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.

In [110]:

```
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
```

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

In [111]:

```
from nndl.neural_net import TwoLayerNet
```

In [112]:

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

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

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

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

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

Compute forward pass scores

In [113]:

```
## 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:
3.381231195725975 5e-08
```

Forward pass loss

In [114]:

```
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
```

Backward pass

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

In [115]:

```
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=Fals
    print('{} max relative error: {}'.format(param_name, rel_error(param_grad_num, g
```

```
W2 max relative error: 2.9632233460136427e-10
b2 max relative error: 1.8392017135950213e-10
W1 max relative error: 1.28328951808708e-09
b1 max relative error: 3.172680285697327e-09
```

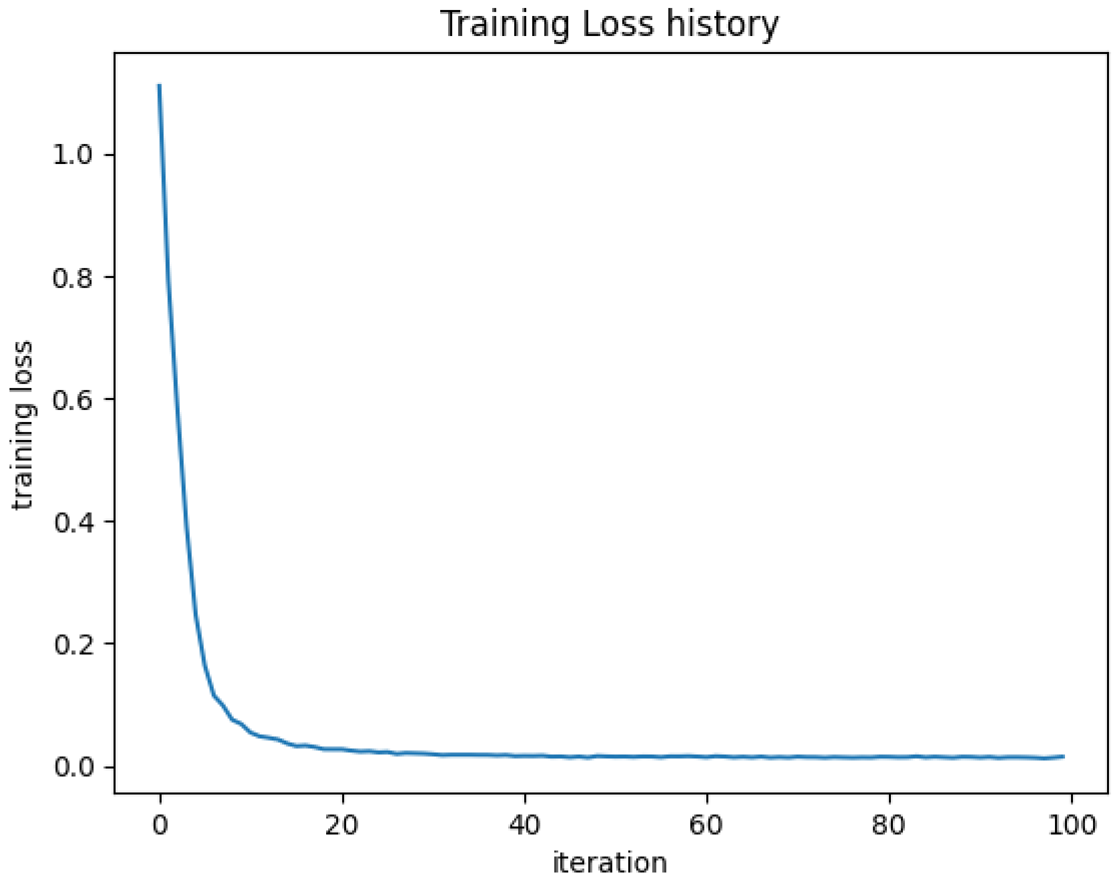
Training the network

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

In [116]:

```
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:  0.014498902952971729
```



Classify CIFAR-10

Do classification on the CIFAR-10 dataset.

In [117]:

```
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 = '/Users/wangyuchen/desktop/COM SCI 247/HW/HW2/hw2_Questions/code/c
    X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

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

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

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

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


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

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

Running SGD

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

In [118]:

```
from nndl.neural_net import TwoLayerNet
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 2.302757518613176
iteration 100 / 1000: loss 2.302120159207236
iteration 200 / 1000: loss 2.2956136007408703
iteration 300 / 1000: loss 2.2518259043164135
iteration 400 / 1000: loss 2.188995235046776
iteration 500 / 1000: loss 2.1162527791897743
iteration 600 / 1000: loss 2.064670827698217
iteration 700 / 1000: loss 1.9901688623083942
iteration 800 / 1000: loss 2.002827640124685
iteration 900 / 1000: loss 1.9465176817856495
Validation accuracy:  0.283
```

Questions:

The training accuracy isn't great.

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

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

In [119]:

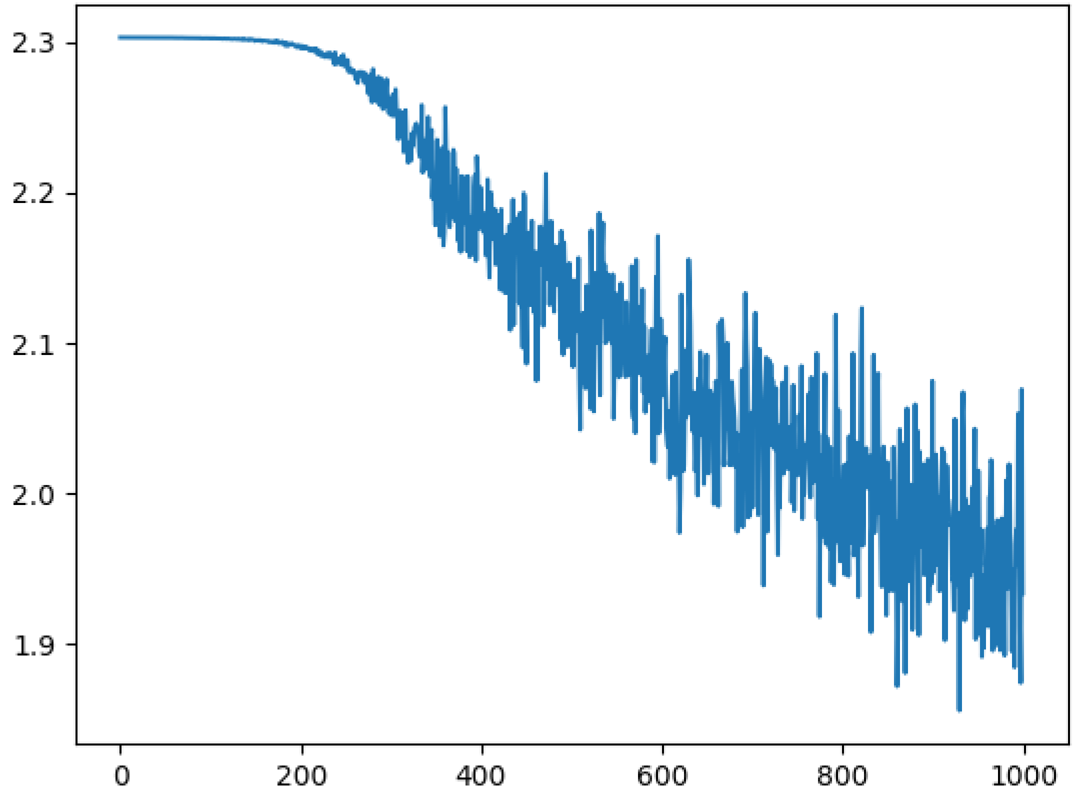
```
stats['train_acc_history']
```

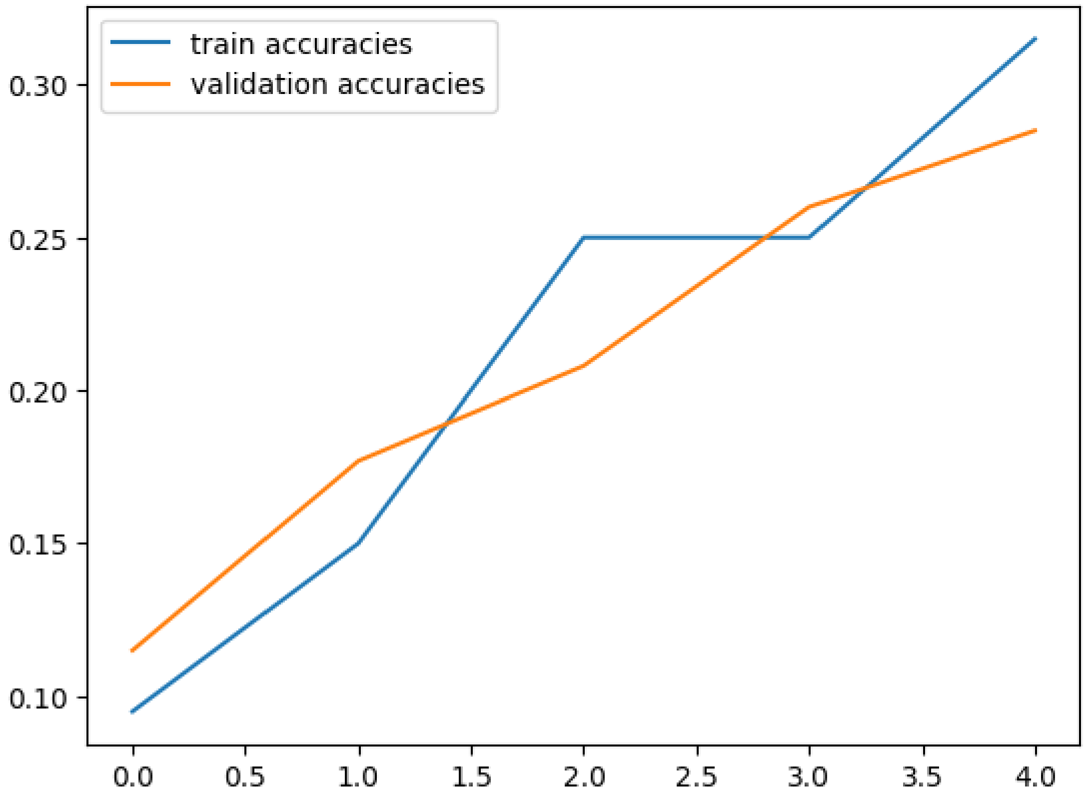
Out[119]:

```
[0.095, 0.15, 0.25, 0.25, 0.315]
```

In [120]:

```
# ================================================================ #
# 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

#plot the loss function
plt.plot(stats['loss_history'])
plt.show()

#plot the train / validation accuracies
#plot the train accuracies
plt.plot(stats['train_acc_history'], label = "train accuracies")
#plot the validation accuracies
plt.plot(stats['val_acc_history'], label = "validation accuracies")
plt.legend() #show the labels
plt.show()


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





Answers:

(1) First of all, it seems like the learning rate is not large enough since the loss in the first graph barely changes during the first 200 iterations. Also, the changes of loss is still unpredictable and the loss function does not go flatten. So, the number of iterations is not enough. On the other hand, the patters of train accuracy and validation accuracy do not match.

(2) Based on my answer to the first question, I will try to increase the learning rate and number of iterations.

Optimize the neural network

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

In [121]:

```
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)!
# ================================================================ #

# Train the network by changing the learning rate

input_size = 32 * 32 * 3
hidden_size = 50
num_classes = 10

learningrates = [1e-5, 1e-4, 1e-3] #checking different learning rate

currentbestacc = 0

for rate in learningrates:
    currentnet = TwoLayerNet(input_size, hidden_size, num_classes)
    print("Current learning rate: ", rate)
    currentstats = currentnet.train(X_train, y_train, X_val, y_val,
                num_iters=6000, batch_size=200,
                #increase the number of iterations from 1000 to 6000
                learning_rate=rate, learning_rate_decay=0.95,
                reg=0.25, verbose=True)

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

    #when we detect a better accuracy, update it
    if currentval_acc > currentbestacc:
        currentbestacc = currentval_acc
        best_net = currentnet #update the best net

#As we can see that when we have learning rate = 1e-3 and 6000 iterations,
#the validation accuracy is 0.525, which is higher than 0.5

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

```
Current learning rate:  1e-05
iteration 0 / 6000: loss 2.3027667167979295
iteration 100 / 6000: loss 2.3027299318867556
iteration 200 / 6000: loss 2.3027045062357443
iteration 300 / 6000: loss 2.3027105833127006
iteration 400 / 6000: loss 2.302681593506126
iteration 500 / 6000: loss 2.302660027738356
```

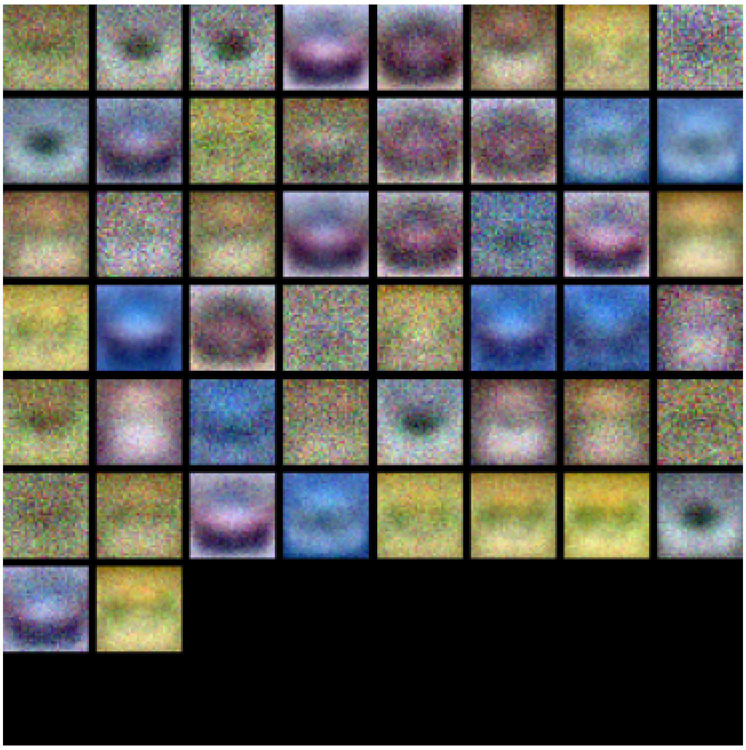
```
iteration 600 / 6000: loss 2.3026070348816576
iteration 700 / 6000: loss 2.3025672488781286
iteration 800 / 6000: loss 2.302511043748264
iteration 900 / 6000: loss 2.302502067374492‌3
iteration 1000 / 6000: loss 2.302416327991673
iteration 1100 / 6000: loss 2.3022083751559155
iteration 1200 / 6000: loss 2.3022747409308537
iteration 1300 / 6000: loss 2.30219325838239
iteration 1400 / 6000: loss 2.3018614049182693
iteration 1500 / 6000: loss 2.3015019270228256
iteration 1600 / 6000: loss 2.301536483683131
iteration 1700 / 6000: loss 2.301767713274723
iteration 1800 / 6000: loss 2.300709678050533
iteration 1900 / 6000: loss 2.301290650219527
iteration 2000 / 6000: loss 2.3010291716275875
iteration 2100 / 6000: loss 2.299650098794119
iteration 2200 / 6000: loss 2.299737857512051
iteration 2300 / 6000: loss 2.2984253983447562
iteration 2400 / 6000: loss 2.2980365011404196
iteration 2500 / 6000: loss 2.2992992291319685
iteration 2600 / 6000: loss 2.299627689999791
iteration 2700 / 6000: loss 2.297543354053057
iteration 2800 / 6000: loss 2.2952355551610513
iteration 2900 / 6000: loss 2.2927049332611946
iteration 3000 / 6000: loss 2.293678763848068
iteration 3100 / 6000: loss 2.293973688735582
iteration 3200 / 6000: loss 2.293091890357758
iteration 3300 / 6000: loss 2.2846736621635326
iteration 3400 / 6000: loss 2.2871805688936333
iteration 3500 / 6000: loss 2.2855967169100486
iteration 3600 / 6000: loss 2.284357044393651
iteration 3700 / 6000: loss 2.2782899805748733
iteration 3800 / 6000: loss 2.2745005389183905
iteration 3900 / 6000: loss 2.275556564698514
iteration 4000 / 6000: loss 2.267487014201895
iteration 4100 / 6000: loss 2.2738931178358768
iteration 4200 / 6000: loss 2.2680568931107175
iteration 4300 / 6000: loss 2.271036059034352
iteration 4400 / 6000: loss 2.250629004050632
iteration 4500 / 6000: loss 2.2535301108529686
iteration 4600 / 6000: loss 2.259513023649877
iteration 4700 / 6000: loss 2.252526427701579
iteration 4800 / 6000: loss 2.254006278577032
iteration 4900 / 6000: loss 2.241832354679842
iteration 5000 / 6000: loss 2.2465206320433695
iteration 5100 / 6000: loss 2.2488472393825907
iteration 5200 / 6000: loss 2.2281221888271623
iteration 5300 / 6000: loss 2.2382524787755127
iteration 5400 / 6000: loss 2.2408751294044436
iteration 5500 / 6000: loss 2.2363632236741484
iteration 5600 / 6000: loss 2.2471540583821232
iteration 5700 / 6000: loss 2.2540115695449665
iteration 5800 / 6000: loss 2.249283057621046
iteration 5900 / 6000: loss 2.2368603802236895
Validation accuracy:  0.198
Current learning rate:  0.0001
iteration 0 / 6000: loss 2.3027523109667447
iteration 100 / 6000: loss 2.3021854434913176
iteration 200 / 6000: loss 2.298166294976898
iteration 300 / 6000: loss 2.262526100713673
iteration 400 / 6000: loss 2.205869247935776
```

```
iteration 500 / 6000: loss 2.1381464515777897
iteration 600 / 6000: loss 2.1036514155918535
iteration 700 / 6000: loss 2.0594896655549246
iteration 800 / 6000: loss 2.0366079150168708
iteration 900 / 6000: loss 1.914690486688410 7
iteration 1000 / 6000: loss 1.9312527048617063
iteration 1100 / 6000: loss 1.9074859034861307
iteration 1200 / 6000: loss 1.997314819472955
iteration 1300 / 6000: loss 1.8867853328379658
iteration 1400 / 6000: loss 1.9830802909845027
iteration 1500 / 6000: loss 1.6580392809598494
iteration 1600 / 6000: loss 1.8514605985629005
iteration 1700 / 6000: loss 1.8313330786671587
iteration 1800 / 6000: loss 1.9347685017299059
iteration 1900 / 6000: loss 1.8975711187583773
iteration 2000 / 6000: loss 1.8135942868523232
iteration 2100 / 6000: loss 1.739037408726185
iteration 2200 / 6000: loss 1.7635052637566293
iteration 2300 / 6000: loss 1.7778587734499245
iteration 2400 / 6000: loss 1.860647488254527
iteration 2500 / 6000: loss 1.7451665341659566
iteration 2600 / 6000: loss 1.756881437270907
iteration 2700 / 6000: loss 1.7143128795162645
iteration 2800 / 6000: loss 1.7118844235931565
iteration 2900 / 6000: loss 1.7051128038606658
iteration 3000 / 6000: loss 1.7787943983776386
iteration 3100 / 6000: loss 1.4481164494113663
iteration 3200 / 6000: loss 1.643941722674297
iteration 3300 / 6000: loss 1.6508049684979538
iteration 3400 / 6000: loss 1.6349524882725375
iteration 3500 / 6000: loss 1.644801761334519
iteration 3600 / 6000: loss 1.717269085028796
iteration 3700 / 6000: loss 1.647661081257863
iteration 3800 / 6000: loss 1.7586038246408173
iteration 3900 / 6000: loss 1.7101576079559133
iteration 4000 / 6000: loss 1.5828600355424058
iteration 4100 / 6000: loss 1.710850224891623
iteration 4200 / 6000: loss 1.5818850994640035
iteration 4300 / 6000: loss 1.6226822742466365
iteration 4400 / 6000: loss 1.5794530722703617
iteration 4500 / 6000: loss 1.6285364651060898
iteration 4600 / 6000: loss 1.8288009831424652
iteration 4700 / 6000: loss 1.6988006269575717
iteration 4800 / 6000: loss 1.6787469755955113
iteration 4900 / 6000: loss 1.5980073772341683
iteration 5000 / 6000: loss 1.6611313639245888
iteration 5100 / 6000: loss 1.5625045265489585
iteration 5200 / 6000: loss 1.7147658090536722
iteration 5300 / 6000: loss 1.6859105439323467
iteration 5400 / 6000: loss 1.670128636683942
iteration 5500 / 6000: loss 1.6193826026862599
iteration 5600 / 6000: loss 1.5478055605738732
iteration 5700 / 6000: loss 1.6041835965683873
iteration 5800 / 6000: loss 1.5014616244770773
iteration 5900 / 6000: loss 1.6162831191704066
Validation accuracy:  0.43
Current learning rate:  0.001
iteration 0 / 6000: loss 2.302756328481318
iteration 100 / 6000: loss 1.9461212550121298
iteration 200 / 6000: loss 1.697576110687341
iteration 300 / 6000: loss 1.7250125483915062
```

```
iteration 400 / 6000: loss 1.6177731688015784
iteration 500 / 6000: loss 1.6003398032960405
iteration 600 / 6000: loss 1.559859892759535
iteration 700 / 6000: loss 1.5254590667177301
iteration 800 / 6000: loss 1.4492035114383475
iteration 900 / 6000: loss 1.539087944583191
iteration 1000 / 6000: loss 1.5171220280124238
iteration 1100 / 6000: loss 1.4627193363712245
iteration 1200 / 6000: loss 1.4477505521330176
iteration 1300 / 6000: loss 1.447764015412449
iteration 1400 / 6000: loss 1.4758072304504524
iteration 1500 / 6000: loss 1.4798457346593645
iteration 1600 / 6000: loss 1.4782316735081764
iteration 1700 / 6000: loss 1.2768191143111087
iteration 1800 / 6000: loss 1.3666078374309203
iteration 1900 / 6000: loss 1.3253896674436156
iteration 2000 / 6000: loss 1.2664653914628123
iteration 2100 / 6000: loss 1.5482195832951884
iteration 2200 / 6000: loss 1.3824775029766827
iteration 2300 / 6000: loss 1.3073928698978514
iteration 2400 / 6000: loss 1.3598722034997857
iteration 2500 / 6000: loss 1.3358141709657865
iteration 2600 / 6000: loss 1.3852410401895743
iteration 2700 / 6000: loss 1.318688949273191
iteration 2800 / 6000: loss 1.2126419671181978
iteration 2900 / 6000: loss 1.3147983613189003
iteration 3000 / 6000: loss 1.4467148185156133
iteration 3100 / 6000: loss 1.266353099644433
iteration 3200 / 6000: loss 1.2949378635506428
iteration 3300 / 6000: loss 1.4232845460423398
iteration 3400 / 6000: loss 1.4118032734833303
iteration 3500 / 6000: loss 1.2636198708361313
iteration 3600 / 6000: loss 1.2497784054513508
iteration 3700 / 6000: loss 1.3293752985734295
iteration 3800 / 6000: loss 1.2768651372227982
iteration 3900 / 6000: loss 1.3048190870093974
iteration 4000 / 6000: loss 1.2838069300615127
iteration 4100 / 6000: loss 1.3858450343085562
iteration 4200 / 6000: loss 1.2041472834348543
iteration 4300 / 6000: loss 1.3360812125533137
iteration 4400 / 6000: loss 1.2518531298151794
iteration 4500 / 6000: loss 1.3050447983553255
iteration 4600 / 6000: loss 1.338364659252226
iteration 4700 / 6000: loss 1.3949491541618557
iteration 4800 / 6000: loss 1.348662163217858
iteration 4900 / 6000: loss 1.3289859340305277
iteration 5000 / 6000: loss 1.3183767059812155
iteration 5100 / 6000: loss 1.3434362914038196
iteration 5200 / 6000: loss 1.183282612926703
iteration 5300 / 6000: loss 1.3351485989775211

iteration 5400 / 6000: loss 1.339260275949583
iteration 5500 / 6000: loss 1.421995477196877
iteration 5600 / 6000: loss 1.3917825384468079
iteration 5700 / 6000: loss 1.2260269411811262
iteration 5800 / 6000: loss 1.2792045580344877
iteration 5900 / 6000: loss 1.3274046520061757
Validation accuracy:  0.508
Validation accuracy:  0.508
```

In [122]:

```
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)
```



Question:

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

Answer:

(1) In the best net, it is easier to recognize the specific shapes or feature, where the suboptimal net has much more noises.

Evaluate on test set

In [123]:

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

```
Test accuracy:  0.507
```

In [ ]:

```

```