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 [ ]:
```
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))))
```

Toy example

Before loading CIFAR-10, there will be a toy example to test your implementation of the forward and backward pass

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

In [ ]:
```
# 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 [ ]:
```
## Implement the forward pass of the neural network.

# 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:
3.381231222787662e-08
```

Forward pass loss

In [ ]:
```
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: [1.07169612]
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 [ ]:

```
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, gr
```

```
b2 max relative error: 1.8392106647421603e-10
W2 max relative error: 2.963226235079295e-10
b1 max relative error: 3.1726804786908923e-09
W1 max relative error: 1.2832908996874818e-09
```

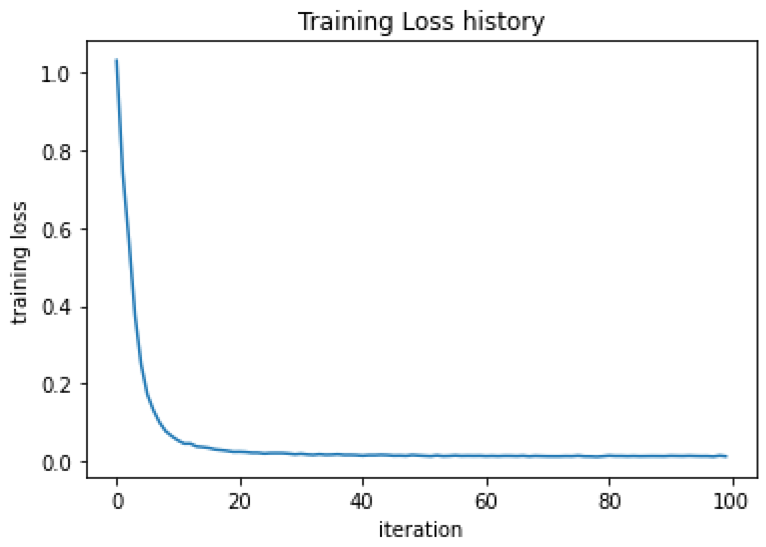
Training the network

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

In [ ]:

```
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:  [0.01291003]
```



Classify CIFAR-10

Do classification on the CIFAR-10 dataset.

In [ ]:

```
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 = '../../hw2/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,)
```

Running SGD

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

In [ ]:

```
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 [2.30276687]
iteration 100 / 1000: loss [2.30222487]
iteration 200 / 1000: loss [2.29620194]
iteration 300 / 1000: loss [2.24045376]
iteration 400 / 1000: loss [2.20925711]
iteration 500 / 1000: loss [2.15988971]
iteration 600 / 1000: loss [2.08085849]
iteration 700 / 1000: loss [2.00040059]
iteration 800 / 1000: loss [2.0523403]
iteration 900 / 1000: loss [1.88119796]
Validation accuracy:  0.278
```

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.

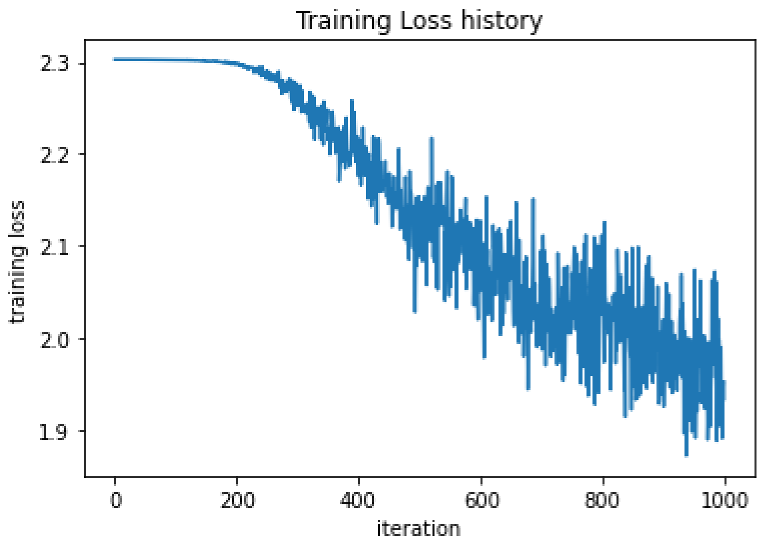
(2) How should you fix the problems you identified in (1)?

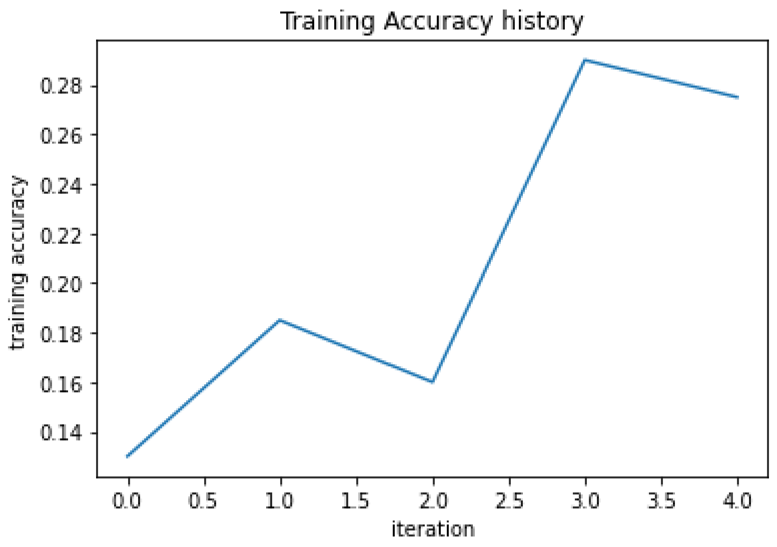
In [ ]:
```
stats['train_acc_history']
```

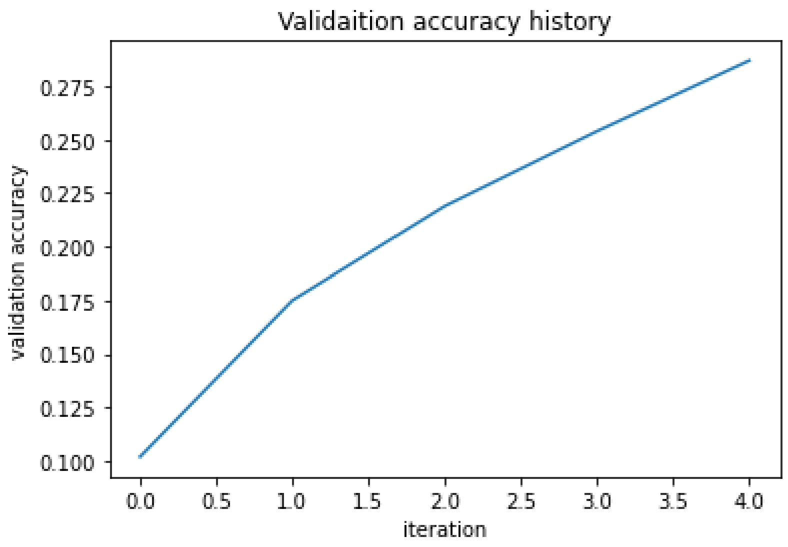
Out[ ]:
```
[0.11, 0.2, 0.165, 0.26, 0.28]
```

In [ ]:
```
# ================================================================ #
# 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

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)

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()
plt.plot(stats['train_acc_history'])
plt.xlabel('iteration')
plt.ylabel('training accuracy')
plt.title('Training Accuracy history')
plt.show()
plt.plot(stats['val_acc_history'])
plt.xlabel('iteration')
plt.ylabel('validation accuracy')
plt.title('Validaition accuracy history')
plt.show()
# ================================================================ #
# END YOUR CODE HERE
# ================================================================ #
```

```
iteration 0 / 1000: loss [2.30277461]
iteration 100 / 1000: loss [2.30229363]
iteration 200 / 1000: loss [2.29847379]
iteration 300 / 1000: loss [2.27079513]
iteration 400 / 1000: loss [2.17533288]
iteration 500 / 1000: loss [2.1323406]
iteration 600 / 1000: loss [2.0977588]
iteration 700 / 1000: loss [1.98762685]
iteration 800 / 1000: loss [2.0522562]
iteration 900 / 1000: loss [1.92541369]
Validation accuracy:  0.285
Final training loss:  [1.95240695]
```







Answers:

(1) The training is terminating premmaturely, we can note that the loss function. validation accuracy, and training accuracy have all yet to plateau when the training completes. In essence we need to train for longer and follow the curve of the loss function down further.

(2) We can solve the non-plateauing issue by simply training longer. The longer we perform gradient descent the further we will go down so we will increase the number of itterations. Additionally, we will increase the learning rate to ensure that we are taking larger steps in the direction of each gradient. Finally, since we will be training longer and want to ensure we reach a minimum of the loss function we will decrease the rate at which the learning rate decays. This will allow us to continually learn for longer, resutling in a lower minimum.

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.

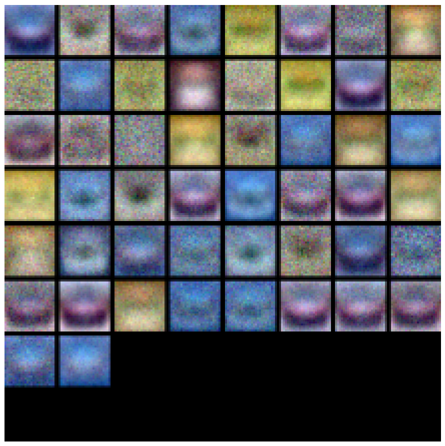
In [ ]:
```
best_net = None # store the best model into this

# ================================================================ #
# 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)!
# ================================================================ #
best_net = TwoLayerNet(input_size, hidden_size, num_classes)

# Train the network
```

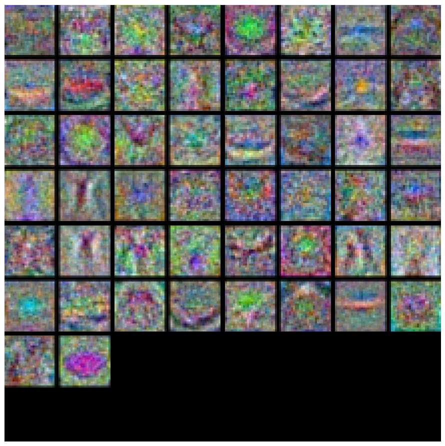
```
stats = best_net.train(X_train, y_train, X_val, y_val,
            num_iters=8000, batch_size=200,
            learning_rate=1e-3, learning_rate_decay=0.99,
            reg=0.25, verbose=False)

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

```
Validation accuracy:  0.532
```

In [ ]:

```
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) we can note that the subotpimal net weights look roughly dientical save for the general color. They contain round and vaugely static images indicative of the fact that the net has not finished training entirely. We can see that the best net has much sharper edges and distinct colors in each set of weights. This is indicative of the fact that it has fulled some information out of the image set to make the weights much more representative of the CIFAR10 data.

Evaluate on test set

In [ ]:

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

```
Test accuracy:  0.507
```