Homework6_report

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1 CS189 : Introduction to Machine Learning

1.1 Homework 6

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Neural Networks for MNIST Digit Recognition In this homework, we will implement neural networks to classify handwritten digits using raw pixels as features. We will be using the MNIST digits dataset that you used in previous homework assignments. The state-of-the-art error rate on this dataset using deep convolutional neural networks is around 0.5%. For this assignment, we should, with appropriate parameter settings, get approximately or better than 6% error using a neural network with one hidden layer.

```
In [1]: import scipy.io as sio
        import numpy as np
        import numpy.random as nr
        from sklearn import preprocessing
```

Preprocessing We import the data and transform each label between 0 and 9 to a vector of length 10 which has single 1 in the position of true class and 0 everywhere else.

```
In [2]: train_data = sio.loadmat('./dataset/train.mat')
        test_data = sio.loadmat('./dataset/test.mat')

        tr_img_orig = train_data['train_images']
        tr_lb_num = train_data['train_labels'][:,0]
        tr_img = np.reshape(tr_img_orig, (784, 60000), order = 'F')

        ts_img = np.reshape(np.swapaxes(np.transpose(test_data['test_images']),0,1), (784, 10000), orde


        temp_lb = np.zeros((len(tr_lb_num),10))

        for i in np.arange(len(tr_lb_num)):
            j = tr_lb_num[i]
            temp_lb[i,j] = 1

        tr_lb = temp_lb

In [3]: data =train_data['train_images'][:,:,20000]
        from PIL import Image
        from matplotlib import cm
        data =train_data['train_images'][:,:,20000]
        im = Image.fromarray(np.uint8(cm.gist_earth(data)*255))
        im.save('out.png')
```

```
data =np.swapaxes(np.transpose(test_data['test_images']),0,1)[:,:,5000]
im = Image.fromarray(np.uint8(cm.gist_earth(data)*255))
im.save('out1.png')
```

Then, we normalize, or standardize, all feature vectors.

In [4]:
```
all_img = np.append(tr_img, ts_img, axis = 1)
all_img = all_img.astype(float) # change data type from int to float, in order to
                                # facilitate calculations for standardization
all_img = preprocessing.scale(all_img, axis = 1)

ts_img = all_img[:, 60000:70000]
tr_img = all_img[:, 0:60000]
valid_ind = nr.choice(60000, 10000, replace = False)
vd_img = tr_img[: , valid_ind]
tr_img = tr_img[:, np.setdiff1d(np.arange(60000), valid_ind)]
vd_lb = tr_lb[valid_ind, :]
tr_lb = tr_lb[np.setdiff1d(np.arange(60000), valid_ind), :]
vd_lb_num = tr_lb_num[valid_ind]
tr_lb_num = tr_lb_num [np.setdiff1d(np.arange(60000), valid_ind)]
```

Neural Network In this assignment, we are asked to implement a neural network with one hidden layer. 1. We will be using a hidden layer of size 200. Let $n_{in} = 784$, the number of features for the digits class. Let $n_{hid} = 200$, the size of the hidden layer. Finally, let $n_{out} = 10$, the number of classes. Then, we will have $n_{in} + 1$ units in the input layer, $n_{hid} + 1$ units in the hidden layer, and n_{out} units in the output layer. The input and hidden layers have one additional unit which always takes a value of 1 to represent bias. The output layer size is set to the number of classes. Each label will have to be transformed to a vector of length 10 which has a single 1 in the position of the true class and 0 everywhere else.

2. The parameters of this model are the following:

- V , a n_{hid}-by-$(n_{in} + 1)$ matrix where the $(i; j)$-entry represents the weight connecting the j-th unit in the input layer to the i-th unit in the hidden layer. The i-th row of V represents the ensemble of weights feeding into the i-th hidden unit. Note: there is an additional row for weights connecting the bias term to each unit in the hidden layer.
- W, a n_{out}-by-$(n_{hid} + 1)$ matrix where the (i; j)-entry represents the weight connecting the j-th unit in the hidden layer to the i-th unit in the output layer. The i-th row of W represents the ensemble of weights feeding into the i-th output unit. Note: again there is an additional row for weights connecting the bias term to each unit in the output layer.

Initialization of Weights We initialize your weights with random values. This allows us to break symmetry that occurs when all weights are initialized to 0. We initialize by drawing values from a uniform distribution from $[-0.01, 0.01]$ or from a Gaussian distribution with mean 0 and variance 0.01^2.

In [5]:
```
nr.seed(0)
n_in = 784
n_hid = 200
n_out = 10
epsilon = 0.01
V0 = nr.normal(scale = epsilon, size = (n_hid, n_in + 1))
W0 = nr.normal(scale = epsilon, size = (n_out, n_hid + 1))
```

Adding one additional unit which always takes a value of 1 to represent bias

```
In [6]: def add_bias(mat):
            if len(mat.shape) > 1:
                ncol = mat.shape[1]
                temp = np.array([[1.0 for j in range(ncol)]])
                mat = np.append(mat, temp, axis = 0)
            else:
                mat = np.append(mat, [1.0], axis = 0)
            return mat

        tr_img = add_bias(tr_img) # add one column of 1's to all data
        ts_img = add_bias(ts_img)
        vd_img = add_bias(vd_img)
```

Two loss functions : Mean-Squared Error and Cross-Entropy Error

```
In [7]: def mean_squared(true, pred):
            temp = np.square(true - pred)
            err = np.sum(temp)
            return err/2

        def cross_entropy(true, pred):
            n,k = true.shape
            ind = (true == 1)
            temp = np.sum(true[ind] * np.log(pred[ind])) + np.sum((1-true[~ind]) * np.log(1-pred[~ind]))
            err = - temp
            return err
```

We use tanh activation function for the hidden layer units and the sigmoid function for the output layer units.

```
In [8]:
        def sigmoid_stb(mat):
            # Numerically-stable sigmoid function

            ind = (mat >= 0)
            temp = np.zeros(mat.shape)
            temp[ind] = 1/(1+np.exp(-mat[ind]))
            z =np.exp(mat[~ind])
            temp[~ind] = z /(1+z)

            return temp


        #def sigmoid(mat):
        #    temp = 1/(1+ np.exp(- mat))
        #    return temp
```

Calculating the loss for coefficient matrices W and V Here we implement a fuction that takes in two coefficient matrices W and V, and returns the values of output units when we use two matrices W and V as coefficients of linear combination for the hidden layer units and for the output layer units, respectively, to train neural network.

```
In [9]: def predict( V,W, img):
            temp = np.dot(V, img)
```

```
        hidden = np.tanh(temp)
        hidden = add_bias(hidden)
        temp = np.dot(W, hidden)
        return np.transpose(sigmoid_stb(temp))

    def calculate_loss(V,W, img, true_label, loss_fun):
        pred_label = predict(V, W, img)
        loss = loss_fun(true_label, pred_label)
        return loss

    def misclassification(V,W,img, true_num):
        pred = predict(V,W,img)
        pred_num = np.argmax(pred, axis = 1)
        return np.sum(pred_num != true_num)/len(true_num)
```

Back propagation in Stochastic Gradient Descent The procedure of matrix V influencing on the final output and thus the total mean squared error can be divided into several steps as follows:

$$V \mapsto A = Vx \mapsto B = \tanh(A) \mapsto C = WB^* \mapsto D = sigmoid(C) \mapsto E = \frac{1}{2}||Y - D||_2^2.$$

Therefore, stepwise,

$$\begin{aligned}
\frac{\partial E}{\partial D} &= (D - Y),\\
\frac{\partial D}{\partial C} &= diag(D)(I - diag(D)),\\
\frac{\partial C}{\partial B} &= W^\top,\\
\frac{\partial B}{\partial A} &= I - diag(B^2),\\
\frac{\partial A}{\partial V_j} &= diag(x_j),\\
\frac{\partial C}{\partial W_j} &= diag(B_j^*)
\end{aligned}$$

where x is a $(n_{in}+1)$-dim column vector, V_j, W_j denotes the jth column of the matrix V, W, respectively, B^* is the matrix that results from adding a row of 1 to B. In case we use cross-entropy instead,

$$\frac{\partial E}{\partial D} = Y/D - (1 - Y)/(1 - D)$$

```
In [10]: def find_gradient(V,W, i, loss_fun_name):

             x = tr_img[:,i:i+1]
             y = np.transpose(tr_lb[i:i+1,:])
             A = np.dot(V, x)
             B = np.tanh(A)
             B_bias = add_bias(B)
             C = np.dot(W, B_bias)
             D = sigmoid_stb(C)

             I = np.identity(n_out)
```

```
        if loss_fun_name == 'mean_squared':
            dEdD = - y + D
        elif loss_fun_name == 'cross_entropy':
            ind = (y == 1)
            temp = np.zeros(y.shape)
            temp[ind] = - y[ind]/D[ind]
            temp[~ind] = (1-y[~ind])/(1-D[~ind])
            dEdD = temp


        dDdC = np.multiply(D, 1-D)
        dCdB = np.transpose(W[:, :n_hid])
        dBdA = 1- np.square(B)

        dEdC = np.multiply(dDdC, dEdD)
        dEdB = np.dot(dCdB, dEdC)
        dEdA = np.multiply(dBdA, dEdB)
        dEdV = np.array([])
        dEdW = np.array([])


        dAdV = x[:,0]
        dEdV = np.outer(dEdA[:,0], dAdV)

        dCdW = B_bias[:,0]
        dEdW = np.outer(dEdC[:,0], dCdW)


        return np.concatenate((dEdV.ravel('F'), dEdW.ravel('F')))

    def column_to_matrix(vec, r, c):
        return vec.reshape((r,c), order = 'F')

    def matrix_to_column(mat):
        return mat.ravel(order = 'F')

    a = find_gradient(V0, W0, 2, 'mean_squared')
    b = find_gradient(V0, W0, 2, 'cross_entropy')
```

Numerical Gradient Checking

```
In [11]: def numerical_gradient(V, W, i, eps = 1e-8):
             grad = np.concatenate((matrix_to_column(V), matrix_to_column(W)))

             num_grad = np.zeros(grad.shape)
             temp = grad
             for j in range(len(grad)):

                 temp[j] = grad[j] + eps
                 V_temp = column_to_matrix(temp[0:n_hid*(n_in + 1)], n_hid, n_in + 1)
                 W_temp = column_to_matrix(temp[n_hid*(n_in + 1):], n_out, n_hid + 1)
                 loss1 = calculate_loss(V_temp,W_temp, tr_img[:, i:i+1], tr_lb[i:i+1,:], mean_squared)
```

```
            temp[j] = grad[j] - 2 * eps
            V_temp = column_to_matrix(temp[0:n_hid*(n_in + 1)], n_hid, n_in + 1)
            W_temp = column_to_matrix(temp[n_hid*(n_in + 1):], n_out, n_hid + 1)
            loss2 = calculate_loss(V_temp,W_temp, tr_img[:, i:i+1],tr_lb[i:i+1,:], mean_squared)

            num_grad[j] = (loss1-loss2)/(2*eps)
            temp = grad

        return num_grad

    def norm(l):
        return np.sqrt(np.sum(np.square(l)))

    num_grad = numerical_gradient(V0, W0, 2)
```

In [12]:
```
norm(a-num_grad)/norm(a + num_grad)
```

Out[12]: 1.9019895521456657e-06

In [13]:
```
def numerical_gradient_cross_entropy(V, W, i, eps = 1e-8):
        grad = np.concatenate((matrix_to_column(V), matrix_to_column(W)))

        num_grad = np.zeros(grad.shape)
        temp = grad
        for j in range(len(grad)):

            temp[j] = grad[j] + eps
            V_temp = column_to_matrix(temp[0:n_hid*(n_in + 1)], n_hid, n_in + 1)
            W_temp = column_to_matrix(temp[n_hid*(n_in + 1):], n_out, n_hid + 1)
            loss1 = calculate_loss(V_temp,W_temp, tr_img[:, i:i+1], tr_lb[i:i+1,:], cross_entropy)


            temp[j] = grad[j] - 2 * eps
            V_temp = column_to_matrix(temp[0:n_hid*(n_in + 1)], n_hid, n_in + 1)
            W_temp = column_to_matrix(temp[n_hid*(n_in + 1):], n_out, n_hid + 1)
            loss2 = calculate_loss(V_temp,W_temp, tr_img[:, i:i+1],tr_lb[i:i+1,:], cross_entropy)

            num_grad[j] = (loss1-loss2)/(2*eps)
            temp = grad

        return num_grad
    num_grad_cross = numerical_gradient_cross_entropy(V0, W0, 2)
    norm(b-num_grad_cross)/norm(b+num_grad_cross)
```

Out[13]: 1.9302602087102173e-06

This proves that our calculation to find a gradient is pretty accurate.

Train Neural Network by Stochastic gradient descent using Mean Squared loss / Cross-entropy

In [14]:
```
def train(V, W, img, true, index, start, end, step):
        n = len(true)
        V_temp = V
        W_temp = W
```

```
        VW_temp = np.concatenate((matrix_to_column(V), matrix_to_column(W)))

        for i in index[start * 1000: end * 1000]:
            grad = find_gradient(V_temp, W_temp, i, 'mean_squared')
            VW_temp = VW_temp - step * grad
            V_temp = column_to_matrix(VW_temp[0:n_hid*(n_in + 1)], n_hid, n_in + 1)
            W_temp = column_to_matrix(VW_temp[n_hid*(n_in + 1):], n_out, n_hid + 1)

        return (V_temp, W_temp)

    def train_cross_entropy(V, W, img, true, index, start, end, step):
        n = len(true)

        V_temp = V
        W_temp = W


        VW_temp = np.concatenate((matrix_to_column(V), matrix_to_column(W)))

        for i in index[start * 1000 : end * 1000]:
            grad = find_gradient(V_temp,W_temp, i, 'cross_entropy')
            VW_temp = VW_temp - step * grad
            V_temp = column_to_matrix(VW_temp[0:n_hid*(n_in + 1)], n_hid, n_in + 1)
            W_temp = column_to_matrix(VW_temp[n_hid*(n_in + 1):], n_out, n_hid + 1)

        return (V_temp, W_temp)
```

Train with cross entropy

- Initial learning rate : 0.01 Every two epoch, we update learning rate by a factor of 0.5.
- Training time: For each epoch, it took about 10 mins to run stochastic gradient descent. 50 mins in total.
- Stopping condition: When classification accuracy on validation data starts to drop, we consider it as a sign of overfitting and stop to train.

```
In [15]: V_temp = V0
         W_temp = W0
         ind = nr.choice(50000,50000, replace = False)
         loss = []
         misclass = []
         for j in range(50):
             V_temp, W_temp = train_cross_entropy(V_temp, W_temp, tr_img, tr_lb, ind, j, j+1, 0.01)
             loss_temp = calculate_loss(V_temp, W_temp, tr_img, tr_lb, cross_entropy)
             mis_temp = misclassification(V_temp, W_temp, tr_img, tr_lb_num)
             loss = np.append(loss, [loss_temp])
             misclass= np.append(misclass, [mis_temp])
```

```
In [16]: V1, W1, loss1, misclass1 = V_temp, W_temp, loss, misclass
         misclassification(V1,W1,vd_img,vd_lb_num)
```

```
Out[16]: 0.067199999999999996
```

```
In [18]: V_temp = V1
         W_temp = W1
         ind = nr.choice(50000,50000, replace = False)
```

```
        loss = loss1
        misclass = misclass1
        for j in range(50):
            V_temp, W_temp = train_cross_entropy(V_temp, W_temp, tr_img, tr_lb, ind, j, j+1, 0.01)
            loss_temp = calculate_loss(V_temp, W_temp, tr_img, tr_lb, cross_entropy)
            mis_temp = misclassification(V_temp, W_temp, tr_img, tr_lb_num)
            loss = np.append(loss, [loss_temp])
            misclass= np.append(misclass, [mis_temp])
```

```
In [20]: V2, W2, loss2, misclass2 = V_temp, W_temp, loss, misclass
         misclassification(V2,W2,vd_img,vd_lb_num)
```

```
Out[20]: 0.0516
```

```
In [21]: V_temp = V2
         W_temp = W2
         ind = nr.choice(50000,50000, replace = False)
         loss = loss2
         misclass = misclass2
         for j in range(50):
             V_temp, W_temp = train_cross_entropy(V_temp, W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5)
             loss_temp = calculate_loss(V_temp, W_temp, tr_img, tr_lb, cross_entropy)
             mis_temp = misclassification(V_temp, W_temp, tr_img, tr_lb_num)
             loss = np.append(loss, [loss_temp])
             misclass= np.append(misclass, [mis_temp])

         V3, W3, loss3, misclass3 = V_temp, W_temp, loss, misclass
         misclassification(V3,W3,vd_img,vd_lb_num)
```

```
Out[21]: 0.043799999999999999
```

```
In [22]: V_temp = V3
         W_temp = W3
         ind = nr.choice(50000,50000, replace = False)
         loss = loss3
         misclass = misclass3
         for j in range(50):
             V_temp, W_temp = train_cross_entropy(V_temp, W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5)
             loss_temp = calculate_loss(V_temp, W_temp, tr_img, tr_lb, cross_entropy)
             mis_temp = misclassification(V_temp, W_temp, tr_img, tr_lb_num)
             loss = np.append(loss, [loss_temp])
             misclass= np.append(misclass, [mis_temp])

         V4, W4, loss4, misclass4 = V_temp, W_temp, loss, misclass
         misclassification(V4,W4,vd_img,vd_lb_num)
```

```
Out[22]: 0.040300000000000002
```

```
In [23]: V_temp = V4
         W_temp = W4
         ind = nr.choice(50000,50000, replace = False)
         loss = loss4
         misclass = misclass4
         for j in range(50):
             V_temp, W_temp = train_cross_entropy(V_temp, W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5*
             loss_temp = calculate_loss(V_temp, W_temp, tr_img, tr_lb, cross_entropy)
```

```
        mis_temp = misclassification(V_temp, W_temp, tr_img, tr_lb_num)
        loss = np.append(loss, [loss_temp])
        misclass= np.append(misclass, [mis_temp])

    V5, W5, loss5, misclass5 = V_temp, W_temp, loss, misclass
    misclassification(V5,W5,vd_img,vd_lb_num)
```

Out[23]: 0.038600000000000002

```
In [24]: V_temp = V5
         W_temp = W5
         ind = nr.choice(50000,50000, replace = False)
         loss = loss5
         misclass = misclass5
         for j in range(50):
             V_temp, W_temp = train_cross_entropy(V_temp, W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5*
             loss_temp = calculate_loss(V_temp, W_temp, tr_img, tr_lb, cross_entropy)
             mis_temp = misclassification(V_temp, W_temp, tr_img, tr_lb_num)
             loss = np.append(loss, [loss_temp])
             misclass= np.append(misclass, [mis_temp])

         V6, W6, loss6, misclass6 = V_temp, W_temp, loss, misclass
         misclassification(V6,W6,vd_img,vd_lb_num)
```

Out[24]: 0.036900000000000002

```
In [25]: V_temp = V6
         W_temp = W6
         ind = nr.choice(50000,50000, replace = False)
         loss = loss6
         misclass = misclass6
         for j in range(50):
             V_temp, W_temp = train_cross_entropy(V_temp, W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5*
             loss_temp = calculate_loss(V_temp, W_temp, tr_img, tr_lb, cross_entropy)
             mis_temp = misclassification(V_temp, W_temp, tr_img, tr_lb_num)
             loss = np.append(loss, [loss_temp])
             misclass= np.append(misclass, [mis_temp])

         V7, W7, loss7, misclass7 = V_temp, W_temp, loss, misclass
         misclassification(V7,W7,vd_img,vd_lb_num)
```

Out[25]: 0.0378

```
In [26]: V_temp = V7
         W_temp = W7
         ind = nr.choice(50000,50000, replace = False)
         loss = loss7
         misclass = misclass7
         for j in range(50):
             V_temp, W_temp = train_cross_entropy(V_temp, W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5*
             loss_temp = calculate_loss(V_temp, W_temp, tr_img, tr_lb, cross_entropy)
             mis_temp = misclassification(V_temp, W_temp, tr_img, tr_lb_num)
             loss = np.append(loss, [loss_temp])
             misclass= np.append(misclass, [mis_temp])

         V8, W8, loss8, misclass8 = V_temp, W_temp, loss, misclass
         misclassification(V8,W8,vd_img,vd_lb_num)
```

Out[26]: 0.037699999999999997

Train with Mean-Squared Error

- Initial learning rate : 0.01 Every two or three epoch, we update learning rate by a factor of 0.5.
- Training time: For each epoch, it took less than 10 mins to run stochastic gradient descent. 60mins in total.
- Stopping condition: When classification accuracy on validation data starts to drop, we consider it as a sign of overfitting and stop to train.

In [27]:
```
_V_temp = V0
_W_temp = W0
_loss = []
ind = nr.choice(50000,50000, replace = False)
_misclass = []
for j in range(50):
    _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01)
    loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
    mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
    _loss = np.append(_loss, [loss_temp])
    _misclass = np.append(_misclass, [mis_temp])

_V1, _W1, _loss1, _misclass1 = _V_temp, _W_temp, _loss, _misclass
misclassification(_V1,_W1,vd_img,vd_lb_num)
```

Out[27]: 0.089999999999999997

In [28]:
```
_V_temp = _V1
_W_temp = _W1
_loss = _loss1
ind = nr.choice(50000,50000, replace = False)
_misclass = _misclass1
for j in range(50):
    _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01)
    loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
    mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
    _loss = np.append(_loss, [loss_temp])
    _misclass = np.append(_misclass, [mis_temp])

_V2, _W2, _loss2, _misclass2 = _V_temp, _W_temp, _loss, _misclass
misclassification(_V1,_W1,vd_img,vd_lb_num)
```

Out[28]: 0.089999999999999997

In [29]:
```
_V_temp = _V2
_W_temp = _W2
_loss = _loss2
ind = nr.choice(50000,50000, replace = False)
_misclass = _misclass2
for j in range(50):
    _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5)
    loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
    mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
    _loss = np.append(_loss, [loss_temp])
```

```
        _misclass = np.append(_misclass, [mis_temp])

    _V3, _W3, _loss3, _misclass3 = _V_temp, _W_temp, _loss, _misclass
    misclassification(_V3,_W3,vd_img,vd_lb_num)
```

Out[29]: 0.060600000000000001

```
In [30]: _V_temp = _V3
         _W_temp = _W3
         _loss = _loss3
         ind = nr.choice(50000,50000, replace = False)
         _misclass = _misclass3
         for j in range(50):
             _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5)
             loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
             mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
             _loss = np.append(_loss, [loss_temp])
             _misclass = np.append(_misclass, [mis_temp])

         _V4, _W4, _loss4, _misclass4 = _V_temp, _W_temp, _loss, _misclass
         misclassification(_V4,_W4,vd_img,vd_lb_num)
```

Out[30]: 0.057299999999999997

```
In [31]: _V_temp = _V4
         _W_temp = _W4
         _loss = _loss4
         ind = nr.choice(50000,50000, replace = False)
         _misclass = _misclass4
         for j in range(50):
             _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5)
             loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
             mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
             _loss = np.append(_loss, [loss_temp])
             _misclass = np.append(_misclass, [mis_temp])

         _V5, _W5, _loss5, _misclass5 = _V_temp, _W_temp, _loss, _misclass
         misclassification(_V5,_W5,vd_img,vd_lb_num)
```

Out[31]: 0.054800000000000001

```
In [32]: _V_temp = _V5
         _W_temp = _W5
         _loss = _loss5
         ind = nr.choice(50000,50000, replace = False)
         _misclass = _misclass5
         for j in range(50):
             _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5*0.5)
             loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
             mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
             _loss = np.append(_loss, [loss_temp])
             _misclass = np.append(_misclass, [mis_temp])

         _V6, _W6, _loss6, _misclass6 = _V_temp, _W_temp, _loss, _misclass
         misclassification(_V6,_W6,vd_img,vd_lb_num)
```

Out[32]: 0.051799999999999999

```python
In [33]: _V_temp = _V6
         _W_temp = _W6
         _loss = _loss6
         ind = nr.choice(50000,50000, replace = False)
         _misclass = _misclass6
         for j in range(50):
             _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5*0.5)
             loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
             mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
             _loss = np.append(_loss, [loss_temp])
             _misclass = np.append(_misclass, [mis_temp])

         _V7, _W7, _loss7, _misclass7 = _V_temp, _W_temp, _loss, _misclass
         misclassification(_V7,_W7,vd_img,vd_lb_num)
```

Out[33]: 0.050000000000000003

```python
In [34]: _V_temp = _V7
         _W_temp = _W7
         _loss = _loss7
         ind = nr.choice(50000,50000, replace = False)
         _misclass = _misclass7
         for j in range(50):
             _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5*0.5)
             loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
             mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
             _loss = np.append(_loss, [loss_temp])
             _misclass = np.append(_misclass, [mis_temp])

         _V8, _W8, _loss8, _misclass8 = _V_temp, _W_temp, _loss, _misclass
         misclassification(_V8,_W8,vd_img,vd_lb_num)
```

Out[34]: 0.049200000000000001

```python
In [35]: _V_temp = _V8
         _W_temp = _W8
         _loss = _loss8
         ind = nr.choice(50000,50000, replace = False)
         _misclass = _misclass8
         for j in range(50):
             _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5*0.5)
             loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
             mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
             _loss = np.append(_loss, [loss_temp])
             _misclass = np.append(_misclass, [mis_temp])

         _V9, _W9, _loss9, _misclass9 = _V_temp, _W_temp, _loss, _misclass
         misclassification(_V9,_W9,vd_img,vd_lb_num)
```

Out[35]: 0.047600000000000003

```python
In [36]: _V_temp = _V9
         _W_temp = _W9
         _loss = _loss9
```

```
        ind = nr.choice(50000,50000, replace = False)
        _misclass = _misclass9
        for j in range(50):
            _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5*0.5*0.5)
            loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
            mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
            _loss = np.append(_loss, [loss_temp])
            _misclass = np.append(_misclass, [mis_temp])

        _V10, _W10, _loss10, _misclass10 = _V_temp, _W_temp, _loss, _misclass
        misclassification(_V10,_W10,vd_img,vd_lb_num)
```

```
Out[36]: 0.047600000000000003
```

```
In [37]: _V_temp = _V10
         _W_temp = _W10
         _loss = _loss10
         ind = nr.choice(50000,50000, replace = False)
         _misclass = _misclass10
         for j in range(50):
             _V_temp, _W_temp = train(_V_temp, _W_temp, tr_img, tr_lb, ind, j, j+1, 0.01*0.5*0.5*0.5)
             loss_temp = calculate_loss(_V_temp, _W_temp, tr_img, tr_lb, mean_squared)
             mis_temp = misclassification(_V_temp, _W_temp, tr_img, tr_lb_num)
             _loss = np.append(_loss, [loss_temp])
             _misclass = np.append(_misclass, [mis_temp])

         _V11, _W11, _loss11, _misclass11 = _V_temp, _W_temp, _loss, _misclass
         misclassification(_V11,_W11,vd_img,vd_lb_num)
```

```
Out[37]: 0.0458
```

Kaggle

- Cross_entropy: 0.96860
- Mean_squared: 0.96200

The classification accuracy on test data were very similar in cross entropy and mean squared loss, and the cross entropy gained slightly higher accuracy rate on test data. Considering the number of epoch by which we trained data, cross entropy seems more time-efficient.

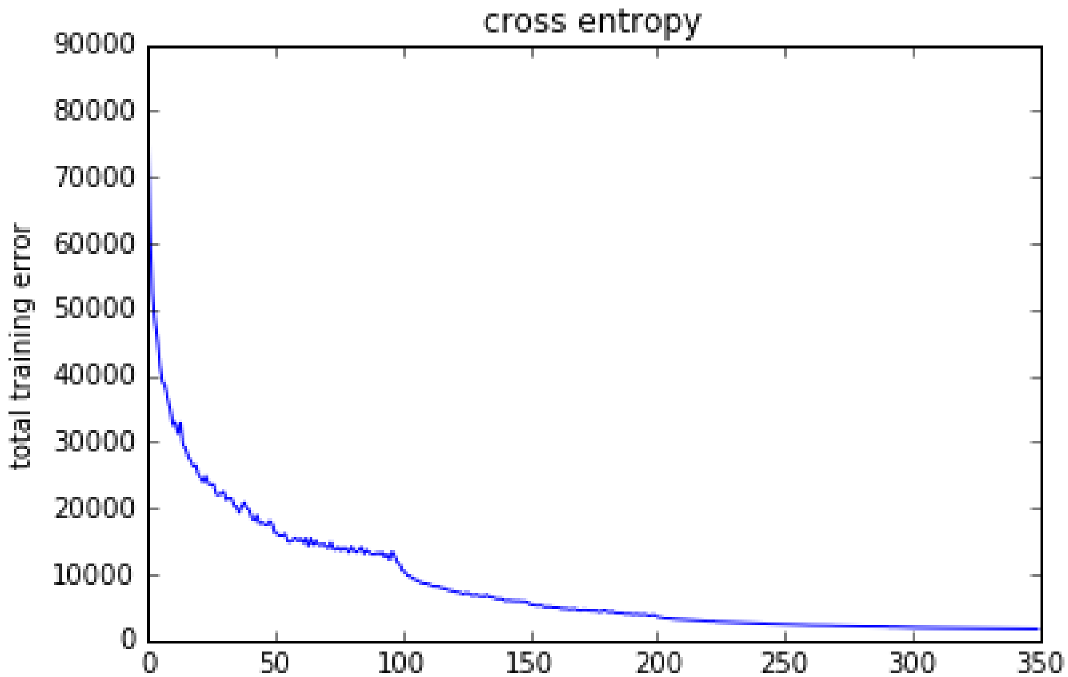
```
In [38]: pred_cross = predict(V7, W7, ts_img)
         pred_num_cross = np.argmax(pred_cross,axis=1)
         pred_cross_txt = np.asarray([[i+1, pred_num_cross[i]] for i in np.arange(10000)])
         np.savetxt('pred_cross.csv',pred_cross_txt,fmt = '%1.u' , delimiter = ',', header = 'Id,Catego
```

```
In [39]: pred_mean = predict(_V10, _W10, ts_img)
         pred_num_mean = np.argmax(pred_mean,axis=1)
         pred_mean_txt = np.asarray([[i+1, pred_num_mean[i]] for i in np.arange(10000)])
         np.savetxt('pred_mean.csv',pred_mean_txt,fmt = '%1.u' , delimiter = ',', header = 'Id,Category
```

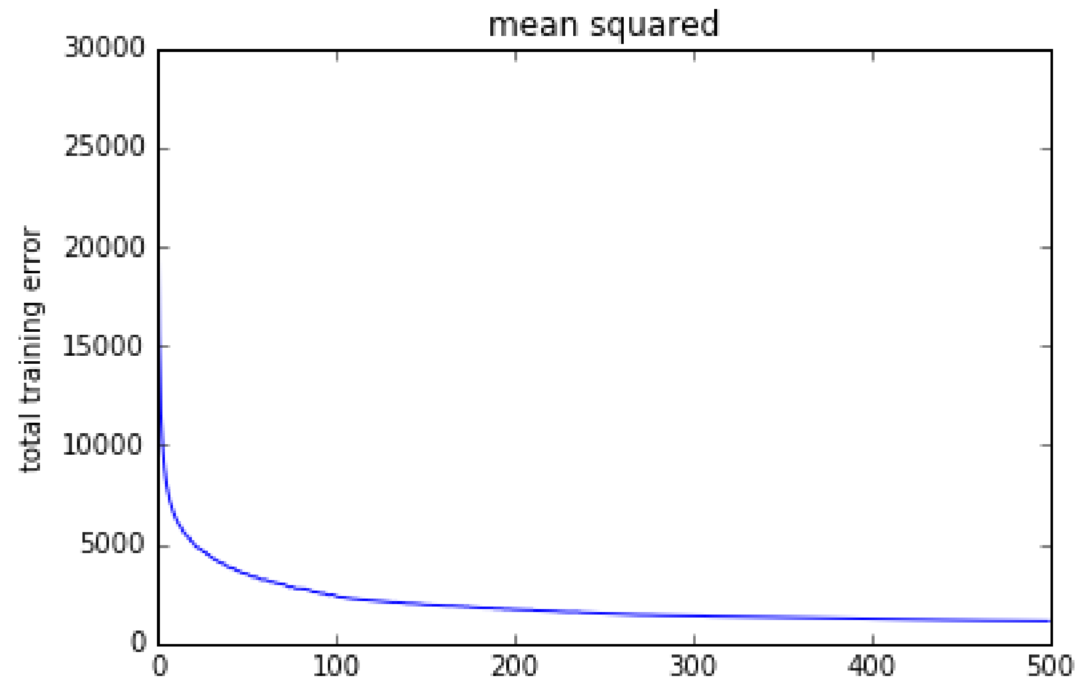
Graph Plots of total training error and classification accuracy on training set vs iteration. We compute the error or accuracy every 1000 iterations.

```
In [40]: import matplotlib
         import matplotlib.pyplot as plt
         %matplotlib inline
```

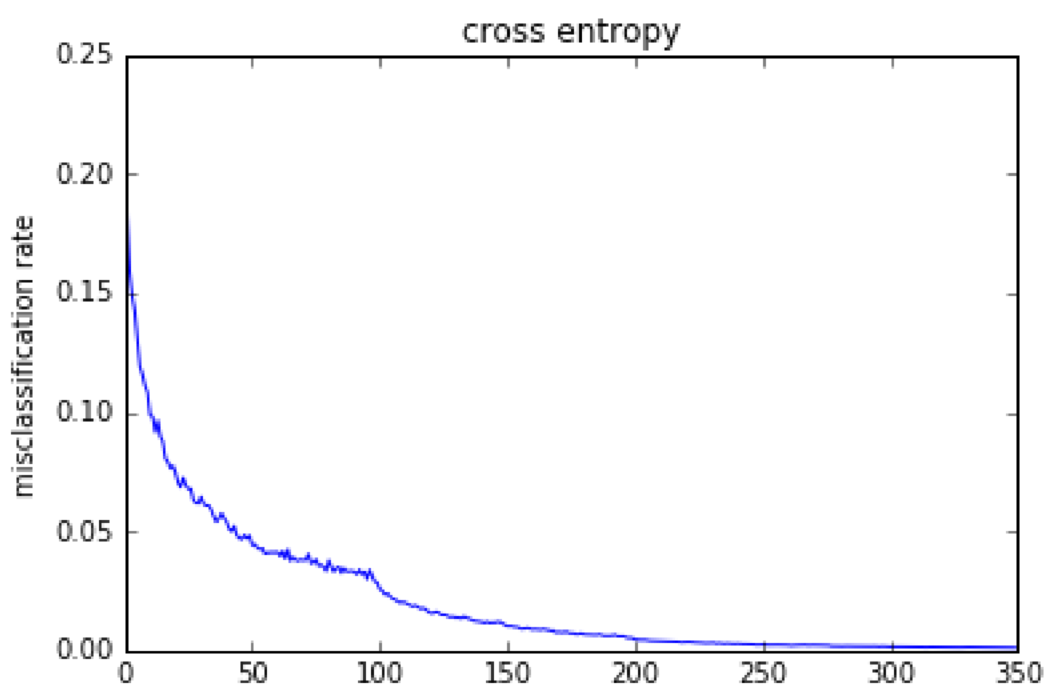
In [41]:
```
plt.plot(loss7)
plt.ylabel('total training error')
plt.title('cross entropy')
plt.show()
```



In [42]:
```
plt.plot(_loss10)
plt.ylabel('total training error')
plt.title('mean squared')
plt.show()
```




```
In [43]: plt.plot(misclass7)
         plt.ylabel('misclassification rate')
         plt.title('cross entropy')
         plt.show()
```



In [44]:
```
plt.plot(_misclass10)
plt.ylabel('misclassification rate')
plt.title('mean squared')
plt.show()
```