two_layer_nn

February 7, 2025

0.1 This is the 2-layer neural network notebook for ECE C147/C247 Homework #3

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

Please print out the notebook entirely when completed.

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

[186]:
```
import random
import numpy as np
from utils.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

%matplotlib inline
%load_ext autoreload
%autoreload 2

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

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

0.2 Toy example

Before loading CIFAR-10, there will be a toy example to test your implementation of the forward and backward pass. Make sure to read the description of TwoLayerNet class in neural_net.py file , understand the architecture and initializations

[189]:
```
from nndl.neural_net import TwoLayerNet
```

[191]:
```
# 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
```

```python
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()
```

0.2.1 Compute forward pass scores

[194]:

```python
## Implement the forward pass of the neural network.
## See the loss() method in TwoLayerNet class for the same

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

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

```
Your scores:
[[-1.07260209  0.05083871 -0.87253915]
 [-2.02778743 -0.10832494 -1.52641362]
 [-0.74225908  0.15259725 -0.39578548]
 [-0.38172726  0.10835902 -0.17328274]
 [-0.64417314 -0.18886813 -0.41106892]]

correct scores:
[[-1.07260209  0.05083871 -0.87253915]
```

```
 [-2.02778743 -0.10832494 -1.52641362]
 [-0.74225908  0.15259725 -0.39578548]
 [-0.38172726  0.10835902 -0.17328274]
 [-0.64417314 -0.18886813 -0.41106892]]

Difference between your scores and correct scores:
3.381231214460989e-08
```

0.2.2 Forward pass loss

[197]:
```python
loss, _ = net.loss(X, y, reg=0.05)
correct_loss = 1.071696123862817

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

```
Loss: 1.071696123862817
Difference between your loss and correct loss:
0.0
```

0.2.3 Backward pass

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

[200]:
```python
from utils.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('{} max relative error: {}'.format(param_name,␣
↪rel_error(param_grad_num, grads[param_name])))
```

```
W2 max relative error: 2.9632227682005116e-10
b2 max relative error: 1.248270530283678e-09
W1 max relative error: 1.2832823337649917e-09
b1 max relative error: 3.172680092703762e-09
```

0.2.4 Training the network

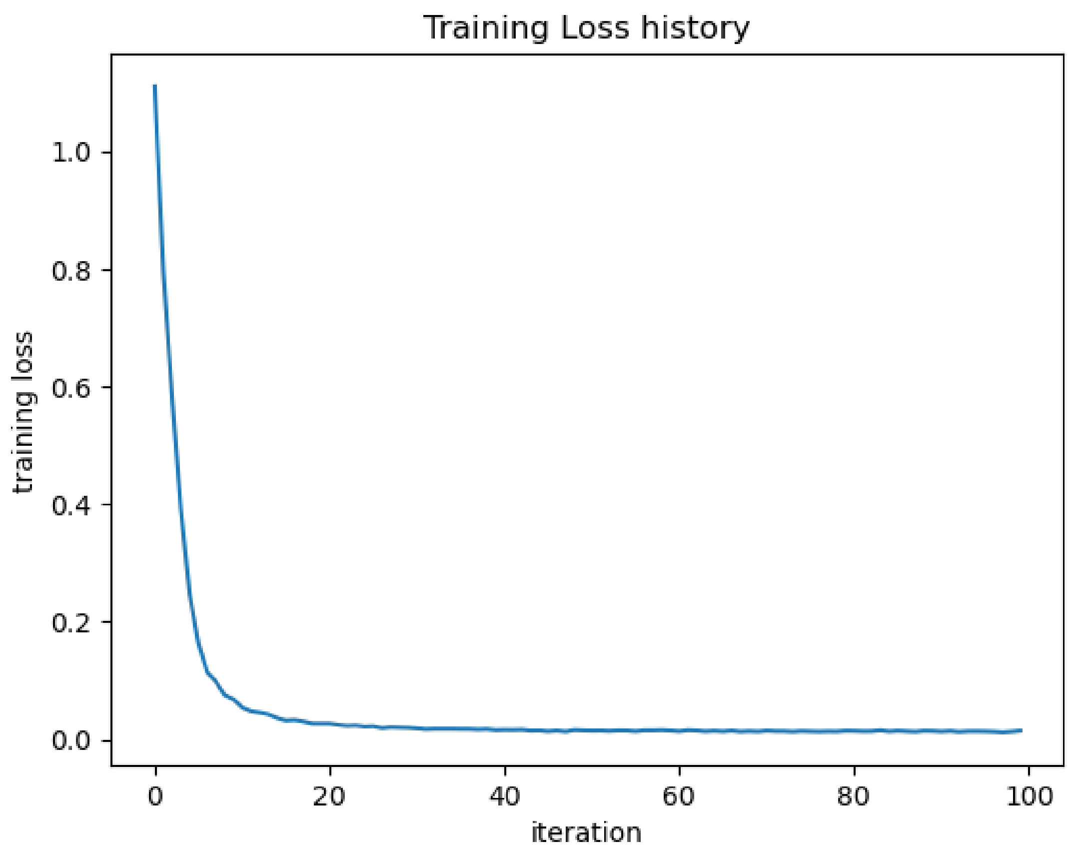
Implement neural_net.train() to train the network via stochastic gradient descent, much like the softmax and SVM.

[203]:
```
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:  0.014497864587765886
```



0.3 Classify CIFAR-10

Do classification on the CIFAR-10 dataset.

[223]:
```python
# Debugging bit -- I found that for some reason, my data_utils.py ROOT function␣
↪was
#having some issues, so I decided to manually have the directory implemented␣
↪and it fixed my issue
import os
print(os.listdir('/Users/ctang/Desktop/ECE_C147/HW3/cifar-10-batches-py/'))
os.getcwd()
```

```
['data_batch_1', 'readme.html', 'batches.meta', 'data_batch_2', 'data_batch_5',
'test_batch', 'data_batch_4', 'data_batch_3']
```

[249]:
```python
from utils.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 = 'cifar-10-batches-py'
    X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

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

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

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

```
    return X_train, y_train, X_val, y_val, X_test, y_test


# Invoke the above function to get our data.
X_train, y_train, X_val, y_val, X_test, y_test = get_CIFAR10_data()
print('Train data shape: ', X_train.shape)
print('Train labels shape: ', y_train.shape)
print('Validation data shape: ', X_val.shape)
print('Validation labels shape: ', y_val.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

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

0.3.1 Running SGD

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

[274]:
```
input_size = 32 * 32 * 3
hidden_size = 50
num_classes = 10
net = TwoLayerNet(input_size, hidden_size, num_classes)

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

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

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

```
iteration 0 / 1000: loss 2.3027813119140244
iteration 100 / 1000: loss 2.3024961721749104
iteration 200 / 1000: loss 2.299855991366158
iteration 300 / 1000: loss 2.277710662196413
iteration 400 / 1000: loss 2.212679860235686
iteration 500 / 1000: loss 2.1422941709858137
iteration 600 / 1000: loss 2.1545996981194038
iteration 700 / 1000: loss 2.085994913133441
```

```
iteration 800 / 1000: loss 2.0831027988682354
iteration 900 / 1000: loss 1.8811796873200608
Validation accuracy:  0.278
```

0.4 Questions:

The training accuracy isn't great.

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

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

[255]:
```
stats['train_acc_history']
```

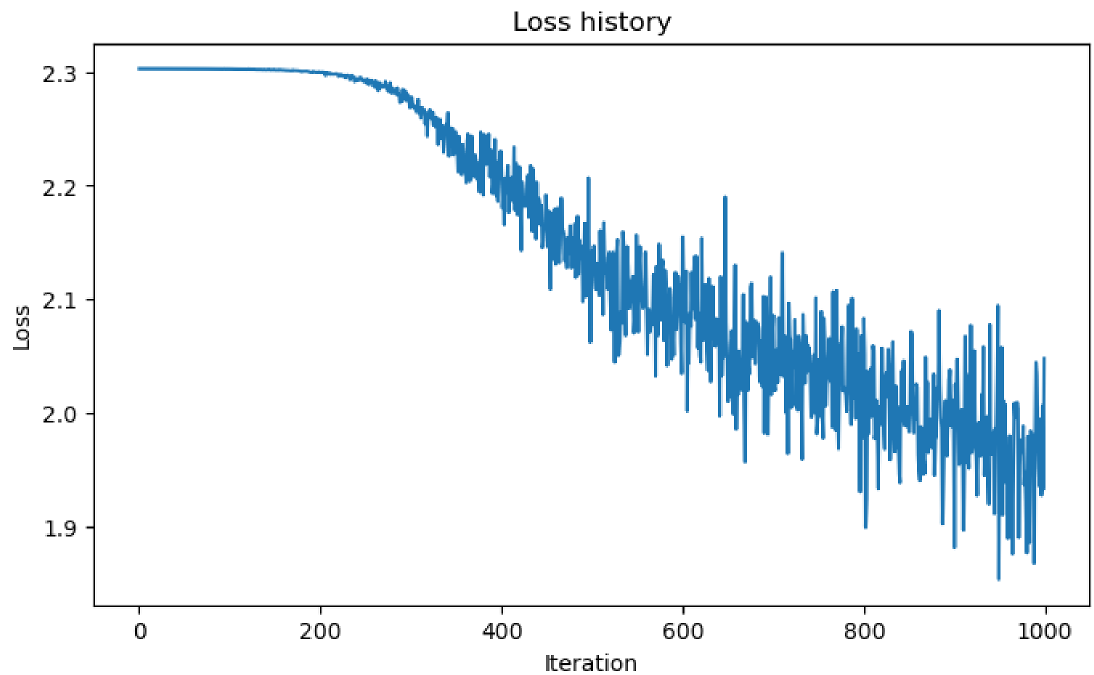
[255]:
```
[0.08, 0.14, 0.25, 0.185, 0.325]
```

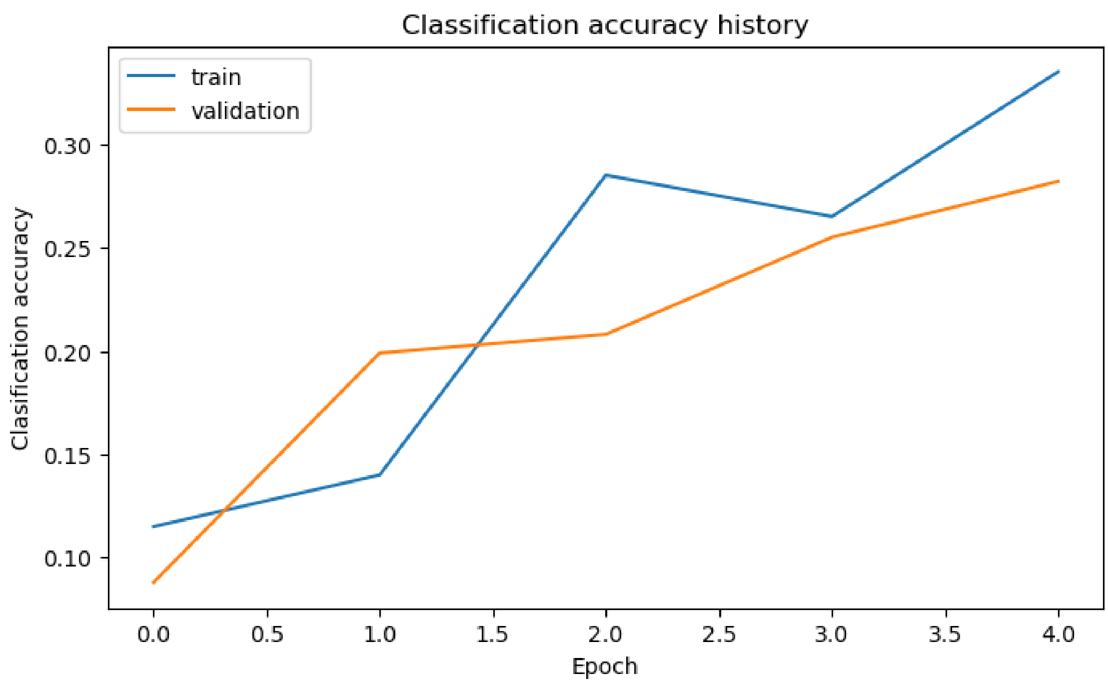
[276]:
```
# ================================================================ #
# YOUR CODE HERE:
#   Do some debugging to gain some insight into why the optimization
#   isn't great.
# ================================================================ #

# Plot the loss function and train / validation accuracies
fig, ax = plt.subplots(2, 1, figsize=(8, 10))
ax[0].plot(stats['loss_history'])
ax[0].set_title('Loss history')
ax[0].set_xlabel('Iteration')
ax[0].set_ylabel('Loss')

ax[1].plot(stats['train_acc_history'], label='train')
ax[1].plot(stats['val_acc_history'], label='validation')
ax[1].set_title('Classification accuracy history')
ax[1].set_xlabel('Epoch')
ax[1].set_ylabel('Clasification accuracy')
ax[1].legend()
plt.show()

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





0.5 Answers:

(1) Based off the Loss vs Iteration graph above, it seems like the loss doesn't decrease by a large amount. It is almost flat, perhaps hinting that the learning rate might be too low. Additionally, with the large number of fluctuations, it seems that the model is not learning consistently and struggling to fit the data. The validation accuracy is not significantly lower

than the training accuracy so we do not have an issue of overfitting, but both are still low, which may indicate underfitting. Lastly, the lack of convergence observed which suggests that we may need to make the model more complex or add iterations in order to observe any improvements in performance.

(2) There are a couple of ways that we can improve (1). We could try adjusting the learning rate, add more complexity by increasing the number of layers or neurons, perform regularization adjustments, or try varying batch sizes. These adjustments would most directly improve the model performance.

0.6 Optimize the neural network

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

[265]:
```
best_net = None # store the best model into this

# ================================================================ #
# YOUR CODE HERE:
#   Optimize over your hyperparameters to arrive at the best neural
#   network.  You should be able to get over 50% validation accuracy.
#   For this part of the notebook, we will give credit based on the
#   accuracy you get.  Your score on this question will be multiplied by:
#      min(floor((X - 28%)) / %22, 1)
#   where if you get 50% or higher validation accuracy, you get full
#   points.
#
#   Note, you need to use the same network structure (keep hidden_size = 50)!
# ================================================================ #
#pass
input_size = 32 * 32 * 3
hidden_size = 50
num_classes = 10

iteration_numbers = np.arange(2, 4) * 10**3
reg_coefs = np.arange(0.1, 0.25, 0.05)
learning_rates = np.power(10, -np.arange(3.0, 4.1, 0.1))
batch_sizes = np.arange(200, 260, 10)

best_val= 0

for iteration_number in iteration_numbers:
    for reg_coef in reg_coefs:
        for batch_size in batch_sizes:
            for learning_rate in learning_rates:
                net = TwoLayerNet(input_size, hidden_size, num_classes)
                stats = net.train(X_train, y_train, X_val,␣
 ↪y_val,num_iters=iteration_number, batch_size=batch_size,
```

```
                                    learning_rate=learning_rate,␣
↪learning_rate_decay=0.95,reg=reg_coef, verbose=False)
                val_acc = (net.predict(X_val)==y_val).mean()
                print("Training accuracy for this iteration:", (net.
↪predict(X_train) == y_train).mean())
                print("Validation accuracy for this iteration:", val_acc)
                print("n_iteration:", iteration_number)
                print("reg_coef:", reg_coef)
                print("batch_size:", batch_size)
                print("learning_rate:", learning_rate)
                if best_val < val_acc:
                    best_val = val_acc
                if val_acc >= 0.5:
                    best_net = net
                    break
            else:
                continue
            break
        else:
            continue
        break
    else:
        continue
    break

# ================================================================ #
# END YOUR CODE HERE
# ================================================================ #
val_acc = (best_net.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)
```

```
Training accuracy for this iteration: 0.533
Validation accuracy for this iteration: 0.494
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.001
Training accuracy for this iteration: 0.5302857142857142
Validation accuracy for this iteration: 0.491
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.0007943282347242813
Training accuracy for this iteration: 0.516
Validation accuracy for this iteration: 0.485
n_iteration: 2000
reg_coef: 0.1
```

```
batch_size: 200
learning_rate: 0.000630957344480193
Training accuracy for this iteration: 0.5000204081632653
Validation accuracy for this iteration: 0.481
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.000501187233627272
Training accuracy for this iteration: 0.4814897959183673
Validation accuracy for this iteration: 0.472
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.0003981071705534969
Training accuracy for this iteration: 0.46851020408163263
Validation accuracy for this iteration: 0.45
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.0003162277660168376
Training accuracy for this iteration: 0.4497551020408163
Validation accuracy for this iteration: 0.45
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.0002511886431509577
Training accuracy for this iteration: 0.4206122448979592
Validation accuracy for this iteration: 0.425
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.00019952623149688769
Training accuracy for this iteration: 0.3998775510204082
Validation accuracy for this iteration: 0.41
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.0001584893192461111
Training accuracy for this iteration: 0.38373469387755105
Validation accuracy for this iteration: 0.384
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.0001258925411794165
Training accuracy for this iteration: 0.36144897959183675
Validation accuracy for this iteration: 0.362
n_iteration: 2000
reg_coef: 0.1
```

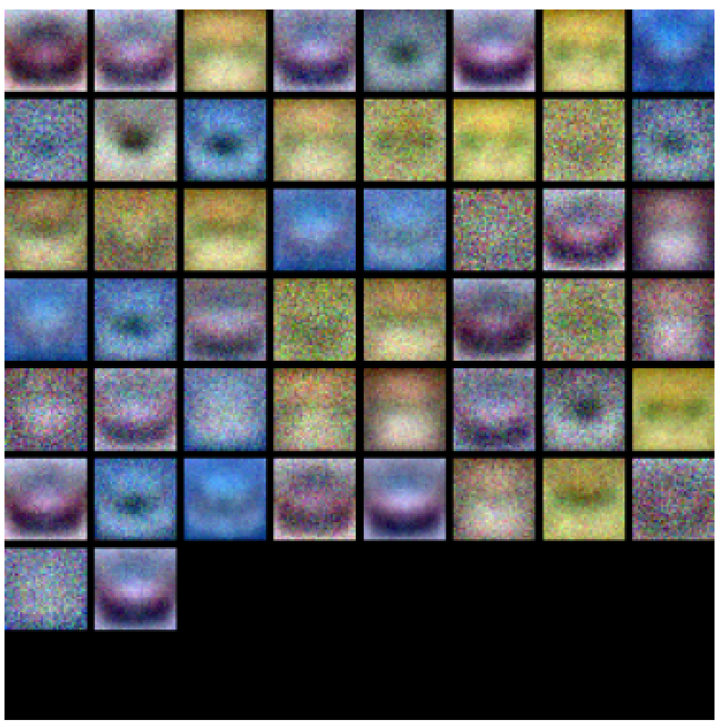
```
batch_size: 200
learning_rate: 9.999999999999998e-05
Training accuracy for this iteration: 0.5327551020408163
Validation accuracy for this iteration: 0.501
n_iteration: 2000
reg_coef: 0.1
batch_size: 210
learning_rate: 0.001
Validation accuracy:  0.501
```

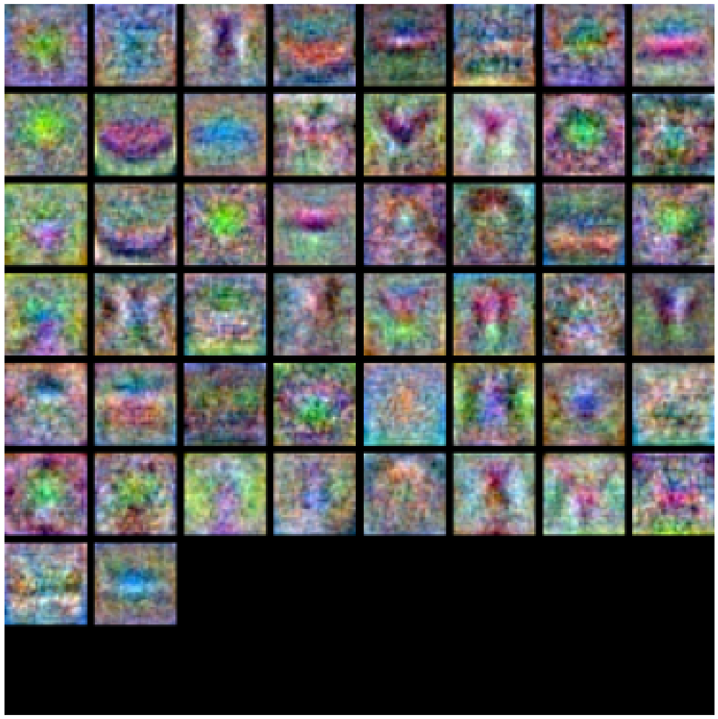
[266]:
```python
from utils.vis_utils import visualize_grid

# Visualize the weights of the network

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

show_net_weights(subopt_net)
show_net_weights(best_net)
```





0.7 Question:

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

0.8 Answer:

(1) Between the suboptimal net and the best net that I arrived at, the best net preserves more visual features and characteristics. At the very least, you could see a difference between the images, whereas the suboptimal net looks like a bunch of spheres of different colors. Therefore, we can see that the suboptimal net did not do as well in preserving the features of the images.

0.9 Evaluate on test set

[270]:
```
test_acc = (best_net.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

```
Test accuracy:  0.497
```

[ ]:

[ ]: