ECE C147 HW #3 Due: February 7, 2025

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# 1. Backpropagation for autoencoders

With an autoencoder, try to reconstruct the original data dimensions after some operation that reduces the data's dimensionality
E.g. Consider $x \in \mathbb{R}^n$ and $W \in \mathbb{R}^{m \times n}$ where $m < n$. Then $Wx$ is of lower dimensionality than $x$.

One way to design $W$ s.t. $Wx$ still contains key features of $x$ is to minimize $\mathcal{L}$ w.r.t. $W$

$$\mathcal{L} = \frac{1}{2}\|W^TWx - x\|^2$$
↑
Linear Example

$$\mathcal{L} = \frac{1}{2}\|f(W^Tf(Wx)) - x\|^2$$
↑
Nonlinear Example

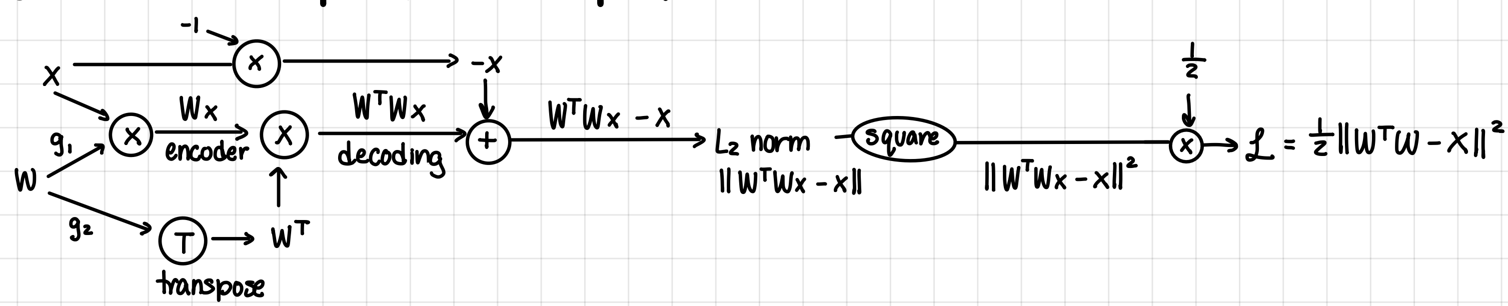
$(n \times m)(m \times n)$
$\hookrightarrow W^TWx \in \mathbb{R}^n$
$(n \times 1)$

Use the linear example for the following:

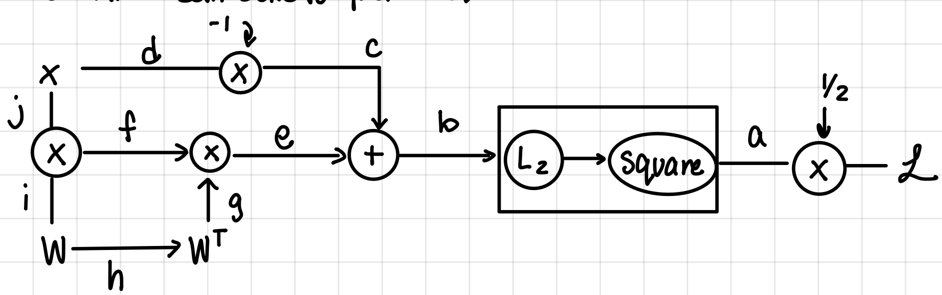
## (a) Why does the minimization find a W that ought to preserve info about x

In this minimization of $\mathcal{L} = \frac{1}{2}\|W^TWx - x\|^2$, we ensure that we find a matrix $W$ that will preserve the features of $X$ because $Wx$ will reduce the dimensions of $x$ to $m$, but $W^T$ will attempt to reconstruct $x$ from the compressed representation. In other words $Wx$ will result in an $n \times 1$ vector from a $(m \times n)(n \times 1)$ multiplication, whereas $W^TWx$ will result in an $n \times 1$ vector from a $(n \times m)(m \times n)(n \times 1)$ multiplication. If $W$ were to be poorly chosen, important information would be lost and have a high reconstruction error. Minimizing $\mathcal{L}$ forces $W$ to learn an optimal low-dimensional representation where it preserves key features (similar to PCA analysis)

## (b) Draw the computational Graph for $\mathcal{L}$




Setup so that I can solve for part (d)




## (c) In the computational graph, there should be 2 paths to W. How do we account for these two paths when calculating $\nabla_W \mathcal{L}$? Should include mathematical argument.

In the computational graph, the matrix $W$ appears when $W$ maps $x$ to a lower dimension $(Wx)$ and when we reconstruct $(W \xrightarrow{T} W^T \rightarrow W^TWx)$. Both will ultimately converge at $W^TWx$.
Mathematically, we defined $g_1$ to be the path that $W$ takes to become $Wx$ and $g_2$ to be the path that $W$ takes to get to $W \xrightarrow{T} W^T \rightarrow W^TWx$

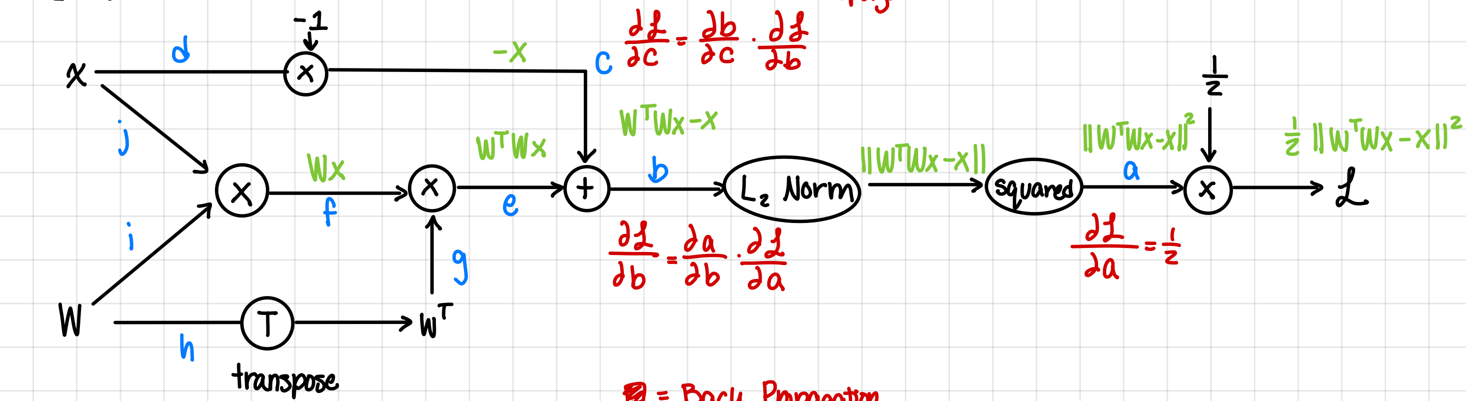
$$\frac{\partial \mathcal{L}}{\partial W} = \frac{\partial g_1}{\partial W} \cdot \frac{\partial \mathcal{L}}{\partial g_1} + \frac{\partial g_2}{\partial W} \cdot \frac{\partial \mathcal{L}}{\partial g_2}$$

## (d) Calculate the gradient $\nabla_W \mathcal{L}$

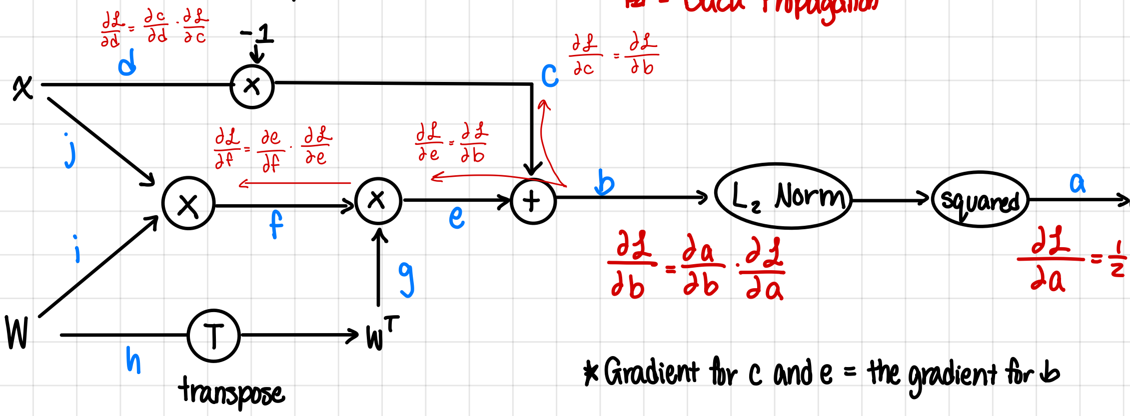
$\mathcal{L} = \frac{1}{2}\|W^TWx - x\|^2$

= Forward Propagation

= Back Propagation



= Back Propagation



**NOTE** (from Lecture 6)

$$\frac{\partial \mathcal{L}}{\partial x} = \underset{\text{local}}{\frac{\partial f}{\partial x}} \; \underset{\text{upstream}}{\frac{\partial \mathcal{L}}{\partial f}}$$

local gradient   upstream gradient

value comes from forward propagation

$$\frac{\partial \mathcal{L}}{\partial a} = \frac{1}{2} \qquad \frac{\partial \mathcal{L}}{\partial b} = \frac{\partial a}{\partial b} \cdot \frac{\partial \mathcal{L}}{\partial a} = 2b \cdot \frac{1}{2} = b = W^TWx - x$$

$\left(a = b^Tb \quad \therefore \frac{\partial a}{\partial b} = 2b\right)$

$$\frac{\partial \mathcal{L}}{\partial c} = \frac{\partial \mathcal{L}}{\partial b} = b = W^TWx - x \quad \text{and} \quad \frac{\partial \mathcal{L}}{\partial e} = \frac{\partial \mathcal{L}}{\partial b} = b = W^TWx - x$$

NOTE: $\frac{\partial \mathcal{L}}{\partial c}$ and $\frac{\partial \mathcal{L}}{\partial e}$ come from $\oplus$ $\therefore$ distributed gradient

$$\frac{\partial \mathcal{L}}{\partial d} = \frac{\partial c}{\partial d} \cdot \frac{\partial \mathcal{L}}{\partial c} = -1 \cdot b = -b = -(W^TWx - x)$$

$$\frac{\partial \mathcal{L}}{\partial f} = \frac{\partial e}{\partial f} \cdot \frac{\partial \mathcal{L}}{\partial e} = \frac{\partial e}{\partial f} \cdot b = \frac{\partial W^TWx}{\partial Wx} \cdot b = (W^T)^T b = Wb = W(W^TWx - x)$$

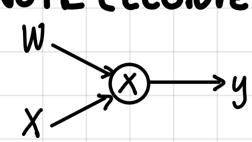
$$\frac{\partial \mathcal{L}}{\partial g} = \frac{\partial e}{\partial g} \times \frac{\partial \mathcal{L}}{\partial e} = b \cdot (Wx)^T = bx^TW^T = (W^TWx - x)x^TW^T$$

Uses the trick in class

$$\frac{\partial \mathcal{L}}{\partial h} = \left(\frac{\partial \mathcal{L}}{\partial g}\right)^T = (bx^TW^T)^T = Wxb^T = Wx(W^TWx - x)^T$$

$$\frac{\partial \mathcal{L}}{\partial i} = \frac{\partial f}{\partial i} \cdot \frac{\partial \mathcal{L}}{\partial f} = Wbx^T$$

**NOTE (Lecture 7)**



$$\frac{\partial \mathcal{L}}{\partial x} = W^T \frac{\partial \mathcal{L}}{\partial y}$$

$$\frac{\partial \mathcal{L}}{\partial W} = \frac{\partial \mathcal{L}}{\partial y} x^T$$

$b = W^TWx - x$

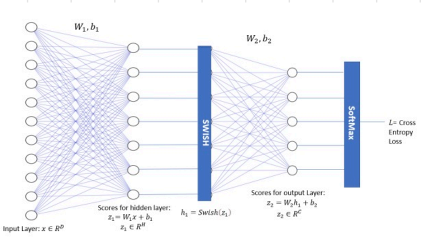
$$\frac{\partial \mathcal{L}}{\partial W} = \frac{\partial \mathcal{L}}{\partial h} + \frac{\partial \mathcal{L}}{\partial i} = Wxb^T + Wbx^T = Wx(W^TWx - x) + W(W^TWx - x)x^T$$

**Problem #2 :** I am a C147 Student

## Problem #3: NNDL

D = # of neurons in input layer, H = # of neurons in the hidden layer, C = # of neurons in the oupt ($C=7$)

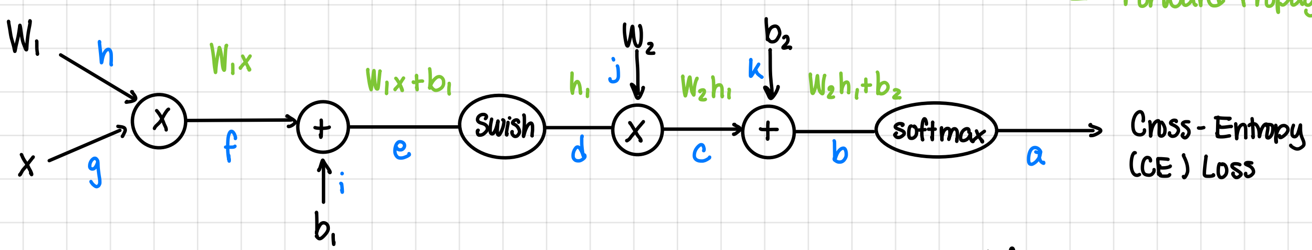
Swish activation function $\text{swish}(k) = \dfrac{k}{1+e^{-k}} = k\sigma(k)$ where $\sigma(k)$ is sigmoid activation function




Hidden Layer: $z_1 = W_1x + b_1$, $z_1 \in R^H$ $\qquad h_1 = \text{Swish}(z_1)$ $\qquad z_2 = W_2h_1 + b_2$, $z_2 \in R^C$

### (a) Draw the computational graph for the 2-layer FC Net

= Forward Propagation




### (b) Compute $\nabla_W \mathcal{L}$ $\nabla_{b_2}\mathcal{L}$ (For the gradient computations you can keep it as $\frac{\partial \mathcal{L}}{\partial z_2}$)

Cross-entropy Loss $= \mathcal{L} = -\sum y_i \log \hat{y}_i$
where $\hat{y}_i$ is the predicted value

$$\hat{y}_i = \frac{e^{z_{2,i}}}{\sum_j e^{z_{2,j}}} \quad \therefore \mathcal{L} = -\sum y_i \log\left(\frac{e^{z_{2,i}}}{\sum_j e^{z_{2,j}}}\right) = -\sum y_i (z_{2,i} - z_{2,j})$$

$$\frac{\partial \mathcal{L}}{\partial z_{2,i}} = \frac{\partial}{\partial z_{2,i}}\left(-\sum y_i (z_{2,i} - z_{2,j})\right) = \hat{y}_i - y_i$$

$$\boxed{\therefore \frac{\partial \mathcal{L}}{\partial z_2} = \hat{y} - y}$$

$$\frac{\partial \mathcal{L}}{\partial W_2} = \frac{\partial \mathcal{L}}{\partial z_2} \cdot \frac{\partial z_2}{\partial W_2}$$ we know that $\frac{\partial \mathcal{L}}{\partial z_2} = \hat{y} - y$ and $\frac{\partial z_2}{\partial W_2} = \frac{\partial W_2h_1 + b_2}{\partial W_2} = h_1^T$

$\hookrightarrow \nabla_{W_2}\mathcal{L} = (\hat{y} - y)h_1^T$

$$\nabla_{b_2}\mathcal{L} = \frac{\partial \mathcal{L}}{\partial b_2} = \frac{\partial \mathcal{L}}{\partial z_2} = (\hat{y} - y)$$

$$\boxed{\begin{array}{l}\text{Results} \\ \nabla_{W_2}\mathcal{L} = (\hat{y} - y)h_1^T \\ \nabla_{b_2}\mathcal{L} = (\hat{y} - y)\end{array}}$$

y comes from the Jacobian

$$J = \frac{\partial y}{\partial x} = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} & \cdots & \frac{\partial y_1}{\partial x_m} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} & \cdots & \frac{\partial y_2}{\partial x_m} \\ \vdots & & & \\ \frac{\partial y_n}{\partial x_1} & \frac{\partial y_n}{\partial x_2} & \cdots & \frac{\partial y_n}{\partial x_m} \end{bmatrix}$$

## (c) Compute $\nabla_{W_1}\mathcal{L}$, $\nabla_{b_1}\mathcal{L}$

Calculating $\nabla W_1 \mathcal{L}$ requires $\frac{\partial}{\partial z_1}$

$h_1 = \text{Swish}(z_1) \rightarrow \text{Swish}(x) = x\sigma(x)$ and $\sigma(x) = \frac{1}{1+e^{-z}}$

$$\frac{\partial\, \text{Swish}(x)}{\partial x} = \sigma(x) + x\sigma(x)(1-\sigma(x))$$

Replacing $x$ with $z_1$ we then have $\sigma(z_1) + z_1\sigma(z_1)(1-\sigma(z_1))$

$$\frac{\partial \mathcal{L}}{\partial z_1} = \frac{\partial \mathcal{L}}{\partial h_1} \cdot \frac{\partial h_1}{\partial z_1} = (W_2^T(\hat{y}-y)) \odot \frac{\partial h_1}{\partial z_1} = ((W_2^T(\hat{y}-y)) \odot [\sigma(z_1) + z_1\sigma(z_1)(1-\sigma(z_1))])$$

we use $\frac{\partial \mathcal{L}}{\partial z_1}$ to find $\frac{\partial \mathcal{L}}{\partial W_1}$ and $\frac{\partial \mathcal{L}}{\partial b_1}$

$$\nabla_{W_1}\mathcal{L} = \frac{\partial \mathcal{L}}{\partial z_1} \cdot \frac{\partial z_1}{\partial W_1} = (\nabla_{z_1}\mathcal{L})(x^T) = [(W_2^T(\hat{y}-y)) \odot (\sigma(z_1) + z_1\sigma(z_1)(1-\sigma(z_1)))]$$

Comes from the trick in class $\frac{\partial z_1}{\partial W_1} = \frac{\partial W_1 x + b_1}{\partial W_1} = x^T$

$$\nabla_{b_1}\mathcal{L} = \nabla_{z_1}\mathcal{L} = (W_2^T(\hat{y}-y)) \odot ($$

# FC_nets

February 7, 2025

## 1 Fully connected networks

In the previous notebook, you implemented a simple two-layer neural network class. However, this class is not modular. If you wanted to change the number of layers, you would need to write a new loss and gradient function. If you wanted to optimize the network with different optimizers, you'd need to write new training functions. If you wanted to incorporate regularizations, you'd have to modify the loss and gradient function.

Instead of having to modify functions each time, for the rest of the class, we'll work in a more modular framework where we define forward and backward layers that calculate losses and gradients respectively. Since the forward and backward layers share intermediate values that are useful for calculating both the loss and the gradient, we'll also have these function return "caches" which store useful intermediate values.

The goal is that through this modular design, we can build different sized neural networks for various applications.

In this HW #3, we'll define the basic architecture, and in HW #4, we'll build on this framework to implement different optimizers and regularizations (like BatchNorm and Dropout).

### 1.1 Modular layers

This notebook will build modular layers in the following manner. First, there will be a forward pass for a given layer with inputs (`x`) and return the output of that layer (`out`) as well as cached variables (`cache`) that will be used to calculate the gradient in the backward pass.

```python
def layer_forward(x, w):
  """ Receive inputs x and weights w """
  # Do some computations ...
  z = # ... some intermediate value
  # Do some more computations ...
  out = # the output

  cache = (x, w, z, out) # Values we need to compute gradients

  return out, cache
```

The backward pass will receive upstream derivatives and the `cache` object, and will return gradients with respect to the inputs and weights, like this:

```
def layer_backward(dout, cache):
  """
  Receive derivative of loss with respect to outputs and cache,
  and compute derivative with respect to inputs.
  """
  # Unpack cache values
  x, w, z, out = cache

  # Use values in cache to compute derivatives
  dx = # Derivative of loss with respect to x
  dw = # Derivative of loss with respect to w

  return dx, dw
```

[68]:
```
## Import and setups

import time
import numpy as np
import matplotlib.pyplot as plt
from nndl.fc_net import *
from utils.data_utils import get_CIFAR10_data
from utils.gradient_check import eval_numerical_gradient,␣
  ↪eval_numerical_gradient_array
from utils.solver import Solver

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

[70]:
```
# Load the (preprocessed) CIFAR10 data.
data = get_CIFAR10_data()
for k in data.keys():
  print('{}: {} '.format(k, data[k].shape))
```

```
X_train: (49000, 3, 32, 32)
y_train: (49000,)
X_val: (1000, 3, 32, 32)
y_val: (1000,)
X_test: (1000, 3, 32, 32)
y_test: (1000,)
```

## 1.2 Linear layers

In this section, we'll implement the forward and backward pass for the linear layers.

The linear layer forward pass is the function `affine_forward` in `nndl/layers.py` and the backward pass is `affine_backward`.

After you have implemented these, test your implementation by running the cell below.

### 1.2.1 Affine layer forward pass

Implement `affine_forward` and then test your code by running the following cell.

[74]:
```
# Test the affine_forward function

num_inputs = 2
input_shape = (4, 5, 6)
output_dim = 3

input_size = num_inputs * np.prod(input_shape)
weight_size = output_dim * np.prod(input_shape)

x = np.linspace(-0.1, 0.5, num=input_size).reshape(num_inputs, *input_shape)
w = np.linspace(-0.2, 0.3, num=weight_size).reshape(np.prod(input_shape),␣
 ↪output_dim)
b = np.linspace(-0.3, 0.1, num=output_dim)

out, _ = affine_forward(x, w, b)
correct_out = np.array([[ 1.49834967,  1.70660132,  1.91485297],
                        [ 3.25553199,  3.5141327,   3.77273342]])

# Compare your output with ours. The error should be around 1e-9.
print('Testing affine_forward function:')
print('difference: {}'.format(rel_error(out, correct_out)))
```

```
Testing affine_forward function:
difference: 9.769849468192957e-10
```

### 1.2.2 Affine layer backward pass

Implement `affine_backward` and then test your code by running the following cell.

```
[77]: # Test the affine_backward function

x = np.random.randn(10, 2, 3)
w = np.random.randn(6, 5)
b = np.random.randn(5)
dout = np.random.randn(10, 5)

dx_num = eval_numerical_gradient_array(lambda x: affine_forward(x, w, b)[0], x,␣
 ↪dout)
dw_num = eval_numerical_gradient_array(lambda w: affine_forward(x, w, b)[0], w,␣
 ↪dout)
db_num = eval_numerical_gradient_array(lambda b: affine_forward(x, w, b)[0], b,␣
 ↪dout)

_, cache = affine_forward(x, w, b)
dx, dw, db = affine_backward(dout, cache)

# The error should be around 1e-10
print('Testing affine_backward function:')
print('dx error: {}'.format(rel_error(dx_num, dx)))
print('dw error: {}'.format(rel_error(dw_num, dw)))
print('db error: {}'.format(rel_error(db_num, db)))
```

```
Testing affine_backward function:
dx error: 1.424893804389996e-10
dw error: 1.1386048038309619e-10
db error: 7.424528816585132e-12
```

### 1.3 Activation layers

In this section you'll implement the ReLU activation.

#### 1.3.1 ReLU forward pass

Implement the `relu_forward` function in `nndl/layers.py` and then test your code by running the following cell.

```
[81]: # Test the relu_forward function

x = np.linspace(-0.5, 0.5, num=12).reshape(3, 4)

out, _ = relu_forward(x)
correct_out = np.array([[ 0.,          0.,          0.,          0.,         ],
                        [ 0.,          0.,          0.04545455,  0.13636364,],
                        [ 0.22727273,  0.31818182,  0.40909091,  0.5,        ]])

# Compare your output with ours. The error should be around 1e-8
print('Testing relu_forward function:')
```

```
print('difference: {}'.format(rel_error(out, correct_out)))
```

```
Testing relu_forward function:
difference: 4.999999798022158e-08
```

### 1.3.2 ReLU backward pass

Implement the `relu_backward` function in `nndl/layers.py` and then test your code by running the following cell.

[84]:
```
x = np.random.randn(10, 10)
dout = np.random.randn(*x.shape)

dx_num = eval_numerical_gradient_array(lambda x: relu_forward(x)[0], x, dout)

_, cache = relu_forward(x)
dx = relu_backward(dout, cache)

# The error should be around 1e-12
print('Testing relu_backward function:')
print('dx error: {}'.format(rel_error(dx_num, dx)))
```

```
Testing relu_backward function:
dx error: 3.2755955085708066e-12
```

## 1.4 Combining the affine and ReLU layers

Often times, an affine layer will be followed by a ReLU layer. So let's make one that puts them together. Layers that are combined are stored in `nndl/layer_utils.py`.

### 1.4.1 Affine-ReLU layers

We've implemented `affine_relu_forward()` and `affine_relu_backward` in `nndl/layer_utils.py`. Take a look at them to make sure you understand what's going on. Then run the following cell to ensure its implemented correctly.

[88]:
```
from nndl.layer_utils import affine_relu_forward, affine_relu_backward

x = np.random.randn(2, 3, 4)
w = np.random.randn(12, 10)
b = np.random.randn(10)
dout = np.random.randn(2, 10)

out, cache = affine_relu_forward(x, w, b)
dx, dw, db = affine_relu_backward(dout, cache)

dx_num = eval_numerical_gradient_array(lambda x: affine_relu_forward(x, w,␣
↪b)[0], x, dout)
```

```
dw_num = eval_numerical_gradient_array(lambda w: affine_relu_forward(x, w,␣
 ↪b)[0], w, dout)
db_num = eval_numerical_gradient_array(lambda b: affine_relu_forward(x, w,␣
 ↪b)[0], b, dout)

print('Testing affine_relu_forward and affine_relu_backward:')
print('dx error: {}'.format(rel_error(dx_num, dx)))
print('dw error: {}'.format(rel_error(dw_num, dw)))
print('db error: {}'.format(rel_error(db_num, db)))
```

```
Testing affine_relu_forward and affine_relu_backward:
dx error: 1.8282623818763632e-09
dw error: 4.1036291520909366e-10
db error: 8.510001445186667e-12
```

### 1.5 Softmax loss

You've already implemented it, so we have written it in `layers.py`. The following code will ensure they are working correctly.

[91]:
```
num_classes, num_inputs = 10, 50
x = 0.001 * np.random.randn(num_inputs, num_classes)
y = np.random.randint(num_classes, size=num_inputs)



dx_num = eval_numerical_gradient(lambda x: softmax_loss(x, y)[0], x,␣
 ↪verbose=False)
loss, dx = softmax_loss(x, y)

# Test softmax_loss function. Loss should be 2.3 and dx error should be 1e-8
print('\nTesting softmax_loss:')
print('loss: {}'.format(loss))
print('dx error: {}'.format(rel_error(dx_num, dx)))
```

```
Testing softmax_loss:
loss: 2.3026202296978404
dx error: 7.77367130496592e-09
```

### 1.6 Implementation of a two-layer NN

In `nndl/fc_net.py`, implement the class `TwoLayerNet` which uses the layers you made here. When you have finished, the following cell will test your implementation.

[106]:
```
N, D, H, C = 3, 5, 50, 7
X = np.random.randn(N, D)
y = np.random.randint(C, size=N)
```

```
std = 1e-2
model = TwoLayerNet(input_dim=D, hidden_dims=H, num_classes=C, weight_scale=std)

print('Testing initialization ... ')
W1_std = abs(model.params['W1'].std() - std)
b1 = model.params['b1']
W2_std = abs(model.params['W2'].std() - std)
b2 = model.params['b2']
assert W1_std < std / 10, 'First layer weights do not seem right'
assert np.all(b1 == 0), 'First layer biases do not seem right'
assert W2_std < std / 10, 'Second layer weights do not seem right'
assert np.all(b2 == 0), 'Second layer biases do not seem right'

print('Testing test-time forward pass ... ')
model.params['W1'] = np.linspace(-0.7, 0.3, num=D*H).reshape(D, H)
model.params['b1'] = np.linspace(-0.1, 0.9, num=H)
model.params['W2'] = np.linspace(-0.3, 0.4, num=H*C).reshape(H, C)
model.params['b2'] = np.linspace(-0.9, 0.1, num=C)
X = np.linspace(-5.5, 4.5, num=N*D).reshape(D, N).T
scores = model.loss(X)
correct_scores = np.asarray(
  [[11.53165108,  12.2917344,   13.05181771,  13.81190102,  14.57198434, 15.
↪33206765,  16.09215096],
   [12.05769098,  12.74614105,  13.43459113,  14.1230412,   14.81149128, 15.
↪49994135,  16.18839143],
   [12.58373087,  13.20054771,  13.81736455,  14.43418138,  15.05099822, 15.
↪66781506,  16.2846319 ]])
scores_diff = np.abs(scores - correct_scores).sum()
assert scores_diff < 1e-6, 'Problem with test-time forward pass'

print('Testing training loss (no regularization)')
y = np.asarray([0, 5, 1])
loss, grads = model.loss(X, y)
correct_loss = 3.4702243556
assert abs(loss - correct_loss) < 1e-10, 'Problem with training-time loss'

model.reg = 1.0
loss, grads = model.loss(X, y)
correct_loss = 26.5948426952
assert abs(loss - correct_loss) < 1e-10, 'Problem with regularization loss'

for reg in [0.0, 0.7]:
  print('Running numeric gradient check with reg = {}'.format(reg))
  model.reg = reg
  loss, grads = model.loss(X, y)

  for name in sorted(grads):
```

```
    f = lambda _: model.loss(X, y)[0]
    grad_num = eval_numerical_gradient(f, model.params[name], verbose=False)
    print('{} relative error: {}'.format(name, rel_error(grad_num,␣
↪grads[name])))
```

```
Testing initialization …
Testing test-time forward pass …
Testing training loss (no regularization)
Running numeric gradient check with reg = 0.0
W1 relative error: 1.5215703686475096e-08
W2 relative error: 3.2068321167375225e-10
b1 relative error: 8.368195737354163e-09
b2 relative error: 4.3291360264321544e-10
Running numeric gradient check with reg = 0.7
W1 relative error: 2.527915175868136e-07
W2 relative error: 2.8508510893102143e-08
b1 relative error: 1.5646801536371197e-08
b2 relative error: 7.759095355706557e-10
```

### 1.7 Solver

We will now use the utils Solver class to train these networks. Familiarize yourself with the API in `utils/solver.py`. After you have done so, declare an instance of a TwoLayerNet with 200 units and then train it with the Solver. Choose parameters so that your validation accuracy is at least 50%.

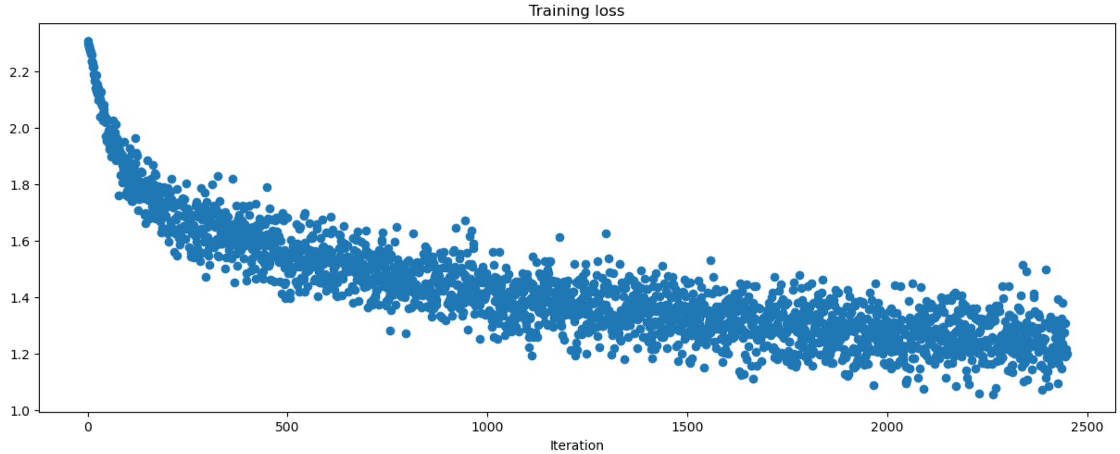
[111]:
```
model = TwoLayerNet()
solver = None

# ================================================================ #
# YOUR CODE HERE:
#   Declare an instance of a TwoLayerNet and then train
#   it with the Solver. Choose hyperparameters so that your validation
#   accuracy is at least 50%.  We won't have you optimize this further
#   since you did it in the previous notebook.
#
# ================================================================ #
model = TwoLayerNet(hidden_dims=200)
solver = Solver(model=model, data=data, optim_config={'learning_rate': 0.0006},␣
↪lr_decay=0.9, num_train_samples=2000, num_epochs=10, batch_size=200,␣
↪print_every=50)
solver.train()
#pass

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

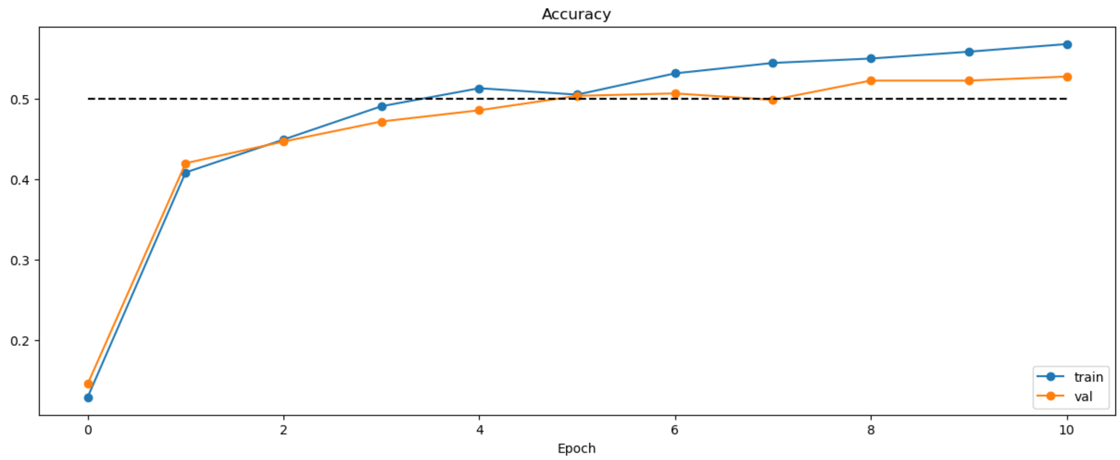
```
(Iteration 1 / 2450) loss: 2.307988
(Epoch 0 / 10) train acc: 0.128500; val_acc: 0.145000
(Iteration 51 / 2450) loss: 1.963220
(Iteration 101 / 2450) loss: 1.756631
(Iteration 151 / 2450) loss: 1.758821
(Iteration 201 / 2450) loss: 1.784621
(Epoch 1 / 10) train acc: 0.408500; val_acc: 0.420000
(Iteration 251 / 2450) loss: 1.692802
(Iteration 301 / 2450) loss: 1.613648
(Iteration 351 / 2450) loss: 1.598459
(Iteration 401 / 2450) loss: 1.598192
(Iteration 451 / 2450) loss: 1.543787
(Epoch 2 / 10) train acc: 0.449500; val_acc: 0.447000
(Iteration 501 / 2450) loss: 1.520708
(Iteration 551 / 2450) loss: 1.438806
(Iteration 601 / 2450) loss: 1.553388
(Iteration 651 / 2450) loss: 1.583617
(Iteration 701 / 2450) loss: 1.460940
(Epoch 3 / 10) train acc: 0.491000; val_acc: 0.472000
(Iteration 751 / 2450) loss: 1.462377
(Iteration 801 / 2450) loss: 1.491363
(Iteration 851 / 2450) loss: 1.551765
(Iteration 901 / 2450) loss: 1.526710
(Iteration 951 / 2450) loss: 1.423289
(Epoch 4 / 10) train acc: 0.513500; val_acc: 0.486000
(Iteration 1001 / 2450) loss: 1.344471
(Iteration 1051 / 2450) loss: 1.401189
(Iteration 1101 / 2450) loss: 1.319237
(Iteration 1151 / 2450) loss: 1.496187
(Iteration 1201 / 2450) loss: 1.458774
(Epoch 5 / 10) train acc: 0.505500; val_acc: 0.504000
(Iteration 1251 / 2450) loss: 1.405884
(Iteration 1301 / 2450) loss: 1.346808
(Iteration 1351 / 2450) loss: 1.459415
(Iteration 1401 / 2450) loss: 1.430178
(Iteration 1451 / 2450) loss: 1.332986
(Epoch 6 / 10) train acc: 0.532000; val_acc: 0.507000
(Iteration 1501 / 2450) loss: 1.351100
(Iteration 1551 / 2450) loss: 1.270266
(Iteration 1601 / 2450) loss: 1.242917
(Iteration 1651 / 2450) loss: 1.327454
(Iteration 1701 / 2450) loss: 1.227854
(Epoch 7 / 10) train acc: 0.545000; val_acc: 0.499000
(Iteration 1751 / 2450) loss: 1.380364
(Iteration 1801 / 2450) loss: 1.268760
(Iteration 1851 / 2450) loss: 1.241902
(Iteration 1901 / 2450) loss: 1.120208
(Iteration 1951 / 2450) loss: 1.243283
```

```
(Epoch 8 / 10) train acc: 0.550500; val_acc: 0.523000
(Iteration 2001 / 2450) loss: 1.315541
(Iteration 2051 / 2450) loss: 1.108118
(Iteration 2101 / 2450) loss: 1.258076
(Iteration 2151 / 2450) loss: 1.390028
(Iteration 2201 / 2450) loss: 1.112451
(Epoch 9 / 10) train acc: 0.559000; val_acc: 0.523000
(Iteration 2251 / 2450) loss: 1.164035
(Iteration 2301 / 2450) loss: 1.252618
(Iteration 2351 / 2450) loss: 1.239053
(Iteration 2401 / 2450) loss: 1.137981
(Epoch 10 / 10) train acc: 0.568500; val_acc: 0.528000
```

[117]:

```
# Run this cell to visualize training loss and train / val accuracy

plt.subplot(2, 1, 1)
plt.title('Training loss')
plt.plot(solver.loss_history, 'o')
plt.xlabel('Iteration')

plt.subplot(2, 1, 2)
plt.title('Accuracy')
plt.plot(solver.train_acc_history, '-o', label='train')
plt.plot(solver.val_acc_history, '-o', label='val')
plt.plot([0.5] * len(solver.val_acc_history), 'k--')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.gcf().set_size_inches(15, 12)
plt.show()
```




### 1.8 Multilayer Neural Network

Now, we implement a multi-layer neural network.

Read through the `FullyConnectedNet` class in the file `nndl/fc_net.py`.

Implement the initialization, the forward pass, and the backward pass. There will be lines for batchnorm and dropout layers and caches; ignore these all for now. That'll be in HW #4.

[126]:
```
N, D, H1, H2, C = 2, 15, 20, 30, 10
X = np.random.randn(N, D)
y = np.random.randint(C, size=(N,))

for reg in [0, 3.14]:
  print('Running check with reg = {}'.format(reg))
  model = FullyConnectedNet([H1, H2], input_dim=D, num_classes=C,
                            reg=reg, weight_scale=5e-2, dtype=np.float64)

  loss, grads = model.loss(X, y)
```

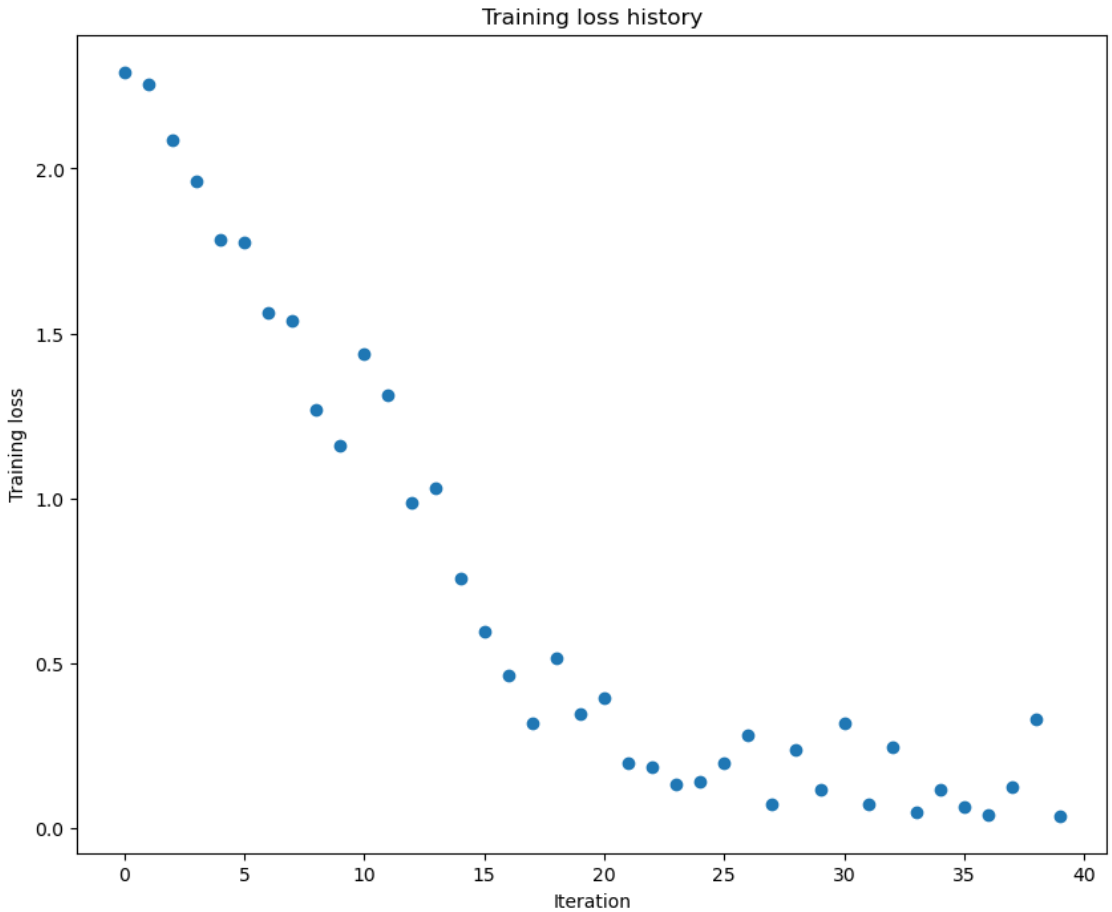
```
print('Initial loss: {}'.format(loss))

for name in sorted(grads):
  f = lambda _: model.loss(X, y)[0]
  grad_num = eval_numerical_gradient(f, model.params[name], verbose=False,␣
↪h=1e-5)
  print('{} relative error: {}'.format(name, rel_error(grad_num,␣
↪grads[name])))
```

```
Running check with reg = 0
Initial loss: 2.299425955043663
W1 relative error: 1.3577863837911974e-06
W2 relative error: 1.2146592058533085e-06
W3 relative error: 1.3673364730356494e-06
b1 relative error: 1.5337500377675094e-08
b2 relative error: 9.764463194145721e-09
b3 relative error: 1.0108006798128004e-10
Running check with reg = 3.14
Initial loss: 6.781308859501199
W1 relative error: 1.2083941274468973e-08
W2 relative error: 7.468613971578291e-08
W3 relative error: 3.1781544144866304e-08
b1 relative error: 8.983789632418418e-09
b2 relative error: 4.755596705575857e-08
b3 relative error: 1.7776365615124096e-10
```

[141]:
```
# Use the three layer neural network to overfit a small dataset.

num_train = 50
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}


#### !!!!!!
# Play around with the weight_scale and learning_rate so that you can overfit a␣
↪small dataset.
# Your training accuracy should be 1.0 to receive full credit on this part.
weight_scale = 1e-2
learning_rate = 1e-2

model = FullyConnectedNet([100, 100],
              weight_scale=weight_scale, dtype=np.float64)
solver = Solver(model, small_data,
```

```
                print_every=10, num_epochs=20, batch_size=25,
                update_rule='sgd',
                optim_config={
                  'learning_rate': learning_rate,
                }
         )
solver.train()

plt.plot(solver.loss_history, 'o')
plt.title('Training loss history')
plt.xlabel('Iteration')
plt.ylabel('Training loss')
plt.show()
```

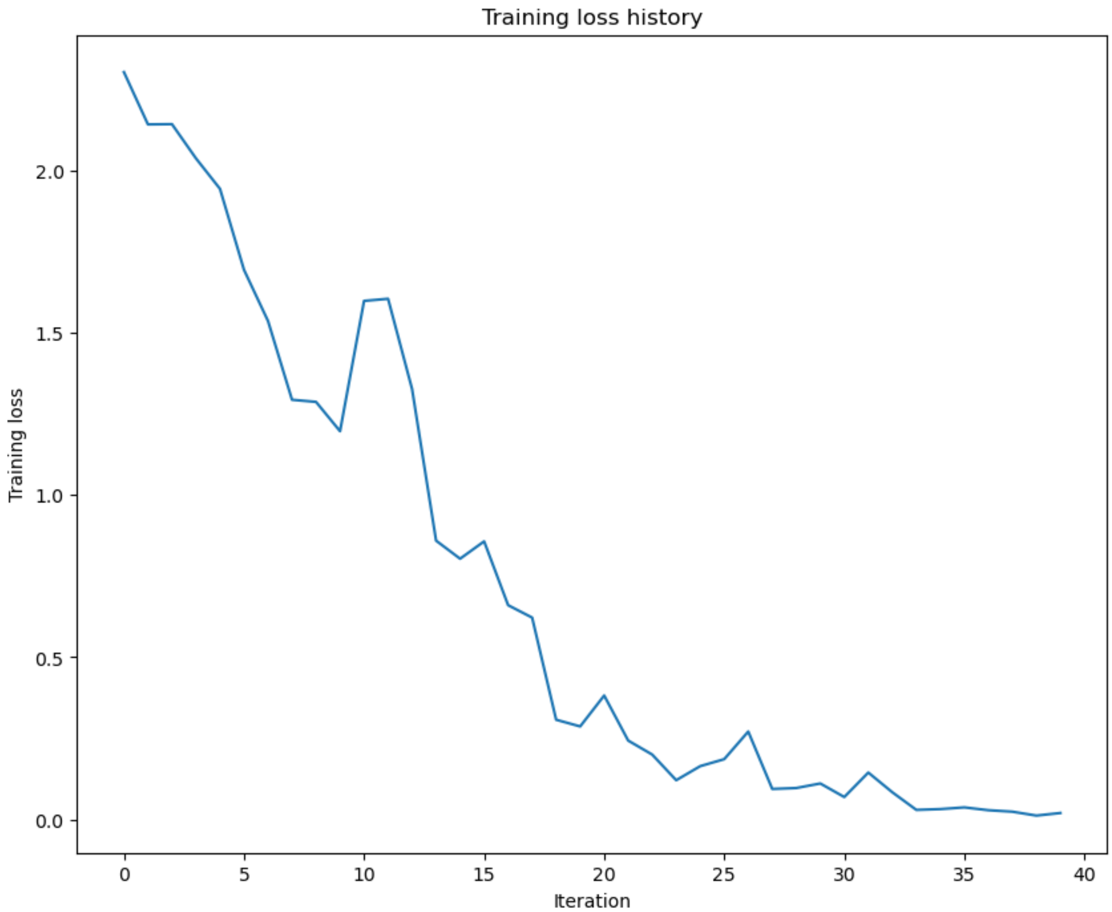
```
(Iteration 1 / 40) loss: 2.292848
(Epoch 0 / 20) train acc: 0.340000; val_acc: 0.123000
(Epoch 1 / 20) train acc: 0.360000; val_acc: 0.143000
(Epoch 2 / 20) train acc: 0.500000; val_acc: 0.157000
(Epoch 3 / 20) train acc: 0.440000; val_acc: 0.129000
(Epoch 4 / 20) train acc: 0.640000; val_acc: 0.139000
(Epoch 5 / 20) train acc: 0.560000; val_acc: 0.133000
(Iteration 11 / 40) loss: 1.437048
(Epoch 6 / 20) train acc: 0.560000; val_acc: 0.122000
(Epoch 7 / 20) train acc: 0.840000; val_acc: 0.190000
(Epoch 8 / 20) train acc: 0.880000; val_acc: 0.191000
(Epoch 9 / 20) train acc: 0.880000; val_acc: 0.167000
(Epoch 10 / 20) train acc: 0.940000; val_acc: 0.178000
(Iteration 21 / 40) loss: 0.392923
(Epoch 11 / 20) train acc: 0.980000; val_acc: 0.173000
(Epoch 12 / 20) train acc: 0.880000; val_acc: 0.158000
(Epoch 13 / 20) train acc: 0.980000; val_acc: 0.185000
(Epoch 14 / 20) train acc: 0.980000; val_acc: 0.174000
(Epoch 15 / 20) train acc: 0.960000; val_acc: 0.175000
(Iteration 31 / 40) loss: 0.318420
(Epoch 16 / 20) train acc: 0.980000; val_acc: 0.173000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.175000
(Epoch 18 / 20) train acc: 0.980000; val_acc: 0.165000
(Epoch 19 / 20) train acc: 0.960000; val_acc: 0.167000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.169000
```




[139]:
```
# Use the three layer neural network to overfit a small dataset.

num_train = 50
small_data = {
  'X_train': data['X_train'][:num_train],
  'y_train': data['y_train'][:num_train],
  'X_val': data['X_val'],
  'y_val': data['y_val'],
}


#### !!!!!!
# Play around with the weight_scale and learning_rate so that you can overfit a␣
↪small dataset.
# Your training accuracy should be 1.0 to receive full credit on this part.
weight_scale = 1e-2
learning_rate = 1e-2
```

```python
model = FullyConnectedNet([100, 100],
              weight_scale=weight_scale, dtype=np.float64)
solver = Solver(model, small_data,
                print_every=10, num_epochs=20, batch_size=25,
                update_rule='sgd',
                optim_config={
                  'learning_rate': learning_rate,
                }
         )
solver.train()

plt.plot(solver.loss_history, '-') #changed this bit because it looked weird as␣
 ↪just dots
plt.title('Training loss history')
plt.xlabel('Iteration')
plt.ylabel('Training loss')
plt.show()
```

```
(Iteration 1 / 40) loss: 2.302883
(Epoch 0 / 20) train acc: 0.260000; val_acc: 0.128000
(Epoch 1 / 20) train acc: 0.280000; val_acc: 0.132000
(Epoch 2 / 20) train acc: 0.440000; val_acc: 0.147000
(Epoch 3 / 20) train acc: 0.620000; val_acc: 0.135000
(Epoch 4 / 20) train acc: 0.620000; val_acc: 0.165000
(Epoch 5 / 20) train acc: 0.560000; val_acc: 0.192000
(Iteration 11 / 40) loss: 1.597968
(Epoch 6 / 20) train acc: 0.760000; val_acc: 0.195000
(Epoch 7 / 20) train acc: 0.880000; val_acc: 0.204000
(Epoch 8 / 20) train acc: 0.920000; val_acc: 0.191000
(Epoch 9 / 20) train acc: 0.900000; val_acc: 0.187000
(Epoch 10 / 20) train acc: 0.960000; val_acc: 0.207000
(Iteration 21 / 40) loss: 0.382056
(Epoch 11 / 20) train acc: 0.980000; val_acc: 0.189000
(Epoch 12 / 20) train acc: 1.000000; val_acc: 0.200000
(Epoch 13 / 20) train acc: 0.940000; val_acc: 0.162000
(Epoch 14 / 20) train acc: 0.980000; val_acc: 0.196000
(Epoch 15 / 20) train acc: 0.980000; val_acc: 0.162000
(Iteration 31 / 40) loss: 0.069257
(Epoch 16 / 20) train acc: 0.980000; val_acc: 0.195000
(Epoch 17 / 20) train acc: 1.000000; val_acc: 0.178000
(Epoch 18 / 20) train acc: 1.000000; val_acc: 0.184000
(Epoch 19 / 20) train acc: 1.000000; val_acc: 0.184000
(Epoch 20 / 20) train acc: 1.000000; val_acc: 0.181000
```


Training loss history
Training loss
Iteration
2.0
1.5
1.0
0.5
0.0
0
5
10
15
20
25
30
35
40

[ ]:

[ ]:

# 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])))
```

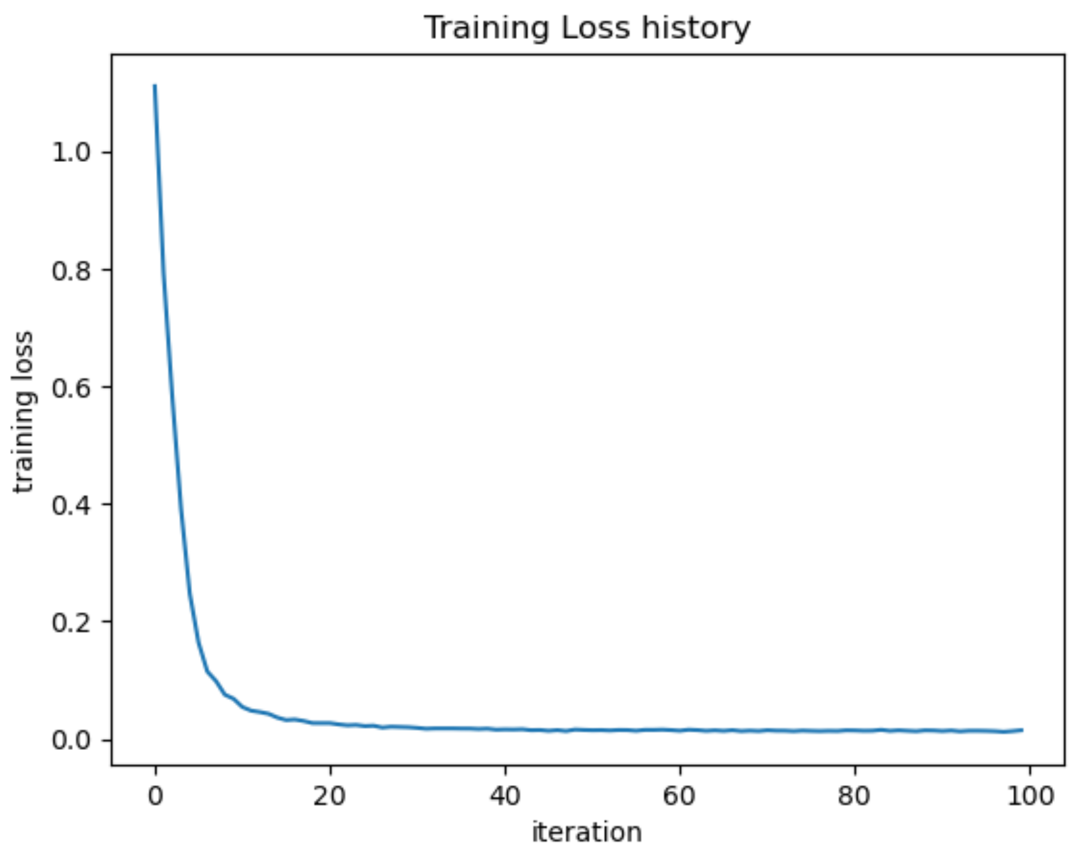
```
W2 max relative error: 2.9632227682005116e-10
b2 max relative error: 1.248270530283678e-09
W1 max relative error: 1.2832823337649917e-09
b1 max relative error: 3.172680092703762e-09
```

### 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]:
```
# 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]:
```
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.

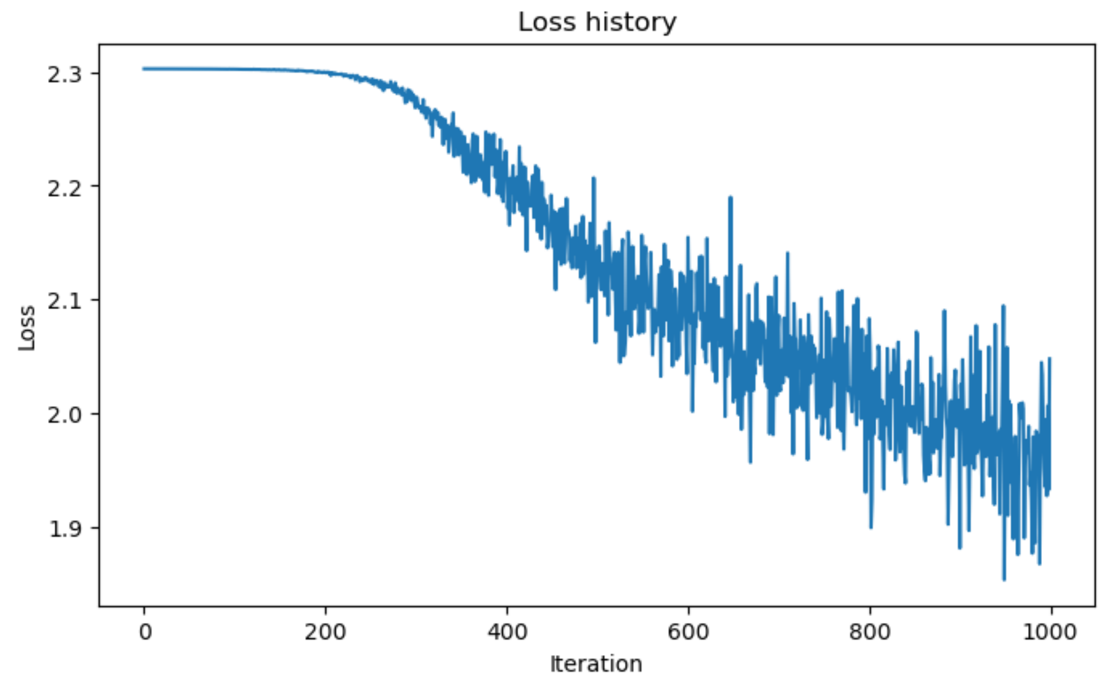
(1) What are some of the reasons why this is the case? Take the following cell to do some analyses and then report your answers in the cell following the one below.

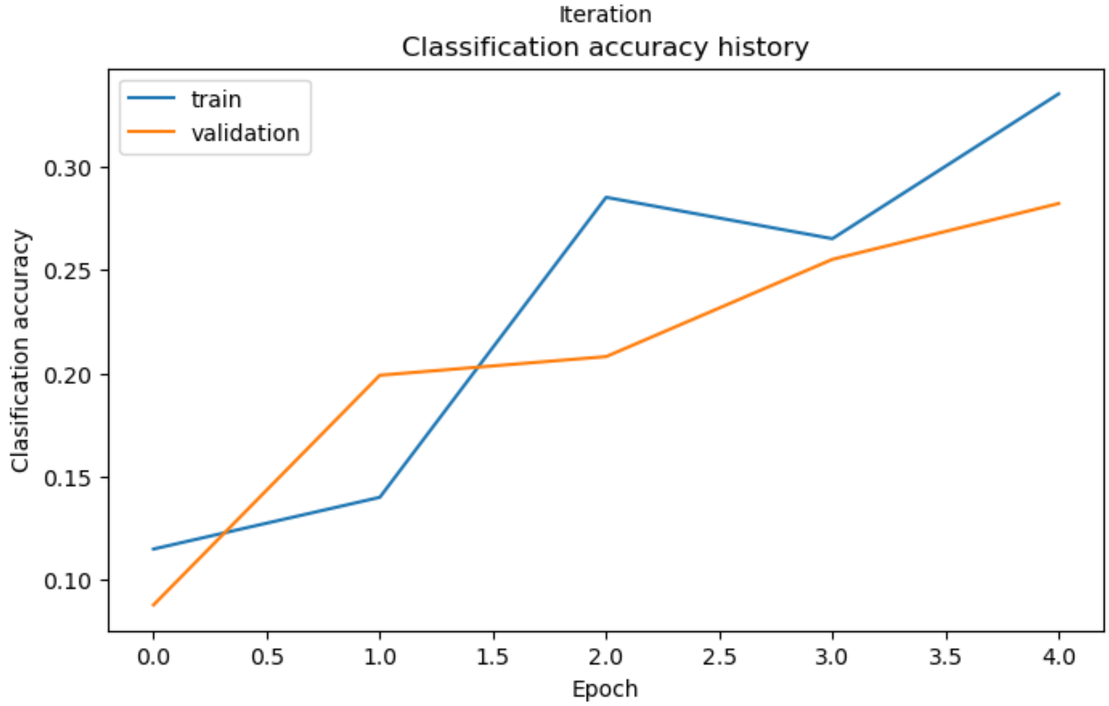
(2) How should you fix the problems you identified in (1)?

[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)
```

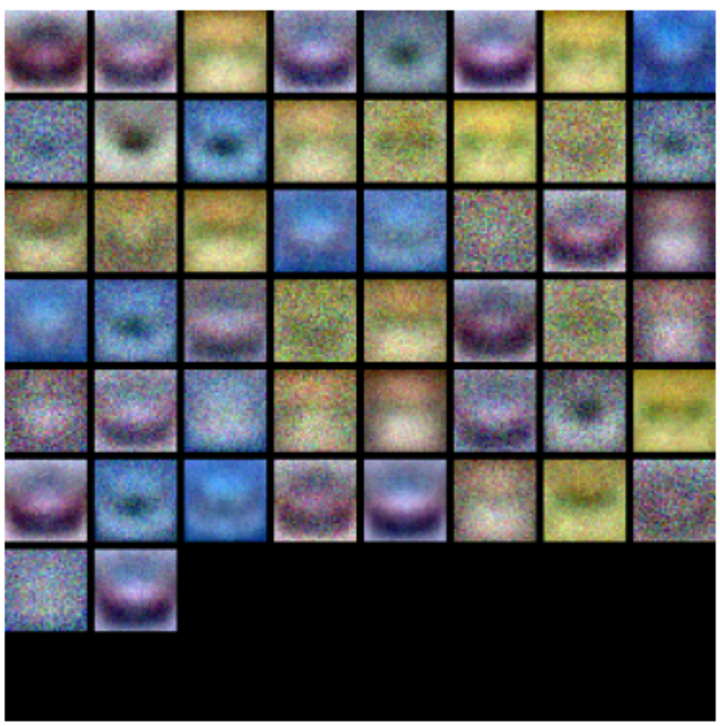
```
Training accuracy for this iteration: 0.533
Validation accuracy for this iteration: 0.494
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.001
Training accuracy for this iteration: 0.5302857142857142
Validation accuracy for this iteration: 0.491
n_iteration: 2000
reg_coef: 0.1
batch_size: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

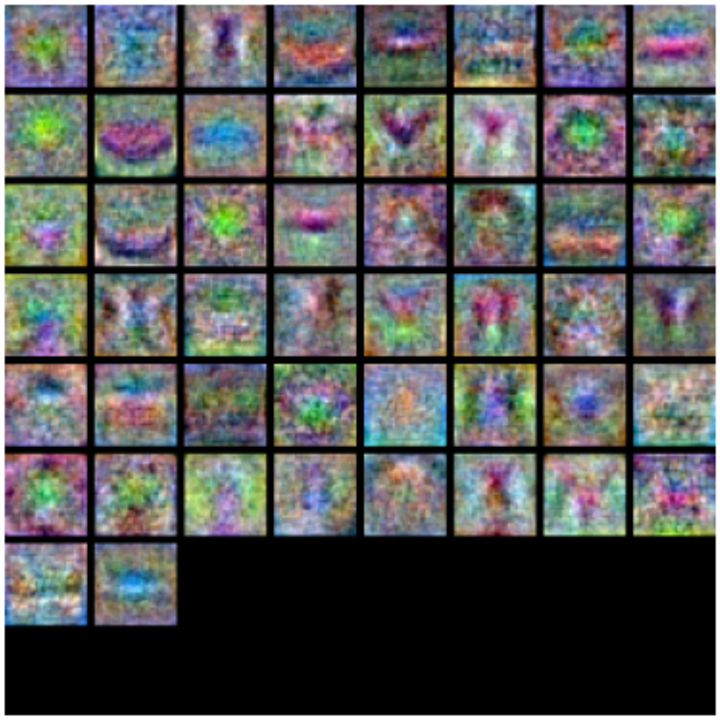
```
batch_size: 200
learning_rate: 0.000630957344480193
Training accuracy for this iteration: 0.5000204081632653
Validation accuracy for this iteration: 0.481
n_iteration: 2000
reg_coef: 0.1
batch_size: 200
learning_rate: 0.000501187233627272
Training accuracy for this iteration: 0.4814897959183673
Validation 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
```

[ ]:
```
```

[ ]:
```
```

HW3_Q4_Q5_Helper_Files

February 7, 2025

# 1 Question 4 - 2 Layer Neural Network

## 1.1 data_utils.py

Complete the two-layer neural network Jupyter notebook. Print out the entire notebook and relevant code and submit it as a pdf to gradescope. Download the CIFAR-10 dataset, as you did in HW #2.

[4]:
```
from __future__ import print_function

from six.moves import cPickle as pickle
import numpy as np
import os
from matplotlib.pyplot import imread
import platform

def load_pickle(f):
    version = platform.python_version_tuple()
    if version[0] == '2':
        return  pickle.load(f)
    elif version[0] == '3':
        return  pickle.load(f, encoding='latin1')
    raise ValueError("invalid python version: {}".format(version))

def load_CIFAR_batch(filename):
    """ load single batch of cifar """
    with open(filename, 'rb') as f:
        datadict = load_pickle(f)
        X = datadict['data']
        Y = datadict['labels']
        X = X.reshape(10000, 3, 32, 32).transpose(0,2,3,1).astype("float")
        Y = np.array(Y)
        return X, Y

# def load_CIFAR10(ROOT):
#     """ load all of cifar """
#     xs = []
#     ys = []
```

```
#     for b in range(1,6):
#         f = os.path.join(ROOT, 'data_batch_%d' % (b, ))
#         X, Y = load_CIFAR_batch(f)
#         xs.append(X)
#         ys.append(Y)
#     Xtr = np.concatenate(xs)
#     Ytr = np.concatenate(ys)
#     del X, Y
#     Xte, Yte = load_CIFAR_batch(os.path.join(ROOT, 'test_batch'))
#     return Xtr, Ytr, Xte, Yte

def load_CIFAR10(ROOT):
    """Load all of CIFAR-10 using absolute paths."""
    xs = []
    ys = []
    """ NOTE FOR THE GRADERS: I had something going on with my join ROOT␣
↪function
        so I decided to simply manually join the file directory with a similar␣
↪for loop
        because I kept getting the same error despite having the correct␣
↪directory
        You can see I tested to see if the directory is present in the normal␣
↪code"""
    for b in range(1, 6):
        f = f"/Users/ctang/Desktop/ECE_C147/HW3/cifar-10-batches-py/
↪data_batch_{b}"
        if not os.path.exists(f):
            raise FileNotFoundError(f"File not found: {f}")
        X, Y = load_CIFAR_batch(f)
        xs.append(X)
        ys.append(Y)

    Xtr = np.concatenate(xs)
    Ytr = np.concatenate(ys)
    del X, Y

    test_file = "/Users/ctang/Desktop/ECE_C147/HW3/cifar-10-batches-py/
↪test_batch"
    if not os.path.exists(test_file):
        raise FileNotFoundError(f"File not found: {test_file}")

    Xte, Yte = load_CIFAR_batch(test_file)
    return Xtr, Ytr, Xte, Yte


def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000,
```

```python
                    subtract_mean=True):
    """
    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for classifiers. 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 = '/Users/ctang/Desktop/ECE_C147/HW3/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
    if subtract_mean:
        mean_image = np.mean(X_train, axis=0)
        X_train -= mean_image
        X_val -= mean_image
        X_test -= mean_image

    # Transpose so that channels come first
    X_train = X_train.transpose(0, 3, 1, 2).copy()
    X_val = X_val.transpose(0, 3, 1, 2).copy()
    X_test = X_test.transpose(0, 3, 1, 2).copy()

    # Package data into a dictionary
    return {
      'X_train': X_train, 'y_train': y_train,
      'X_val': X_val, 'y_val': y_val,
      'X_test': X_test, 'y_test': y_test,
    }


def load_tiny_imagenet(path, dtype=np.float32, subtract_mean=True):
    """
    Load TinyImageNet. Each of TinyImageNet-100-A, TinyImageNet-100-B, and
    TinyImageNet-200 have the same directory structure, so this can be used
    to load any of them.
```

```
    Inputs:
    - path: String giving path to the directory to load.
    - dtype: numpy datatype used to load the data.
    - subtract_mean: Whether to subtract the mean training image.

    Returns: A dictionary with the following entries:
    - class_names: A list where class_names[i] is a list of strings giving the
    WordNet names for class i in the loaded dataset.
    - X_train: (N_tr, 3, 64, 64) array of training images
    - y_train: (N_tr,) array of training labels
    - X_val: (N_val, 3, 64, 64) array of validation images
    - y_val: (N_val,) array of validation labels
    - X_test: (N_test, 3, 64, 64) array of testing images.
    - y_test: (N_test,) array of test labels; if test labels are not available
    (such as in student code) then y_test will be None.
    - mean_image: (3, 64, 64) array giving mean training image
    """
    # First load wnids
    with open(os.path.join(path, 'wnids.txt'), 'r') as f:
        wnids = [x.strip() for x in f]

    # Map wnids to integer labels
    wnid_to_label = {wnid: i for i, wnid in enumerate(wnids)}

    # Use words.txt to get names for each class
    with open(os.path.join(path, 'words.txt'), 'r') as f:
        wnid_to_words = dict(line.split('\t') for line in f)
        for wnid, words in wnid_to_words.iteritems():
          wnid_to_words[wnid] = [w.strip() for w in words.split(',')]
    class_names = [wnid_to_words[wnid] for wnid in wnids]

    # Next load training data.
    X_train = []
    y_train = []
    for i, wnid in enumerate(wnids):
        if (i + 1) % 20 == 0:
            print('loading training data for synset %d / %d' % (i + 1,␣
↪len(wnids)))
    # To figure out the filenames we need to open the boxes file
    boxes_file = os.path.join(path, 'train', wnid, '%s_boxes.txt' % wnid)
    with open(boxes_file, 'r') as f:
      filenames = [x.split('\t')[0] for x in f]
    num_images = len(filenames)

    X_train_block = np.zeros((num_images, 3, 64, 64), dtype=dtype)
    y_train_block = wnid_to_label[wnid] * np.ones(num_images, dtype=np.int64)
    for j, img_file in enumerate(filenames):
```

```
    img_file = os.path.join(path, 'train', wnid, 'images', img_file)
    img = imread(img_file)
    if img.ndim == 2:
    ## grayscale file
        img.shape = (64, 64, 1)
    X_train_block[j] = img.transpose(2, 0, 1)
X_train.append(X_train_block)
y_train.append(y_train_block)

# We need to concatenate all training data
X_train = np.concatenate(X_train, axis=0)
y_train = np.concatenate(y_train, axis=0)

# Next load validation data
with open(os.path.join(path, 'val', 'val_annotations.txt'), 'r') as f:
    img_files = []
    val_wnids = []
    for line in f:
        img_file, wnid = line.split('\t')[:2]
        img_files.append(img_file)
        val_wnids.append(wnid)
    num_val = len(img_files)
    y_val = np.array([wnid_to_label[wnid] for wnid in val_wnids])
    X_val = np.zeros((num_val, 3, 64, 64), dtype=dtype)
    for i, img_file in enumerate(img_files):
      img_file = os.path.join(path, 'val', 'images', img_file)
      img = imread(img_file)
      if img.ndim == 2:
        img.shape = (64, 64, 1)
      X_val[i] = img.transpose(2, 0, 1)

# Next load test images
# Students won't have test labels, so we need to iterate over files in the
# images directory.
img_files = os.listdir(os.path.join(path, 'test', 'images'))
X_test = np.zeros((len(img_files), 3, 64, 64), dtype=dtype)
for i, img_file in enumerate(img_files):
    img_file = os.path.join(path, 'test', 'images', img_file)
    img = imread(img_file)
    if img.ndim == 2:
        img.shape = (64, 64, 1)
    X_test[i] = img.transpose(2, 0, 1)

y_test = None
y_test_file = os.path.join(path, 'test', 'test_annotations.txt')
if os.path.isfile(y_test_file):
    with open(y_test_file, 'r') as f:
```

```
        img_file_to_wnid = {}
        for line in f:
          line = line.split('\t')
          img_file_to_wnid[line[0]] = line[1]
      y_test = [wnid_to_label[img_file_to_wnid[img_file]] for img_file in␣
↪img_files]
      y_test = np.array(y_test)

      mean_image = X_train.mean(axis=0)
      if subtract_mean:
          X_train -= mean_image[None]
          X_val -= mean_image[None]
          X_test -= mean_image[None]

      return {
      'class_names': class_names,
      'X_train': X_train,
      'y_train': y_train,
      'X_val': X_val,
      'y_val': y_val,
      'X_test': X_test,
      'y_test': y_test,
      'class_names': class_names,
      'mean_image': mean_image,
      }


def load_models(models_dir):
    """
    Load saved models from disk. This will attempt to unpickle all files in a
    directory; any files that give errors on unpickling (such as README.txt)␣
↪will
    be skipped.

    Inputs:
    - models_dir: String giving the path to a directory containing model files.
    Each model file is a pickled dictionary with a 'model' field.

    Returns:
    A dictionary mapping model file names to models.
    """
    models = {}
    for model_file in os.listdir(models_dir):
        with open(os.path.join(models_dir, model_file), 'rb') as f:
            try:
                models[model_file] = load_pickle(f)['model']
            except pickle.UnpicklingError:
```

```
                continue
    return models
```

### 1.2 neural_net.py

[7]:
```
import numpy as np
import matplotlib.pyplot as plt


class TwoLayerNet(object):
    """
    A two-layer fully-connected neural network. The net has an input dimension␣
 ↪of
    D, a hidden layer dimension of H, and performs classification over C␣
 ↪classes.
    We train the network with a softmax loss function and L2 regularization on␣
 ↪the
    weight matrices. The network uses a ReLU nonlinearity after the first fully
    connected layer.

    In other words, the network has the following architecture:

    input - fully connected layer - ReLU - fully connected layer - softmax

    The outputs of the second fully-connected layer are the scores for each␣
 ↪class.
    """

    def __init__(self, input_size, hidden_size, output_size, std=1e-4):
        """
        Initialize the model. Weights are initialized to small random values and
        biases are initialized to zero. Weights and biases are stored in the
        variable self.params, which is a dictionary with the following keys:

        W1: First layer weights; has shape (H, D)
        b1: First layer biases; has shape (H,)
        W2: Second layer weights; has shape (C, H)
        b2: Second layer biases; has shape (C,)

        Inputs:
        - input_size: The dimension D of the input data.
        - hidden_size: The number of neurons H in the hidden layer.
        - output_size: The number of classes C.
        """
        # self.params = {}
        # self.params['W1'] = std * np.random.randn(hidden_size, input_size)
        # self.params['b1'] = np.zeros(hidden_size)
```

```python
        # self.params['W2'] = std * np.random.randn(output_size, hidden_size)
        # self.params['b2'] = np.zeros(output_size)
        self.params = {}
        self.params['W1'] = std * np.random.randn(hidden_size, input_size)
        self.params['b1'] = np.zeros(hidden_size)
        self.params['W2'] = std * np.random.randn(output_size, hidden_size)
        self.params['b2'] = np.zeros(output_size)

    def loss(self, X, y=None, reg=0.0):
        """
        Compute the loss and gradients for a two layer fully connected neural
        network.

        Inputs:
        - X: Input data of shape (N, D). Each X[i] is a training sample.
        - y: Vector of training labels. y[i] is the label for X[i], and each␣
↪y[i] is
        an integer in the range 0 <= y[i] < C. This parameter is optional; if it
        is not passed then we only return scores, and if it is passed then we
        instead return the loss and gradients.
        - reg: Regularization strength.

        Returns:
        If y is None, return a matrix scores of shape (N, C) where scores[i, c]␣
↪is
        the score for class c on input X[i].

        If y is not None, instead return a tuple of:
        - loss: Loss (data loss and regularization loss) for this batch of␣
↪training
        samples.
        - grads: Dictionary mapping parameter names to gradients of those␣
↪parameters
        with respect to the loss function; has the same keys as self.params.
        """
        # Unpack variables from the params dictionary
        W1, b1 = self.params['W1'], self.params['b1']
        W2, b2 = self.params['W2'], self.params['b2']
        N, D = X.shape

        # Compute the forward pass
        scores = None
        h1 = np.dot(X, W1.T) + b1
        h1[h1 <= 0] = 0
        h2 = np.dot(h1, W2.T) + b2
        # ================================================================ #
        # YOUR CODE HERE:
```

```python
    #   Calculate the output scores of the neural network.  The result
    #   should be (N, C). As stated in the description for this class,
    #   there should not be a ReLU layer after the second FC layer.
    #   The output of the second FC layer is the output scores. Do not
    #   use a for loop in your implementation.
    # ================================================================ #
    real_scores = h2
    scores = h2 - np.max(h2, axis=1, keepdims=True)
    exp_scores = np.exp(scores)
    probs = exp_scores / np.sum(exp_scores, axis=1, keepdims=True)
    #pass

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


    # If the targets are not given then jump out, we're done
    if y is None:
        #return scores
        return real_scores

    # Compute the loss
    loss = None

    # ================================================================ #
    # YOUR CODE HERE:
    #   Calculate the loss of the neural network.  This includes the
    #   softmax loss and the L2 regularization for W1 and W2. Store the
    #   total loss in teh variable loss.  Multiply the regularization
    #   loss by 0.5 (in addition to the factor reg).
    # ================================================================ #
    # scores is num_examples by num_classes
    num_examples = X.shape[0]
    correct_logprobs = -np.log(probs[range(num_examples), y])
    data_loss = np.sum(correct_logprobs) / num_examples
    reg_loss = 0.5*reg*(np.sum(W1 * W1) + np.sum(W2 * W2))
    loss = data_loss + reg_loss
    #pass
    # ================================================================ #
    # END YOUR CODE HERE
    # ================================================================ #

    grads = {}

    # ================================================================ #
    # YOUR CODE HERE:
```

```
        #   Implement the backward pass.  Compute the derivatives of the
        #   weights and the biases.  Store the results in the grads
        #   dictionary.  e.g., grads['W1'] should store the gradient for
        #   W1, and be of the same size as W1.
        # ================================================================ #
        dscores = probs
        dscores[range(N), y] -= 1
        dscores /= N
        grads['W2'] = np.dot(dscores.T, h1) + reg*W2
        grads['b2'] = np.sum(dscores, axis=0)
        dh1 = np.dot(dscores, W2)
        dh1[h1<=0]=0
        grads['W1'] = np.dot(dh1.T, X) + reg * W1
        grads['b1'] = np.sum(dh1, axis=0)

        #pass

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

        return loss, grads

    def train(self, X, y, X_val, y_val,
            learning_rate=1e-3, learning_rate_decay=0.95,
            reg=1e-5, num_iters=100,
            batch_size=200, verbose=False):
        """
        Train this neural network using stochastic gradient descent.

        Inputs:
        - X: A numpy array of shape (N, D) giving training data.
        - y: A numpy array f shape (N,) giving training labels; y[i] = c means␣
↪that
          X[i] has label c, where 0 <= c < C.
        - X_val: A numpy array of shape (N_val, D) giving validation data.
        - y_val: A numpy array of shape (N_val,) giving validation labels.
        - learning_rate: Scalar giving learning rate for optimization.
        - learning_rate_decay: Scalar giving factor used to decay the learning␣
↪rate
          after each epoch.
        - reg: Scalar giving regularization strength.
        - num_iters: Number of steps to take when optimizing.
        - batch_size: Number of training examples to use per step.
        - verbose: boolean; if true print progress during optimization.
        """
        num_train = X.shape[0]
```

```
        iterations_per_epoch = max(num_train / batch_size, 1)

        # Use SGD to optimize the parameters in self.model
        loss_history = []
        train_acc_history = []
        val_acc_history = []

        for it in np.arange(num_iters):
            X_batch = None
            y_batch = None

            # ================================================================ #
            # YOUR CODE HERE:
            #   Create a minibatch by sampling batch_size samples randomly.
            # ================================================================ #
            #pass
            indexes = np.random.choice(num_train, batch_size)
            X_batch = X[indexes]
            y_batch = y[indexes]


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

            # Compute loss and gradients using the current minibatch
            loss, grads = self.loss(X_batch, y=y_batch, reg=reg)
            loss_history.append(loss)

            # ================================================================ #
            # YOUR CODE HERE:
            #   Perform a gradient descent step using the minibatch to update
            #   all parameters (i.e., W1, W2, b1, and b2).
            # ================================================================ #

            self.params['W1'] -= learning_rate*grads['W1']
            self.params['W2'] -= learning_rate*grads['W2']
            self.params['b1'] -= learning_rate*grads['b1']
            self.params['b2'] -= learning_rate*grads['b2']
            #pass

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

            if verbose and it % 100 == 0:
                print('iteration {} / {}: loss {}'.format(it, num_iters, loss))
```

```
            # Every epoch, check train and val accuracy and decay learning rate.
            if it % iterations_per_epoch == 0:
                # Check accuracy
                train_acc = (self.predict(X_batch) == y_batch).mean()
                val_acc = (self.predict(X_val) == y_val).mean()
                train_acc_history.append(train_acc)
                val_acc_history.append(val_acc)

                # Decay learning rate
                learning_rate *= learning_rate_decay

        return {
          'loss_history': loss_history,
          'train_acc_history': train_acc_history,
          'val_acc_history': val_acc_history,
        }

    def predict(self, X):
        """
        Use the trained weights of this two-layer network to predict labels for
        data points. For each data point we predict scores for each of the C
        classes, and assign each data point to the class with the highest score.

        Inputs:
        - X: A numpy array of shape (N, D) giving N D-dimensional data points to
          classify.

        Returns:
        - y_pred: A numpy array of shape (N,) giving predicted labels for each␣
↪of
          the elements of X. For all i, y_pred[i] = c means that X[i] is␣
↪predicted
          to have class c, where 0 <= c < C.
        """
        y_pred = None

        # ================================================================ #
        # YOUR CODE HERE:
        #   Predict the class given the input data.
        # ================================================================ #
        #pass
        predicted_output = np.dot(np.maximum(0, np.dot(X, self.params['W1'].T)+␣
↪self.params['b1']), self.params['W2'].T) + self.params['b2']
        y_pred = np.argmax(predicted_output, axis=1)
```

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

        return y_pred
```

## 2 Question 5 FC Nets

Complete the FC Net Jupyter notebook. Print out the entire notebook and relevant code and submit it as a pdf to gradescope

### 2.1 layers.py

[14]:
```
import numpy as np
import pdb

def affine_forward(x, w, b):
    """
    Computes the forward pass for an affine (fully-connected) layer.

    The input x has shape (N, d_1, ..., d_k) and contains a minibatch of N
    examples, where each example x[i] has shape (d_1, ..., d_k). We will
    reshape each input into a vector of dimension D = d_1 * ... * d_k, and
    then transform it to an output vector of dimension M.

    Inputs:
    - x: A numpy array containing input data, of shape (N, d_1, ..., d_k)
    - w: A numpy array of weights, of shape (D, M)
    - b: A numpy array of biases, of shape (M,)

    Returns a tuple of:
    - out: output, of shape (N, M)
    - cache: (x, w, b)
    """

    # ================================================================ #
    # YOUR CODE HERE:
    #   Calculate the output of the forward pass.  Notice the dimensions
    #   of w are D x M, which is the transpose of what we did in earlier
    #   assignments.
    # ================================================================ #
    X = x.reshape((x.shape[0], -1))
    out = np.dot(X,w) + b
    #pass

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

```python
    # ======================================================================= #

    cache = (x, w, b)
    return out, cache


def affine_backward(dout, cache):
    """
    Computes the backward pass for an affine layer.

    Inputs:
    - dout: Upstream derivative, of shape (N, M)
    - cache: Tuple of:
    - x: Input data, of shape (N, d_1, ... d_k)
    - w: Weights, of shape (D, M)

    Returns a tuple of:
    - dx: Gradient with respect to x, of shape (N, d1, ..., d_k)
    - dw: Gradient with respect to w, of shape (D, M)
    - db: Gradient with respect to b, of shape (M,)
    """
    x, w, b = cache
    dx, dw, db = None, None, None

    # ======================================================================= #
    # YOUR CODE HERE:
    #   Calculate the gradients for the backward pass.
    # ======================================================================= #

    # dout is N x M
    # dx should be N x d1 x ... x dk; it relates to dout through multiplication␣
 ↪with w, which is D x M
    # dw should be D x M; it relates to dout through multiplication with x,␣
 ↪which is N x D after reshaping
    # db should be M; it is just the sum over dout examples
    X = x.reshape((x.shape[0], -1))
    db = np.sum(dout, axis = 0)
    dw = np.dot(X.T, dout)
    dx = np.dot(dout, w.T).reshape(x.shape)
    #pass

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

    return dx, dw, db
```

```python
def relu_forward(x):
    """
    Computes the forward pass for a layer of rectified linear units (ReLUs).

    Input:
    - x: Inputs, of any shape

    Returns a tuple of:
    - out: Output, of the same shape as x
    - cache: x
    """
    # ================================================================ #
    # YOUR CODE HERE:
    #   Implement the ReLU forward pass.
    # ================================================================ #
    out = np.maximum(0,x)
    #pass
    # ================================================================ #
    # END YOUR CODE HERE
    # ================================================================ #

    cache = x
    return out, cache


def relu_backward(dout, cache):
    """
    Computes the backward pass for a layer of rectified linear units (ReLUs).

    Input:
    - dout: Upstream derivatives, of any shape
    - cache: Input x, of same shape as dout

    Returns:
    - dx: Gradient with respect to x
    """
    x = cache

    # ================================================================ #
    # YOUR CODE HERE:
    #   Implement the ReLU backward pass
    # ================================================================ #

    # ReLU directs linearly to those > 0
    #pass
    dx = dout*(x>0)
```

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

    return dx


def softmax_loss(x, y):
    """
    Computes the loss and gradient for softmax classification.

    Inputs:
    - x: Input data, of shape (N, C) where x[i, j] is the score for the jth␣
 ↪class
    for the ith input.
    - y: Vector of labels, of shape (N,) where y[i] is the label for x[i] and
    0 <= y[i] < C

    Returns a tuple of:
    - loss: Scalar giving the loss
    - dx: Gradient of the loss with respect to x
    """

    probs = np.exp(x - np.max(x, axis=1, keepdims=True))
    probs /= np.sum(probs, axis=1, keepdims=True)
    N = x.shape[0]
    loss = -np.sum(np.log(probs[np.arange(N), y])) / N
    dx = probs.copy()
    dx[np.arange(N), y] -= 1
    dx /= N
    return loss, dx
```

### 2.2 fc_net.py

[ ]:
```
import numpy as np

from .layers import *
from .layer_utils import *


class TwoLayerNet(object):
    """
    A two-layer fully-connected neural network with ReLU nonlinearity and
    softmax loss that uses a modular layer design. We assume an input dimension
    of D, a hidden dimension of H, and perform classification over C classes.

    The architecure should be affine - relu - affine - softmax.
```

```
    Note that this class does not implement gradient descent; instead, it
    will interact with a separate Solver object that is responsible for running
    optimization.

    The learnable parameters of the model are stored in the dictionary
    self.params that maps parameter names to numpy arrays.
    """

    def __init__(self, input_dim=3*32*32, hidden_dims=100, num_classes=10,
                 dropout=0, weight_scale=1e-3, reg=0.0):
        """
        Initialize a new network.

        Inputs:
        - input_dim: An integer giving the size of the input
        - hidden_dims: An integer giving the size of the hidden layer
        - num_classes: An integer giving the number of classes to classify
        - dropout: Scalar between 0 and 1 giving dropout strength.
        - weight_scale: Scalar giving the standard deviation for random
          initialization of the weights.
        - reg: Scalar giving L2 regularization strength.
        """
        self.params = {}
        self.reg = reg

        # ================================================================ #
        # YOUR CODE HERE:
        #   Initialize W1, W2, b1, and b2.  Store these as self.params['W1'],
        #   self.params['W2'], self.params['b1'] and self.params['b2']. The
        #   biases are initialized to zero and the weights are initialized
        #   so that each parameter has mean 0 and standard deviation␣
↪weight_scale.
        #   The dimensions of W1 should be (input_dim, hidden_dim) and the
        #   dimensions of W2 should be (hidden_dims, num_classes)
        # ================================================================ #
        self.params['W1'] = np.random.normal(0, weight_scale, (input_dim,␣
↪hidden_dims))
        self.params['W2'] = np.random.normal(0, weight_scale, (hidden_dims,␣
↪num_classes))
        self.params['b1'] = np.zeros(hidden_dims)
        self.params['b2'] = np.zeros(num_classes)
        #pass

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

```
  def loss(self, X, y=None):
      """
      Compute loss and gradient for a minibatch of data.

      Inputs:
      - X: Array of input data of shape (N, d_1, ..., d_k)
      - y: Array of labels, of shape (N,). y[i] gives the label for X[i].

      Returns:
      If y is None, then run a test-time forward pass of the model and return:
      - scores: Array of shape (N, C) giving classification scores, where
        scores[i, c] is the classification score for X[i] and class c.

      If y is not None, then run a training-time forward and backward pass and
      return a tuple of:
      - loss: Scalar value giving the loss
      - grads: Dictionary with the same keys as self.params, mapping parameter
        names to gradients of the loss with respect to those parameters.
      """
      scores = None

      # ================================================================ #
      # YOUR CODE HERE:
      #   Implement the forward pass of the two-layer neural network. Store
      #   the class scores as the variable 'scores'.  Be sure to use the␣
↪layers
      #   you prior implemented.
      # ================================================================ #
      hidden, cache_hidden = affine_relu_forward(X, self.params['W1'], self.
↪params['b1'])
      scores, cache_scores = affine_forward(hidden, self.params['W2'], self.
↪params['b2'])
      #pass
      # ================================================================ #
      # END YOUR CODE HERE
      # ================================================================ #

      # If y is None then we are in test mode so just return scores
      if y is None:
        return scores

      loss, grads = 0, {}
      # ================================================================ #
      # YOUR CODE HERE:
      #   Implement the backward pass of the two-layer neural net.  Store
      #   the loss as the variable 'loss' and store the gradients in the
```

```
        #   'grads' dictionary.  For the grads dictionary, grads['W1'] holds
        #   the gradient for W1, grads['b1'] holds the gradient for b1, etc.
        #   i.e., grads[k] holds the gradient for self.params[k].
        #
        #   Add L2 regularization, where there is an added cost 0.5*self.reg*W^2
        #   for each W.  Be sure to include the 0.5 multiplying factor to
        #   match our implementation.
        #
        #   And be sure to use the layers you prior implemented.
        # ================================================================ #
        loss, dout = softmax_loss(scores,y)
        loss += 0.5 * self.reg * (np.sum(self.params['W1']**2) + np.sum(self.
 ↪params['W2']**2))

        dh, dw2, db2 = affine_backward(dout, cache_scores)
        dx, dw1, db1 = affine_relu_backward(dh, cache_hidden)

        grads['W1'] = dw1 + self.reg * self.params['W1']
        grads['b1'] = db1
        grads['W2'] = dw2 + self.reg * self.params['W2']
        grads['b2'] = db2

        #pass

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

        return loss, grads


class FullyConnectedNet(object):
    """
    A fully-connected neural network with an arbitrary number of hidden layers,
    ReLU nonlinearities, and a softmax loss function. This will also implement
    dropout and batch normalization as options. For a network with L layers,
    the architecture will be

    {affine - [batch norm] - relu - [dropout]} x (L - 1) - affine - softmax

    where batch normalization and dropout are optional, and the {...} block is
    repeated L - 1 times.

    Similar to the TwoLayerNet above, learnable parameters are stored in the
    self.params dictionary and will be learned using the Solver class.
    """
```

```
    def __init__(self, hidden_dims, input_dim=3*32*32, num_classes=10,
                 dropout=0, use_batchnorm=False, reg=0.0,
                 weight_scale=1e-2, dtype=np.float32, seed=None):
        """
        Initialize a new FullyConnectedNet.

        Inputs:
        - hidden_dims: A list of integers giving the size of each hidden layer.
        - input_dim: An integer giving the size of the input.
        - num_classes: An integer giving the number of classes to classify.
        - dropout: Scalar between 0 and 1 giving dropout strength. If dropout=0␣
↪then
          the network should not use dropout at all.
        - use_batchnorm: Whether or not the network should use batch␣
↪normalization.
        - reg: Scalar giving L2 regularization strength.
        - weight_scale: Scalar giving the standard deviation for random
          initialization of the weights.
        - dtype: A numpy datatype object; all computations will be performed␣
↪using
          this datatype. float32 is faster but less accurate, so you should use
          float64 for numeric gradient checking.
        - seed: If not None, then pass this random seed to the dropout layers.␣
↪This
          will make the dropout layers deteriminstic so we can gradient check␣
↪the
          model.
        """
        self.use_batchnorm = use_batchnorm
        self.use_dropout = dropout > 0
        self.reg = reg
        self.num_layers = 1 + len(hidden_dims)
        self.dtype = dtype
        self.params = {}

        # ================================================================ #
        # YOUR CODE HERE:
        #   Initialize all parameters of the network in the self.params␣
↪dictionary.
        #   The weights and biases of layer 1 are W1 and b1; and in general the
        #   weights and biases of layer i are Wi and bi. The
        #   biases are initialized to zero and the weights are initialized
        #   so that each parameter has mean 0 and standard deviation␣
↪weight_scale.
        # ================================================================ #
        for i in np.arange(self.num_layers):
```

```
            if(i == 0):
                self.params['W' + str(i+1)] = np.random.normal(0, weight_scale,␣
↪(input_dim, hidden_dims[i]))
                self.params['b' + str(i+1)] = np.zeros(hidden_dims[i])
            elif(i == self.num_layers - 1):
                self.params['W' + str(i+1)] = np.random.normal(0, weight_scale,␣
↪(hidden_dims[i-1], num_classes))
                self.params['b' + str(i+1)] = np.zeros(num_classes)
            else:
                self.params['W' + str(i+1)] = np.random.normal(0, weight_scale,␣
↪(hidden_dims[i-1], hidden_dims[i]))
                self.params['b' + str(i+1)] = np.zeros(hidden_dims[i])
        #pass

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

        # When using dropout we need to pass a dropout_param dictionary to each
        # dropout layer so that the layer knows the dropout probability and the␣
↪mode
        # (train / test). You can pass the same dropout_param to each dropout␣
↪layer.
        self.dropout_param = {}
        if self.use_dropout:
          self.dropout_param = {'mode': 'train', 'p': dropout}
          if seed is not None:
            self.dropout_param['seed'] = seed

        # With batch normalization we need to keep track of running means and
        # variances, so we need to pass a special bn_param object to each batch
        # normalization layer. You should pass self.bn_params[0] to the forward␣
↪pass
        # of the first batch normalization layer, self.bn_params[1] to the␣
↪forward
        # pass of the second batch normalization layer, etc.
        self.bn_params = []
        if self.use_batchnorm:
          self.bn_params = [{'mode': 'train'} for i in np.arange(self.
↪num_layers - 1)]

        # Cast all parameters to the correct datatype
        for k, v in self.params.items():
          self.params[k] = v.astype(dtype)
```

```
  def loss(self, X, y=None):
      """
      Compute loss and gradient for the fully-connected net.

      Input / output: Same as TwoLayerNet above.
      """
      X = X.astype(self.dtype)
      mode = 'test' if y is None else 'train'

      # Set train/test mode for batchnorm params and dropout param since they
      # behave differently during training and testing.
      if self.dropout_param is not None:
        self.dropout_param['mode'] = mode
      if self.use_batchnorm:
        for bn_param in self.bn_params:
          bn_param[mode] = mode

      scores = None

      # ================================================================ #
      # YOUR CODE HERE:
      #   Implement the forward pass of the FC net and store the output
      #   scores as the variable "scores".
      # ================================================================ #
      H = []
      H_cache = []
      for i in range(self.num_layers):
          H_app = None
          H_cache_app = None
          if(i==0):
              H_app, H_cache_app = affine_relu_forward(X, self.params['W' +␣
↪str(i+1)], self.params['b' + str(i+1)])
              H.append(H_app)
              H_cache.append(H_cache_app)
          elif(i == self.num_layers - 1):
              scores, H_cache_app = affine_forward(H[i-1], self.params['W' +␣
↪str(i+1)], self.params['b' + str(i+1)])
              H_cache.append(H_cache_app)
          else:
              H_app, H_cache_app = affine_relu_forward(H[i-1], self.
↪params['W' + str(i+1)], self.params['b' + str(i+1)])
              H.append(H_app)
              H_cache.append(H_cache_app)

      #pass

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

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

        # If test mode return early
        if mode == 'test':
          return scores

        loss, grads = 0.0, {}
        # ================================================================ #
        # YOUR CODE HERE:
        #   Implement the backwards pass of the FC net and store the gradients
        #   in the grads dict, so that grads[k] is the gradient of self.
↪params[k]
        #   Be sure your L2 regularization includes a 0.5 factor.
        # ================================================================ #

        #pass
        loss, dhidden = softmax_loss(scores, y)
        for i in range(self.num_layers,0,-1):
          loss += 0.5*self.reg*np.sum(self.params['W{}'.format(i)]*self.
↪params['W{}'.format(i)])
          if i == self.num_layers:
            dH1, dW, db = affine_backward(dhidden,H_cache[i-1])
            grads['W{}'.format(i)] = dW + self.reg*self.params['W{}'.format(i)]
            grads['b{}'.format(i)] = db
          else:
            dH1, dW, db = affine_relu_backward(dH1,H_cache[i-1])
            grads['W{}'.format(i)] = dW + self.reg*self.params['W{}'.format(i)]
            grads['b{}'.format(i)] = db
        # loss, dhidden = softmax_loss(scores, y)
        # for i in range(self.num_layers,0,-1):
        #     loss += 0.5 * self.reg*np.sum(self.params['W{}'.format(i)]*self.
↪params['W{}'.format(i)])
        #     if i == self.num_layers:
        #         dFC1, dW, db = affine_backward(dhidden,FC_cache[i-1])
        #         grads['W{}'.format(i)] = dW + self.reg*self.params['W{}'.
↪format(i)]
        #         grads['b{}'.format(i)] = db
        #     else:
        #       dFC1, dW, db = affine_relu_backward(dFC1,FC_cache[i-1])
        #         grads['W{}'.format(i)] = dW + self.reg*self.params['W{}'.
↪format(i)]
        #         grads['b{}'.format(i)] = db
        # ================================================================ #
        # END YOUR CODE HERE
        # ================================================================ #
        return loss, grads
```