Alex Walczak | HW6 | Neural Networks

Part I Backpropogation

Please see attached written portion.

Part II Training

I used 50,000 training points and 10,000 validation points in my neural net testing.

Preprocessing:

All the images were first scaled by 255 and then the mean was subtracted. The mean of the training data was also subtracted the validation set.

Labels adjusted from {0, 1} to {0.02, 0.98} since these target reachable by logistic and tanh functions.

Weight initialization:

As suggested here http://cs231n.github.io/neural-networks-2/ and other places, it is recommended to adjust the variances of the weights. This is done so that the output of each neuron has the same variance (and the network can converge faster). The variance of the output of the neuron depends on the variance of the input, so our goal can be to make the variance of the output equal the variance of the input. For my weight initialization, I sampled weights from the unit Gaussian, and scaled this matrix by 1/sqrt(number of input features) to achieve that goal.

Learning Rate:

Different layers learn at different rates (cs.cmu.edu/afs/cs/academic/class/15883-f15/slides/backprop.pdf).
Input-to-hidden (in code: i2h) weights learn more slowly than hidden-to-output (h2o) weights.
I made the learning rate variable,so that decayed over time, yet in later iterations it wouldn't jump out of the local minimum of the cost function.

Stopping Conditions:

None, basically. I'm a little impatient, so whenever the calculated loss was the smallest ever seen by my neural net, I pickled it, naming the files using the unique ID generated for each instance of the neural net (a pickled NN is included with the submission). Luckily, my convergence was fast (less than 15 mins). When I was tuning parameters, I would run the neural net for 20*10^4 iterations at a time. I suppose I would never let my net run for longer than 60 mins, so that would be my only true stopping condition.

Momentum:

I implemented the common learning rate technique of adding a momentum term (a fraction of the previous weight update) every fixed number of iterations (10^4, usually). This let gradient updates from previous iterations to persist in later iterations.

Part III

Kaggle:
0.97640

Runtime:

The neural net took 10 seconds to run 1,000 iterations. Generating the two plots directly below took 200*10 seconds ~ 33 minutes.

However, in about a quarter of that time (8.3 minutes), the loss was already flat-lining, and this corresponded to 2.7% error on the validation set.

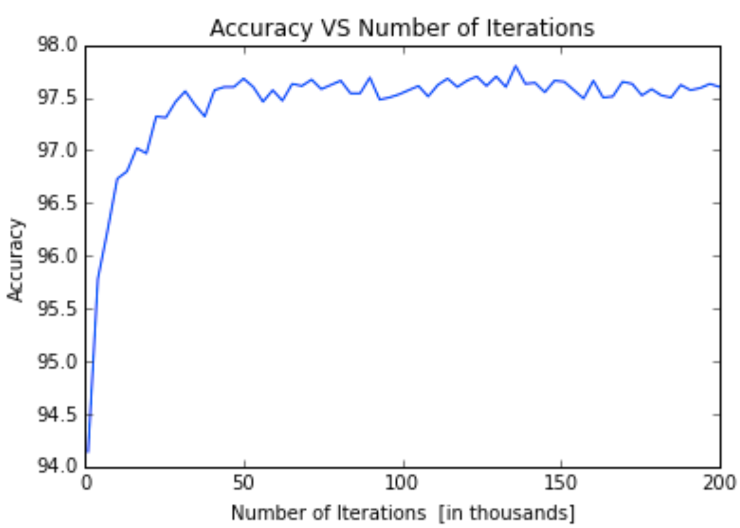
Accuracy:

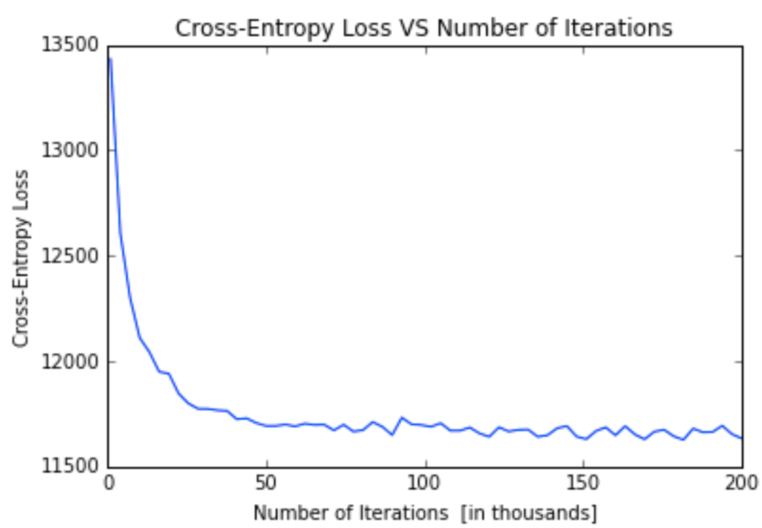
On the best neural net, the validation set error was 2.4%, i.e., 97.6% accuracy (same as Kaggle). The training set error was 0.02% (99.98% accuracy). Knowing this, overfitting must have occurred, even though the loss on the validation set was minimized for this net.

Loss Functions:

Cross-entropy (XE) loss resulted in faster convergence than square error (SE) loss on the same neural net. The rate was very roughly double. On the validation set, the XE loss-trained net started with 5.9% error at 1000 iterations in, and then settled to 2.5% after 50,000 iterations.

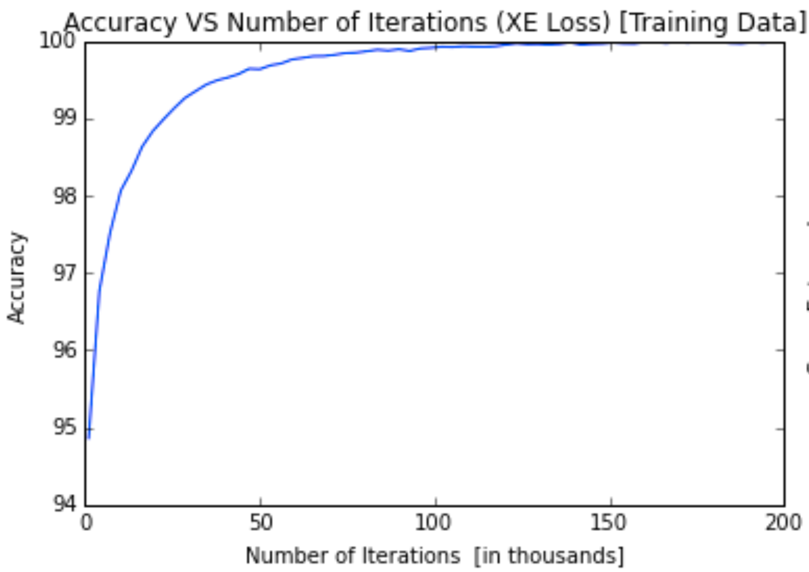
The SE loss-trained net began at 9.5% error and after 50,000 iterations reached 3.0% error. Interestingly, the SE loss saw much greater improvements in cost — almost 50% in 50,000 iterations. However, the XE loss was only reduced by 13%. This leads me think that the topology of the SE loss function was steeper, whereas the XE loss function had smaller gradients and could only decrease slightly with each iteration.

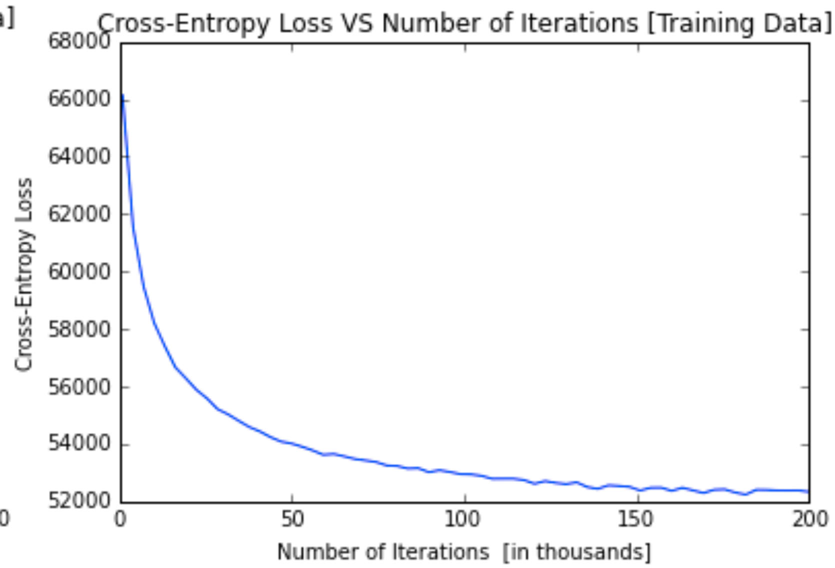


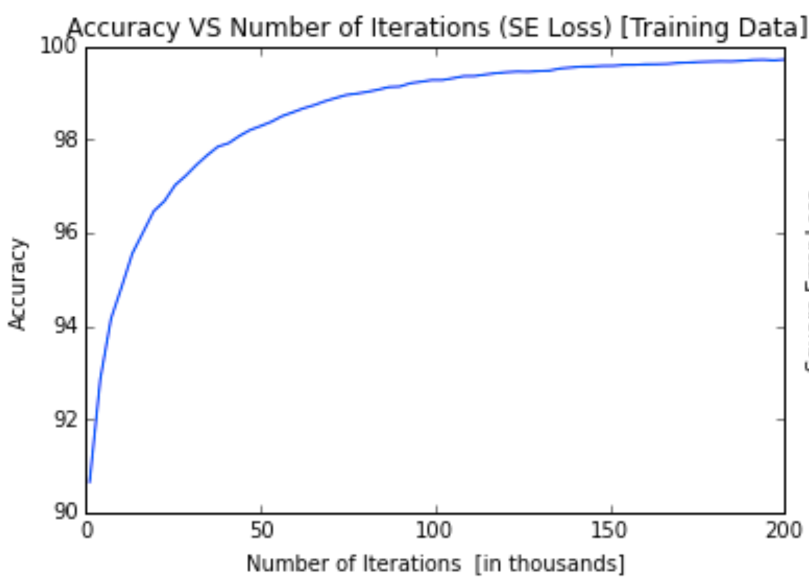


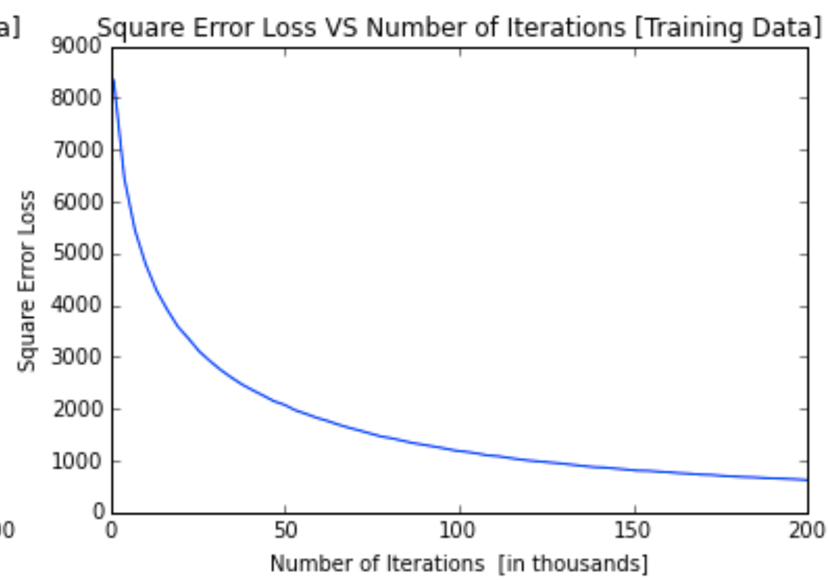
The plots above were generated using the validation set.

The plots below were generated with the training set.









Alex Walczak | CS189 | HW6 | PART I.

#1. MSE Loss.

$$J = \frac{1}{2}\sum_{k}^{n}\left(y_k - \overset{\text{predictor}}{f(x_k)}\right)^2$$

Let:

① $z_k(x) = \tanh(W_k x)$, ② $W = \begin{bmatrix} - w_1^T - \\ \vdots \\ - w_i^T - \end{bmatrix}$, (V, same arrangement),

③ $z = \tanh(Wx)$, ← applied to each entry.

④ $f(x_k) = \sigma(Vz)$.

So (i) $\frac{d}{dV} J = \frac{d}{dV}\left[\frac{1}{2}\|y - f(x)\|_2^2\right]$

$$= \frac{d}{dV}\left[\frac{1}{2}\|y - \sigma(Vz)\|_2^2\right].$$

$$= \frac{1}{2}\left(\frac{d}{dV}\left[\|\sigma(Vz)\|_2^2\right] + 2\frac{d}{dV}\left[\sigma(Vz)^T y\right]\right) = \frac{d}{dV}\left\|\begin{pmatrix}\vdots \\ \sigma(v_i^T z) \\ \vdots\end{pmatrix}\right\|_2^2 + 2\frac{d}{dV}\left[\begin{pmatrix}\vdots \\ \sigma(v_i^T z) \\ \vdots\end{pmatrix}^T y\right]\left(\frac{1}{2}\right.$$

$$= \frac{2}{2}\begin{bmatrix}\vdots \\ -z^T\sigma(v_i^T z)\sigma'(v_i^T z) \\ \vdots\end{bmatrix} + \frac{2}{2}\begin{bmatrix}\vdots \\ -y_i\sigma'(v_i^T z)z^T - \\ \vdots\end{bmatrix} \Rightarrow \boxed{\left[\frac{d}{dV}J\right]_{i\text{th row}} = \left[-(y - \sigma(Vz)) * \sigma'(Vz)\right]_{i\text{th row}} z^T.}$$

* multiply across in vector

(ii) $\frac{d}{dW}J = \frac{1}{2}\frac{d}{dW}\|y - \sigma(Vz)\|_2^2 = \frac{1}{2}\frac{d}{dW}\left[\left\|\begin{pmatrix}\vdots \\ \sigma(v_i \tanh(Wx)) \\ \vdots\end{pmatrix}\right\|_2^2\right] = \frac{1}{2}\frac{d}{dW}\left[\dots + \sigma(v_i^T \tanh(Wx))^2 + \dots\right].$

now, $\frac{d}{dw_1}[\text{prev}] = \frac{2}{2}\sigma(v_1^T \tanh(Wx) \cdot \sigma'(v_1 \tanh(Wx)) \cdot \frac{d}{dw_1}\left[v_1^T \tanh(Wx)\right]$

$\Rightarrow \frac{d}{dw_i} = \sigma(v_i^T \tanh(Wx) \cdot \sigma'(v_i \tanh(Wx)) \cdot \frac{d}{dw_i}\left[v_i^T \tanh(Wx)\right]$

$$\Rightarrow \boxed{\frac{d}{dw_j}J = \left(-\sum_i (y_i - \sigma(v_i^T z)) \cdot \sigma'(v_i^T z) V_j\right) \tanh'(w_j^T x)\, x^T}$$

SGD: $v_i^T \longleftarrow v_i^T + \lambda \frac{d}{dv_i}J$

$w_j^T \longleftarrow w_j^T + \lambda \frac{d}{dw_j}J$

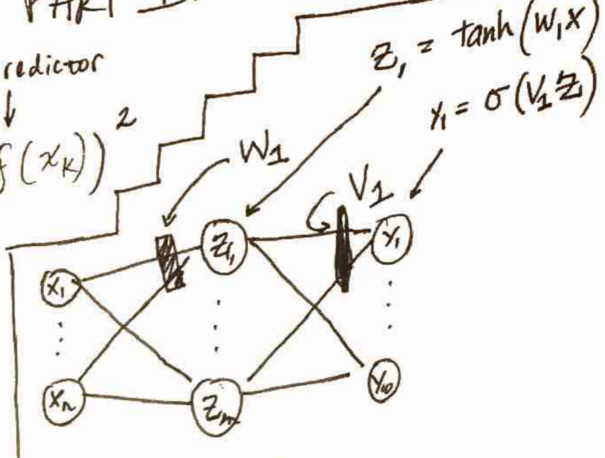


Figure 1.
The conventions used in deriving SGD.

#1 $X\mathcal{E}$- Loss SGD derivation.

now,
$$J = -\sum_{k=1}^{n}\left(y_k \ln\left(\sigma\left(\overbrace{v_k^T \tanh(x)}^{z_k(x)}\right)\right) + (1-y_k)\ln\left(1-\sigma(z_k(x))\right)\right)$$

$$\frac{dJ}{dV}\left(\left(y_k \ln\left(\sigma\left(z_k(x)\right)\right) + (1-y_k)\ln\left(1-\sigma(z_k(x))\right)\right)\right)$$

$$= \frac{y_k}{\sigma(z_k(x))}\cdot\sigma'(z_k(x))\cdot\frac{d}{dV}\left[v_k^T \tanh(Wx)\right] + \frac{(1-y_k)}{1-\sigma(z_k(x))}\cdot\left(-\sigma'(z_k(x))\cdot\frac{d}{dV}\left[v_k^T \tanh(Wx)\right]\right)$$

$$= y_k\left(1-\sigma(z_k(x))\right)\cdot\frac{d}{dV}\left(v_k^T\tanh(Wx)\right) + (1-y_k)\cdot\left(-\sigma(z_k(x))\cdot\frac{d}{dV}\left[v_k^T\tanh(Wx)\right]\right),$$

$(\sigma(z_k) \triangleq \sigma(z_k(x)))$ $z_k \triangleq z_k(x)$

$$\Rightarrow \boxed{\left(y_k - \sigma(z_k(x))\right)\cdot\tanh(Wx) = \frac{d}{dV_k}J}$$

$$\frac{d}{dW_i}J = \frac{d}{dW_i}\left[-\sum\left(y_k \ln\sigma(z_k) + (1-y_k)\ln(1-\sigma(z_k)\right)\right],$$

$$\frac{d}{dW_i}\left(y_k\ln\sigma(z_k) + (1-y_k)\ln(1-\sigma(z_k))\right) = \frac{y_k}{\sigma(z_k)}\sigma'(z_k)\frac{d}{dW_i}z_k + \frac{(1-y_k)}{\sigma(z_k)}(1-\sigma(z_k))\frac{d}{dW_i}z_k$$

$= (1-\sigma(z_k))y_k\frac{d}{dW_i}z_k + \sigma(z_k)(1-y_k)\cdot\frac{d}{dW_i}z_k$. Since $\frac{d}{dW_i}z_k = \frac{d}{dW_i}\left(v_k^T\tanh(Wx)\right)$

$= v_k^T\tanh'(Wx)\cdot x$, then putting it all together, we get:

$$\boxed{\frac{d}{dW_i}J = \left[V^T\left(y - \sigma\left(V\tanh(Wx)\right)\right)\tanh'(Wx)\right]_{\substack{i\text{th}\\ \text{row (entry)}}} x^T}$$

So SGD equations are:

$$v_i^T \leftarrow \lambda\left(\frac{d}{dv_i}J\right) + v_i$$

$$w_j^T \leftarrow \lambda\left(\frac{d}{dW_j}J\right) + w_j$$

```python
# coding: utf-8

# In[2484]:

# Alex Walczak | CS 189 | Homework 6: Neural Networks

# Import functions and libraries
from __future__ import division, print_function
import cPickle as pickle
import numpy as np, matplotlib.pyplot as plt
from matplotlib.pyplot import *
import scipy.io
from pylab import rcParams
from sklearn.cross_validation import KFold
rcParams['figure.figsize'] = 7, 7
import csv
get_ipython().magic(u'matplotlib inline')
from scipy import ndimage


# In[2996]:

# # # Serialize object
# f = open('pick_name.pickle', 'wb')
# pickle.dump(NN, f, protocol=pickle.HIGHEST_PROTOCOL)
# f.close()


# In[2997]:

# # Load object
# f = open('pick_name.pickle', 'rb')
# _NN = pickle.load(f)
# f.close()


# In[2999]:

# rand_inds = np.random.permutation(60000)


# In[3000]:

# Load & Preprocess (training and validation sets)
# To enable bias, I append a 1 to front of each feature. x0 = 1. Then later, w0 = TBD.
data = scipy.io.loadmat("dataset/train.mat")
imgs = np.reshape( data["train_images"], (-1, 60000)).T[rand_inds]
labels0 = data["train_labels"][rand_inds]

####### gooooooood ######## ######## ######## ########
imgs = imgs/255
imgs_mean = np.mean(imgs, axis = 0)
imgs = imgs - imgs_mean # zero-center the data (important)
######## ######## ######## ######## ######## ########

# 0.1/.9 target reachable by logistic and tanh functions.
# cs.cmu.edu/afs/cs/academic/class/15883-f15/slides/backprop.pdf
# Compare to: normal (unreachable) 0/1 targets.

all_labels = []
for label in labels0:
    l = np.zeros(10) + 0.02
    l[label] = 0.98
    all_labels += [l]
all_labels = np.array(all_labels)

images_with_concated1 = np.c_[ np.ones(len(imgs)) , imgs ]

images = images_with_concated1[10000:]
labels = all_labels[10000:]

# Create validation set, size 10,000.
vimages = images_with_concated1[:10000]
vlabels = all_labels[:10000]

# Uncomment and run for sanity check on preprocessing.
# I = 35;
# plt.figure(); showme(images[I]); print('First image (train):',labels[I].argmax())
# plt.figure(); showme(vimages[I]); print('Second image (validation):', vlabels[I].argmax())


# In[3001]:

# Load & Preprocess (test set)
test_images = scipy.io.loadmat("dataset/test.mat")['test_images']
test_imgs = []
# Load and norm test images.
for i in range(len(test_images)):
    ti = test_images[i]
    ti = np.ndarray.flatten(np.fliplr(((np.rot90(np.reshape(ti, (28,-1)))).T)))
    # ^ Reshape data
    test_imgs += [ti]

test_imgs = np.array(test_imgs)

# test_imgs = np.reshape( test_images, (-1, 10000)).T
test_imgs_scaled = test_imgs/255
test_imgs = test_imgs_scaled - imgs_mean
test_imgs = np.c_[ np.ones(len(test_imgs)) , test_imgs ]


# In[3004]:

# Computation

def sigmoid(gamma):
    # activiation function for output units
    return 1/(1+np.exp(-gamma))

def deriv_sigmoid(gamma):
    # d/d(gamma) sigmoid
    return sigmoid(gamma)*(1-sigmoid(gamma))

def tanh(gamma):
    # activiation function for hidden units
    return np.tanh(gamma)

def deriv_tanh(gamma):
    # d/d(gamma) tanh
    return -tanh(gamma)**2 + 1

def square_error(x,y,W,V):
    return -1*-1*0.5*np.sum((y - sigmoid(V.dot(tanh(W.dot(x)))))**2)

def cross_entropy(x,y,W,V):
    return -1*-1*-np.sum(y*np.log(sigmoid(V.dot(tanh(W.dot(x))))) + (1-y)*np.log(1-sigmoid(V.dot(tanh(W.dot(x))))))

def evaluate_grad(gW,gV,W,V):
```

```python
    wnum, wden = np.linalg.norm(gW-W), np.linalg.norm(gW+W)
    vnum, vden = np.linalg.norm(gV-V), np.linalg.norm(gV+V)
    if vnum == vden == 0:
        vden = 1
    if wnum == wden == 0:
        wden = 1
    return wnum/wden, vnum/vden

# Utilities

def showme(img):
    # skip first entry of array because it's always a one.
    plt.figure()
    plt.imshow(np.reshape(img[1:],(28,-1)))

def save_labels(labels, fname):
    # Ex. save_labels(spam_labels,'kaggle_spam_mean.csv')
    f1 = open(fname, 'w+')
    print('Id,Category', file = f1)
    for i in range(len(labels)):
        print(str(i+1)+","+str(int(labels[i])), file = f1)


# In[3015]:

class Neural_Network():
    # (785-200-10)
    # with a single hidden layer.
    # classifies MNIST images.

    def __init__(self, learn_weights, cost_fn=None, Lambda=0.1, momentum=0.5, MAX_ITERS=10e6):
        self.ID = str(np.random.randint(10e4,10e8))
        self.cost_fn = cost_fn
        self.Lambda = Lambda
        self.momentumW = momentum
        self.momentumV = momentum
        self.stddW = 1/np.sqrt(785)
        self.stddV = 1/np.sqrt(200)
        self.W = self.stddW*np.random.randn(200, 785)
        self.V = self.stddV*np.random.randn(10, 200)

        self.prev_gradV = 0
        self.prev_gradW = 0

#       Different layers learn at different rates.
#       This was also mentioned in the same CMU ppt as in the early slides.
#       Input-to-hidden (i2h) weights learn more slowly than hidden-to-output (h2o) weights.

        # learn_weights = (i2h_lr, i2h_inc, i2h_dec, h2o_lr, h2o_inc, h2o_dec)
        # 7.75% error for (0.1, 1.02, 0.6, 0.02, 1.002, 0.4)

        self.i2h_lr = learn_weights[0]
        self.i2h_inc = learn_weights[1]
        self.i2h_dec = learn_weights[2]
        self.h2o_lr = learn_weights[3]
        self.h2o_inc = learn_weights[4]
        self.h2o_dec = learn_weights[5]

        self.iters = 1
        self.total_iters = 1
        self.MAX_ITERS = MAX_ITERS

        self.W_dot_x = 'Nothing yet!'
        self.tanh_W_dot_x = 'Nothing yet!'
        self.forward = 'Nothing yet!'

        self.last_error = 10e90
        self.oldW = None
        self.oldV = None
        self.alternateVW = 1

        self.errors = np.array([10,20,30])

    def train(self, images, labels, learn_weights, epoch, error_inc=1.0001, error_func=None, iters=None, reset_iters=False, vimages=None, vlabels=None):

        self.epoch = epoch #4*10e3
        self.error_inc = error_inc # if the error increased by more than this percentage of last epoch, then we did worse. Change back weights.

        self.i2h_lr = learn_weights[0]
        self.i2h_inc = learn_weights[1]
        self.i2h_dec = learn_weights[2]
        self.h2o_lr = learn_weights[3]
        self.h2o_inc = learn_weights[4]
        self.h2o_dec = learn_weights[5]

        self.iters = 1

        if reset_iters:
            self.total_iters = 1

        if error_func == None:
            print('Please choose an error function.')
            return
        if error_func == 'square_error':
            gradVfunc = self.gradV_square_error
            gradWfunc = self.gradW_square_error
            _error = square_error
        if error_func == 'cross_entropy':
            gradVfunc = self.gradV_cross_entropy_error
            gradWfunc = self.gradW_cross_entropy_error
            _error = cross_entropy

        if iters == None:
            iters = self.MAX_ITERS

        while self.iters <= iters:
            idx = np.random.randint(1,len(images))
            x = images[idx]

            self.W_dot_x = self.W.dot(x)
            self.tanh_W_dot_x = tanh(self.W_dot_x)
            self.forward = sigmoid(self.V.dot(self.tanh_W_dot_x))

            _gradV = self.h2o_lr*gradVfunc(x, labels[idx])
            _gradW = self.i2h_lr*gradWfunc(x, labels[idx])

            self.V += (_gradV + self.momentumV*self.prev_gradV) # does sign/order matter?
            self.W += (_gradW + self.momentumW*self.prev_gradW) #       ''

            self.prev_gradV = _gradV
            self.prev_gradW = _gradW

            self.iters += 1
            self.total_iters += 1

            # Adjust learning rate.

```

```
            if (self.total_iters % self.epoch) == 0:

                self.i2h_inc = self.i2h_inc*(1 - (self.total_iters/self.MAX_ITERS))
                self.i2h_dec = self.i2h_dec*(1 - (self.total_iters/self.MAX_ITERS))
                self.h2o_inc = self.h2o_inc*(1 - (self.total_iters/self.MAX_ITERS))
                self.h2o_dec = self.h2o_dec*(1 - (self.total_iters/self.MAX_ITERS))

                data_error, XXX = self.check_error(vimages, vlabels)

                if error_func == 'cross_entropy':
                    error = self.cost_xe(vimages, vlabels)
                if error_func == 'square_error':
                    error = self.cost_se(vimages, vlabels)

                self.errors = np.append(self.errors,error)

                self.alternateVW += 1

                if error < self.last_error:

                    if (error == self.errors[3:].min()):
                        # Pickle if best.
                        # # # Serialize object
                        f = open('BEST_ECOUNTERED_'+self.ID+'_.pickle', 'wb')
                        pickle.dump(self, f, protocol=pickle.HIGHEST_PROTOCOL)
                        f.close()
                        print('pickled!')

                    print('better!')

                    if (error < 1.0):
                        print('good enough!')
                        break

                    # Doing well? Speed up!
                    if self.alternateVW % 2 == 0:
                        self.i2h_lr = self.i2h_lr*self.i2h_inc
                        self.oldW = np.copy(self.W)
                        self.momentumW = self.momentumW*1.1

                    else:
                        self.h2o_lr = self.h2o_lr*self.h2o_inc
                        self.oldV = np.copy(self.V)
                        self.momentumV = self.momentumV*1.05

                if error >= self.last_error*self.error_inc:

                    print('worse')

                    # Getting worse? Slow down!
                    if self.alternateVW % 2 == 1: # (sometimes) trying 1 not 0 because if I just change W, that was a bad change bc error increased.
                                                  # experiment with this!
                        self.i2h_lr = self.i2h_dec*self.i2h_lr # i2h_dec should be at least bigger than h2o_dec because don't want i2h_lr to slow down too much (takes longer to get up)
                        self.W = np.copy(self.oldW)
                        self.momentumW = self.momentumW*0.6

                    else:
                        self.h2o_lr = self.h2o_dec*self.h2o_lr
                        self.V = np.copy(self.oldV)
                        self.momentumV = self.momentumV*0.3

                self.last_error = error

                # If std dev of most recent errors is low, assume we are stuck in a local minimum.
                if np.std(self.errors[-3:]) < 0.10:
                    print('Errors not changing! Time to shake things up.')
                    self.momentumW = np.random.randint(5,20)/150
                    self.momentumV = np.random.randint(5,100)/1000
                    self.i2h_lr += 0.0001*np.random.randint(1,61)
                    self.h2o_lr += 0.0001**np.random.randint(1,61)
                    self.errors[-1]+=10e9

                if self.i2h_lr < 10e-8:
                    print('i2h too small!')
                    self.i2h_lr += 10e-6

                if self.h2o_lr < 10e-14:
                    print('h2o too small!')
                    self.h2o_lr += 10e-10

                print(self.i2h_lr, self.h2o_lr, self.momentumW, self.momentumV)

    def cost_xe(self, vimages, vlabels):
        tot=0
        for i in range(len(vimages)):
            tot+=-np.sum(vlabels[i]*np.log(sigmoid(self.V.dot(tanh(self.W.dot(vimages[i]))))) + (1-vlabels[i])*np.log(1-sigmoid(self.V.dot(tanh(self.W.dot(vimages[i]))))))
        print('XE Cost', tot)
        return tot

    def cost_se(self, vimages, vlabels):
        tot=0
        for i in range(len(vimages)):
            tot+=np.sum( (vlabels[i] - sigmoid(self.V.dot(tanh(self.W.dot(vimages[i])))))**2 )
        print('SE Cost', tot)
        return tot

    def predict(self, image):
        return sigmoid(self.V.dot(tanh(self.W.dot(image))))

    def predict_all(self, images):
        return(np.array(map(self.predict, images)))

    def check_error(self, images, labels):
        # labels are assumed to be each of size 10 as in preprocessing.
        pdn = self.predict_all(images)
        pdn_labels = np.array([p.argmax() for p in pdn])
        labels = np.array([l.argmax() for l in labels])
        error = 100*np.sum(pdn_labels != labels)/len(labels)
        print('Error', error,'%')
        return error, pdn_labels

    def check_grad(self, error_func, x, y, eps=10e-5):
        # Call check grad to set self.forward before comparing to grad_XXX_error
        self.forward = sigmoid(self.V.dot(tanh(self.W.dot(x))))

        ogW, ogV = np.copy(self.W), np.copy(self.V)
        gradW, gradV = np.zeros(self.W.shape),np.copy( np.zeros(self.V.shape))

        for j in range(len(self.W)):
            for i in range(len(self.W[j])):
                og = self.W[j][i]
                self.W[j][i] = og + eps
                res1 = error_func(x,y,self.W,self.V)
                self.W[j][i] = og - eps
```

```python
                res2 = error_func(x,y,self.W,self.V)
                gradW[j][i] = (res1 - res2)/(2*eps)
                self.W[j][i] = og

        for j in range(len(self.V)):
            for i in range(len(self.V[j])):
                og = self.V[j][i]
                self.V[j][i] = og + eps
                res1 = error_func(x,y,self.W,self.V)
                self.V[j][i] = og - eps
                res2 = error_func(x,y,self.W,self.V)
                gradV[j][i] = (res1 - res2)/(2*eps)
                self.V[j][i] = og

        self.W, self.V = ogW, ogV
        return gradW, gradV

    def gradW_square_error(self, x,y):
        a = (((y - self.forward)*deriv_sigmoid(self.V.dot(self.tanh_W_dot_x))))
        return np.outer(self.V.T.dot(a)*deriv_tanh(self.W_dot_x), x.T)

    def gradV_square_error(self, x,y):
        return np.outer((y - self.forward)*deriv_sigmoid(self.V.dot(self.tanh_W_dot_x)), self.tanh_W_dot_x.T)

    def gradV_cross_entropy_error(self, x,y):
        return np.outer((y - self.forward), self.tanh_W_dot_x.T)

    def gradW_cross_entropy_error(self,x,y):
        return np.outer(((self.V.T.dot(y - self.forward))*deriv_tanh(self.W_dot_x)), x.T)

    def grad_cross_entropy(self, x,y):
        return self.gradW_cross_entropy_error(x,y), self.gradV_cross_entropy_error(x,y)

    def grad_square_error(self, x,y):
        return self.gradW_square_error(x,y), self.gradV_square_error(x,y)


# In[3038]:

# Training and testing


# In[ ]:

# Values I had good results using.
_i2h_lr =  0.1
_i2h_inc = 1.015
_i2h_dec = 0.8
_h2o_lr = 0.001
_h2o_inc = 1.0001
_h2o_dec = 0.45
_epoch = 3*10e3
_error_inc = 1+10e-6
_momentum = 0.001

learning_rate_weights = (_i2h_lr, _i2h_inc, _i2h_dec, _h2o_lr, _h2o_inc, _h2o_dec)


# In[3020]:

# Training with XE Loss

NN = Neural_Network(learn_weights=learning_rate_weights, momentum=_momentum)

for i in range(10):
    print(i)
    NN.train(images, labels, epoch=_epoch, error_inc=_error_inc, learn_weights=learning_rate_weights, error_func='cross_entropy', iters=10e4, reset_iters=False, vimages=vimages, vlabels=vlabels)
    print()

# This gets printed: (error, self.i2h_lr, self.h2o_lr, self.momentumW, self.momentumV)


# In[3036]:

# Training with SE Loss

# Run this line if not creating new instance of NN
# learning_rate_weights = (NN.i2h_lr, _i2h_inc, _i2h_dec, NN.h2o_lr, _h2o_inc, _h2o_dec)

NN = Neural_Network(learn_weights=learning_rate_weights, momentum=_momentum)

for i in range(10):
    print(i)
    NN.train(images, labels, epoch=_epoch, error_inc=_error_inc, learn_weights=learning_rate_weights, error_func='square_error', iters=10e4, reset_iters=False, vimages=vimages, vlabels=vlabels)
    print()


# In[3037]:

ti = vimages[900]
pdn = NN.predict(ti)
print(pdn.argmax())
showme(ti)


# In[ ]:

# Generate test data labels.


# In[2974]:

# __, predicted_labels = best_NN.check_error(test_imgs, vlabels)

# # Sanity check.
# _t = np.array([test_imgs[1], test_imgs[22], test_imgs[333], test_imgs[4444]])
# _l = np.array([predicted_labels[1], predicted_labels[22], predicted_labels[333], predicted_labels[4444]])
# for i in range(len(_t)):
#     showme(_t[i])
#     print('Label:', _l[i])

# Save labels.
# save_labels(predicted_labels, '784_200_10_NN_simple_preproc_labels.csv')

# Kaggle Score: 0.97640
# NN ID: 354600521


# In[ ]:

# Below, data saved for reference
#
# iterations: 10e3 to 20*10e4 with 67 pts.
# loss = array([ 13432.93569313,  12606.51591719,  12301.06718922,  12110.30162897,
```

```
#         12042.57279805,  11949.50139832,  11940.63769764,  11846.70304254,
#         11799.9777952 ,  11774.20877548,  11773.6444034 ,  11767.0068726 ,
#         11764.23110766,  11724.4665161 ,  11729.1478896 ,  11706.98543717,
#         11693.03176399,  11693.04117115,  11699.62146882,  11690.84224179,
#         11703.65743183,  11697.59636369,  11699.06362548,  11671.76060895,
#         11698.92654993,  11666.41520784,  11673.01219267,  11711.40579961,
#         11688.67719221,  11649.71231889,  11732.35222877,  11700.34949357,
#         11697.32432718,  11688.9760188 ,  11705.92981412,  11670.40111919,
#         11670.51814198,  11685.40041635,  11657.34283291,  11641.43742866,
#         11686.59015803,  11666.59176936,  11674.29694423,  11675.79256358,
#         11641.35108495,  11648.90007011,  11682.20514718,  11692.19700681,
#         11642.26152735,  11630.38092284,  11669.01027341,  11686.12114843,
#         11648.40395379,  11692.13425494,  11652.37114204,  11629.60390472,
#         11665.57532849,  11674.92947925,  11643.88537853,  11626.71857277,
#         11680.50829383,  11662.69287411,  11663.85694344,  11693.98101753,
#         11653.85801366,  11633.78618821])
# accuracy = np.array([5.86 , 4.22 , 3.76 , 3.27 , 3.2 , 2.98 , 3.03 , 2.68 , 2.69 , 2.54 , 2.44 , 2.57 , 2.68 , 2.43 , 2.4 , 2.4 , 2.32 , 2.4 , 2.54 , 2.43 , 2.53 , 2.37 , 2.39 , 2.33 , 2.42 , 2.38 , 2.34 , 2.46 , 2.46 , 2.31 , 2.52 , 2.5 , 2.47 , 2.43 , 2.39 , 2.49 , 2.38 , 2.32 , 2.4 , 2.34 , 2.3 , 2.39 , 2.3 , 2.4 , 2.2 , 2.37 , 2.36 , 2.45 , 2.34 , 2.35 , 2.43 , 2.51 , 2.34 , 2.5 , 2.49 , 2.35 , 2.37 , 2.48 , 2.42 , 2.48 , 2.5 , 2.38 , 2.43 , 2.41 , 2.37 , 2.4])


# In[3039]:

# plt.plot(np.linspace(10e3,20*10e4,66)/10e3,NN.errors[3:])
# plt.title('Cross-Entropy Loss VS Number of Iterations')
# plt.xlabel('Number of Iterations  [in thousands]')
# plt.ylabel('Cross-Entropy Loss')


# In[3040]:

# plt.plot(np.linspace(10e3,20*10e4,66)/10e3,accuracy)
# plt.title('Accuracy VS Number of Iterations')
# plt.xlabel('Number of Iterations  [in thousands]')
# plt.ylabel('Accuracy')
```