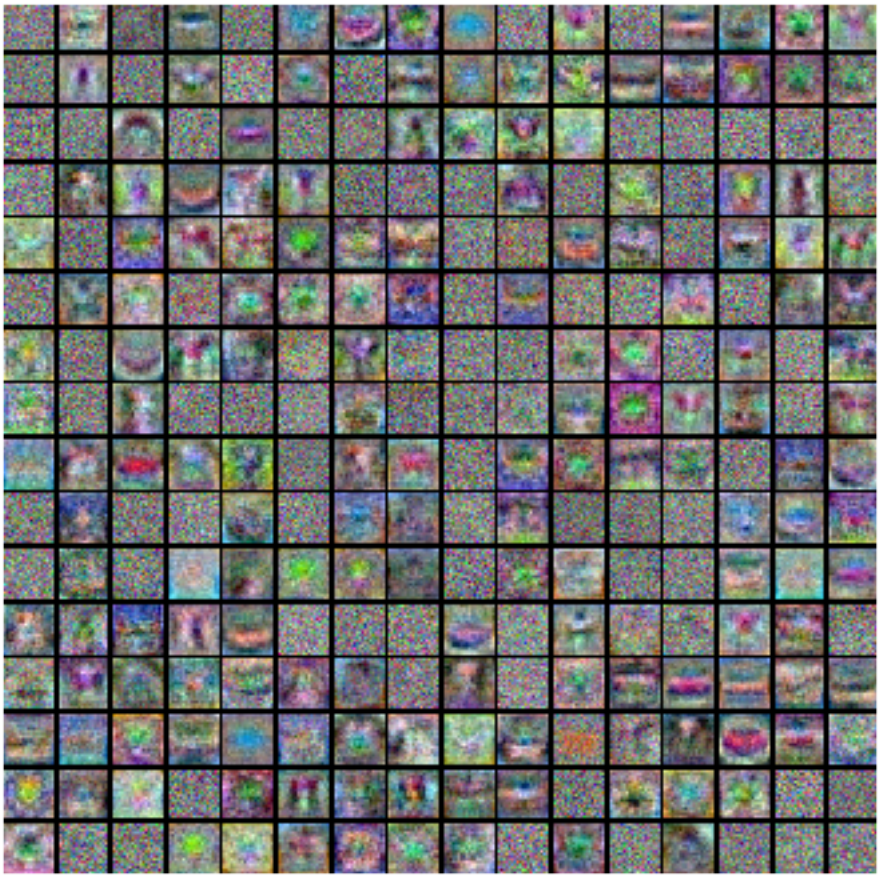
Approximate results. You should be aim to achieve a classification accuracy of greater than 48% on the validation set. Our best network gets over 52% on the validation set.

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. Feel free implement your own techniques (e.g. PCA to reduce dimensionality, or adding dropout, or adding features to the solver, etc.).

In [41]:
```
################################################################################
# TODO: 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.                          #
################################################################################
# Your code
"""
hidden_sizes = [50,60,70]
regs = [1,5,10]
learning_decays = [.95]
learning_rates = [1e-4,5e-5,1e-5,5e-6,1e-6]

for hidden_size in hidden_sizes:
    for reg in regs:
        for learning_decay in learning_decays:
            for learning_rate in learning_rates:
                print('Hidden Size: %d, Regularization: %.2f, Learning Rate: %.2e, Le
                      %(hidden_size,reg,learning_rate,learning_decay))
                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-5, learning_rate_decay=learning_decay,
                            reg=reg, verbose=False)

                # Predict on the validation set
                #print(X_val_processed.shape)
                val_acc = np.float32(np.equal(net.predict(X_val), y_val)).mean()
                print('Validation accuracy: ', val_acc)
```

```
                    if not best_net:
                        best_net = net
                        best_params = [hidden_size,reg,learning_rate,learning_decay]
                    elif val_acc > best_val:
                        best_val = val_acc
                        best_net = net
                        best_params = [hidden_size,reg,learning_rate,learning_decay]

                    del net
        """
        best_net = net # store the best model into this
        best_val = 0
        best_params = []
        ################################################################################
        #                                END OF YOUR CODE                              #
        ################################################################################
```

In [37]:
```
        # visualize the weights of the best network
        plt.figure(figsize = (8,6))
        learned_params = net.get_learned_parameters()
        show_net_weights(learned_params)
```



10 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 48%.

```
In [39]: test_acc = (best_net.predict(X_test) == y_test).mean()
         print('Test accuracy: ', test_acc)
```

```
Test accuracy:  0.523
```

Inline Question

Now that you have trained a Neural Network classifier, you may find that your testing accuracy is much lower than the training accuracy. In what ways can we decrease this gap? Select all that apply. 1. Train on a larger dataset. 2. Add more hidden units. 3. Increase the regularization strength. 4. None of the above.

Your answer: **1 and 3**

Your explanation: **The explanation for much lower testing accuracy than training accuracy would be overfitting. 1, training on a larger dataset would be a good potential fix because if we have a small dataset then we might overfit on features in our training dataset that are not necessarily representative of the true distribution of that dataset. 3, increasing the regularization strength would be a good fix because the point of regularization is to prevent overfitting: as we increase regularization, our weights decrease in magnitude and our model space decreases, decreasing the likelihood of overfitting.**

2, adding more hidden units, probably wouldn't help since this would increase the model space and could even lead to more overfitting as a result.