

**\*\*Please submit Lab F with this project\*\***

**Background:**

In Lab 15, you have trained a classifier to recognize a single digit. Now the classifier is to be extended to recognize any digit. You will need to import the training and testing data as you did for your *single-digit classifier*. The classifier you built for the lab worked for a *single* class. Each data point (an image, encoded as a single row of a  $785 \times 60K$  matrix), is classified as the digit in question, or not. The classifier uses the columns of the  $785 \times 60K$  as *features* (the  $X_i$ s in the **sum** below) to learn the labels using the labels for the training set: ( $Y$ ). The process took the images (rows of the  $X$  matrix), computed a *regression prediction* by computing the regression coefficients,  $\beta$ s, by minimizing the *log-loss* using *gradient descent*. The sum:

$$b_0 + b_1 \cdot X_1 + \dots + b_{784} \cdot X_{784}$$

is then put through a *Logistic* (*i.e.* the Sigmoid) function to produce a prediction:  $\hat{Y}$  for the label ( $Y$ ).

**The Extended Classifier:**

The basic idea is to have 10 *single-digit classifiers*, each built to recognize a single digit, working in *parallel*. Recall that *all* the features of *all* the images are presented at the same time to the classifier using the  $X$  matrix. Then, each image, put through the classifier built above, to obtain the regression prediction followed by being put through the Sigmoid (before using `np.round()`), delivers a value between 0 & 1. The prediction value giving the *confidence* in the prediction.

A similar approach will be used for the extended classifier. Each of the 10 single digit classifiers will return a value between 0 & 1 for each image presented to it. Matrix algebra offers a particularly simple way to put the single-digit classifiers in parallel:

- Write a function to create and return the encoded- $Y$  *matrix*, that as before, has 60K rows (one per training sample) & has number of columns equal to the *classes* of images (you have 10 classes: representing digits from 0 to 9). Each row of this matrix will have exactly one “1”.
- Remember, the labels are in  $Y_{train}$ . In the function, and the label number corresponds to the column number in the encoded- $Y$  *matrix*. Use these to create the encoded- $Y$  *matrix* which is `numImages × numClasses = m × c`.

- These being matrices, the right hand side of the regression equation;  $X \cdot \beta$  must have the **same** dimensions as the encoded- $Y$ .

$$\begin{array}{ccc} \text{encoded} - Y & = & X \cdot \beta \\ (m \times c) & = & (m \times f) \cdot (f \times c) \end{array}$$

Where  $f$  are the number of *features* (*i.e.* columns) of  $X$ . You will need to initialize a  $\beta$  matrix of appropriate size.

- The above changes in the regression equation dimensions means that the predicted- $Y$ , *i.e.*  $\hat{Y}$ , is a matrix of dimensions  $(m \times c)$ . Each row of  $\hat{Y}$  contains  $c(= 10)$  numbers.

Modify the `classify(X,  $\beta$ )` function you wrote earlier, to return an  $(m \times 1)$  array  $L$ . Each row of  $L$  contains is **indexed** by a label (*i.e.* one of: 0, 1, ..., 9), that corresponds to the **column number** of the largest value in to each row of  $\hat{Y}$ . The content of the array should be the *largest value* in that particular row of the  $\hat{Y}$  matrix.

The `numpy` function `argmax()` can with find the largest column ( $\text{axis} = 1$ ) value in each row.

To transform the array into a one dimensional array as required for  $L$ , the `numpy` function `reshape(-1,1)` will flatten an array to a 1-D array that is compatible to the original array. For examples, see:

[https://stackoverflow.com/questions/18691084/  
what-does-1-mean-in-numpy-reshape](https://stackoverflow.com/questions/18691084/what-does-1-mean-in-numpy-reshape)

- Create a report that show the iteration number, the percentage of correct matches and the loss, for the test examples. This is best done by a function that takes: `iteration number`, `X_train`, `Y_train`, `X_test`, `Y_test`,  $\beta$  as arguments. This function should be called from your `train(...)` function.