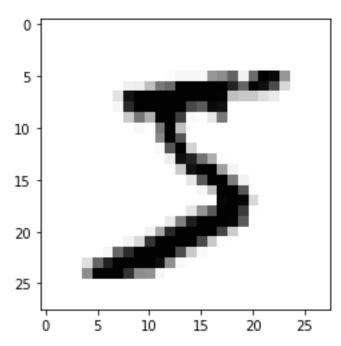
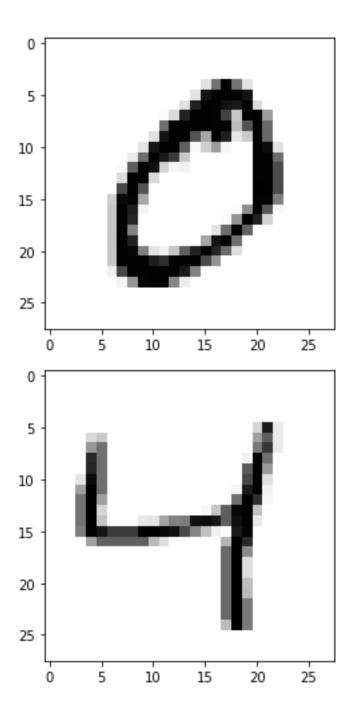
## Neural Network(NN)

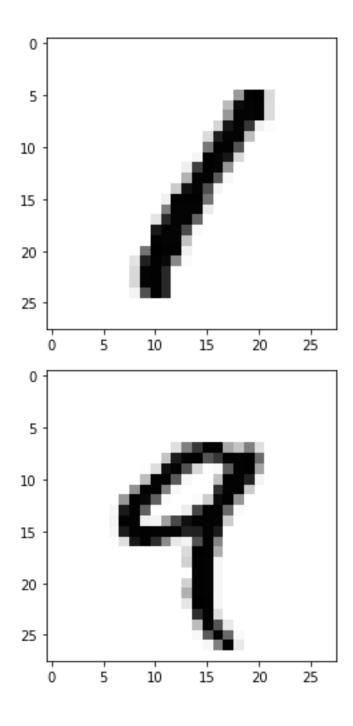
## May 7, 2020

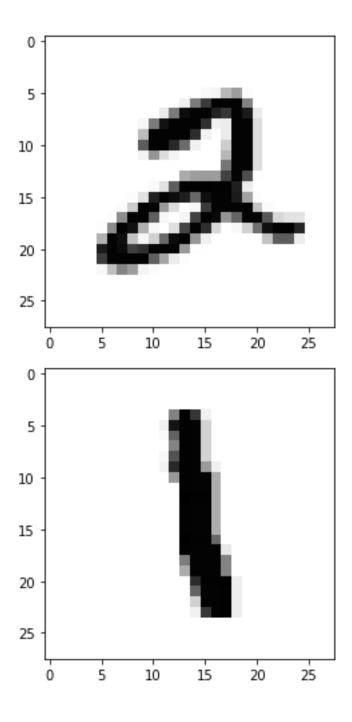
```
[13]: #Amul Neupane
      #Machine Learning Fundamentals
      %matplotlib inline
      import numpy as np
      import matplotlib.pyplot as plt
[14]: image size = 28 # width and length
      no of different labels = 10 # i.e. 0, 1, 2, 3, ..., 9
      image pixels = image size * image size
      train data = np.loadtxt("mnist train.csv", delimiter=",")
      test data = np.loadtxt("mnist test.csv", delimiter=",")
      test data[:10]
[14]: array([[7., 0., 0., ..., 0., 0., 0.],
             [2., 0., 0., ..., 0., 0., 0.],
             [1., 0., 0., ..., 0., 0., 0.],
             [9., 0., 0., ..., 0., 0., 0.],
             [5., 0., 0., ..., 0., 0., 0.],
             [9., 0., 0., ..., 0., 0., 0.]])
[15]: test data[test data==255]
      test data.shape
[15]: (10000, 785)
[16]: fac = 0.99 / 255
      train imgs = np.asfarray(train data[:, 1:]) * fac + 0.01
      test imgs = np.asfarray(test data[:, 1:]) * fac + 0.01
      train labels = np.asfarray(train data[:, :1])
      test labels = np.asfarray(test data[:, :1])
[17]: import numpy as np
      lr = np.arange(10)
      for label in range(10):
          one hot = (lr==label).astype(np.int)
          print("label: ", label, " in one-hot representation: ", one hot)
```

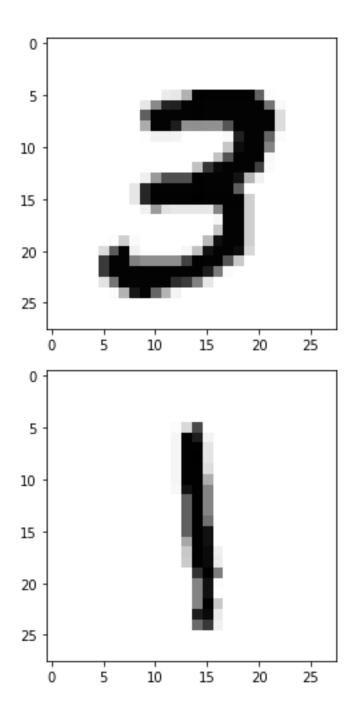
```
label: 0 in one-hot representation: [1 0 0 0 0 0 0 0 0]
  label: 1 in one-hot representation: [0 1 0 0 0 0 0 0 0]
  label: 2 in one-hot representation: [0 0 1 0 0 0 0 0 0]
  label: 3 in one-hot representation: [0 0 0 1 0 0 0 0 0]
  label: 4 in one-hot representation: [0 0 0 0 1 0 0 0 0]
  label: 5 in one-hot representation: [0 0 0 0 0 1 0 0 0 0]
  label: 6 in one-hot representation: [0 0 0 0 0 1 0 0 0]
  label: 7 in one-hot representation: [0 0 0 0 0 0 1 0 0]
  label: 8 in one-hot representation: [0 0 0 0 0 0 0 1 0]
  label: 9 in one-hot representation: [0 0 0 0 0 0 0 0 1]
[18]: lr = np.arange(no of different labels) #
     transform labels into one hot representation
     train labels one hot =
     (lr==train labels).astype(np.float)
     test labels one hot =
     (lr==test_labels).astype(np.float) # we don't want
     zeroes and ones in the labels neither:
     train_labels_one hot[train labels one hot==0] =
     0.01 train labels one hot[train labels one hot==1]
     = 0.99 test labels one hot[test labels one hot==0]
     = 0.01 test labels one hot[test labels one hot==1]
     = 0.99
[19]: for i in range(10):
        ima =
        train imgs[i].reshape((28,28))
        plt.imshow(img, cmap="Greys")
        plt.show()
```

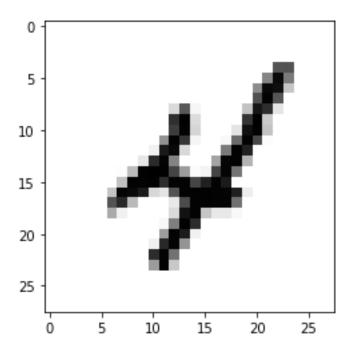












```
[20]: import numpy as np
    @np.vectorize
    def sigmoid(x):
```

```
return 1 / (1 + np.e ** -x)
activation function = sigmoid
from scipy.stats import truncnorm
def truncated normal(mean=0, sd=1, low=0, upp=10):
    return truncnorm((low - mean) / sd,
                     (upp - mean) / sd,
                     loc=mean,
                     scale=sd)
class NeuralNetwork:
    def init (self,
                 no of in nodes,
                 no of out nodes,
                 no of hidden nodes,
                 learning rate):
        self.no of in nodes = no of in nodes
        self.no of out nodes = no of out nodes
        self.no of hidden nodes = no of hidden nodes
        self.learning rate = learning rate
        self.create weight matrices()
    def create weight matrices(self):
        A method to initialize the weight
        matrices of the neural network
        rad = 1 / np.sqrt(self.no of in nodes)
        X = truncated normal(mean=0,
                             sd=1,
                             low=-rad,
                             upp=rad)
        self.wih = X.rvs((self.no of hidden nodes,
                                        self.no of in nodes))
        rad = 1 / np.sqrt(self.no of hidden nodes)
        X = truncated normal (mean=0, sd=1, low=-rad, upp=rad)
        self.who = X.rvs((self.no of out nodes,
                                         self.no of hidden nodes))
    def train(self, input vector, target vector):
        input vector and target vector can
        be tuple, list or ndarray
```

```
input vector = np.array(input vector, ndmin=2).T
    target vector = np.array(target vector, ndmin=2).T
    output vector1 = np.dot(self.wih,
                            input vector)
    output hidden = activation function(output vector1)
    output vector2 = np.dot(self.who,
                            output hidden)
    output network = activation function(output vector2)
    output errors = target vector - output network
    # update the weights:
    tmp = output errors * output network \
          * (1.0 - output network)
    tmp = self.learning rate * np.dot(tmp,
                                       output hidden.T)
    self.who += tmp
    # calculate hidden errors:
    hidden errors = np.dot(self.who.T,
                           output errors)
    # update the weights:
    tmp = hidden errors * output hidden * \
          (1.0 - output hidden)
    self.wih += self.learning rate \
                      * np.dot(tmp, input vector.T)
def run(self, input vector):
    # input vector can be tuple, list or ndarray
    input vector = np.array(input vector, ndmin=2).T
    output vector = np.dot(self.wih,
                           input vector)
    output vector = activation function(output vector)
    output vector = np.dot(self.who,
                           output vector)
    output vector = activation function(output vector)
    return output vector
```

```
def confusion matrix(self, data array, labels):
              cm = np.zeros((10, 10), int)
              for i in range(len(data array)):
                  res = self.run(data array[i])
                  res max = res.argmax()
                  target = labels[i][0]
                  cm[res max, int(target)] += 1
              return cm
          def precision(self, label, confusion matrix):
              col = confusion matrix[:, label]
              return confusion matrix[label, label] / col.sum()
          def recall(self, label, confusion matrix):
              row = confusion matrix[label, :]
              return confusion matrix[label, label] / row.sum()
          def evaluate(self, data, labels):
              corrects, wrongs = 0, 0
              for i in range(len(data)):
                  res = self.run(data[i])
                  res max = res.argmax()
                  if res max == labels[i]:
                     corrects += 1
                  else:
                      wrongs += 1
              return corrects, wrongs
[21]: ANN = NeuralNetwork(no_of_in_nodes = image_pixels,
                          no of out nodes = 10,
                          no of hidden nodes = 100,
                          learning rate = 0.1)
      for i in range(len(train imgs)):
          ANN.train(train imgs[i], train labels one hot[i])
[22]: for i in range(20):
          res = ANN.run(test imgs[i])
          print(test labels[i], np.argmax(res), np.max(res))
     [7.] 7 0.9842548971366076
     [2.] 2 0.9653023396196856
     [1.] 1 0.9892975291775858 [0.] 0 0.9762807408727853
```

```
[1.] 1 0.9885194311291068
    [4.] 4 0.9796051458149712
    [9.] 9 0.9873741454725488
    [5.] 5 0.42485686807350503
    [9.] 9 0.9341463979200473
    [0.] 0 0.97665545422355
    [6.] 6 0.747960016606698
    [9.] 9 0.9918615724951698
    [0.] 0 0.9773171789413514
    [1.] 1 0.9925353898764244
    [5.] 5 0.9192422056600144
    [9.] 9 0.9936136684680693
    [7.] 7 0.9754448384597486
    [3.] 3 0.7916037440633885
    [4.] 4 0.9896618681664278
[23]: corrects, wrongs = ANN.evaluate(train imgs,
     train labels) print("accuracy train: ", corrects /
     ( corrects + wrongs)) corrects, wrongs =
     ANN.evaluate(test imgs, test labels)
     print("accuracy: test", corrects / ( corrects +
     wrongs))
     cm = ANN.confusion matrix(train imgs,
     train labels) print(cm)
     for i in range(10):
        print("digit: ", i, "precision: ", ANN.precision(i, cm),
      "recall: ", ANN. ,→recall(i, cm))
    accuracy train: 0.94725
    accuracy: test 0.945
    [[5808 0 51 17
                        10
                             30
                                 35 11
                                          19 301
       0 6627 73
                    28
                         15
                             28
                                 22
                                      63
                                          96
                                              101
        2 19 5422 42
                         21
                             10
                                      33
                                          6
                                               21
                                  8
                                      33 140
        3
          38 124 5819
                        0 135
                                  5
                                             75]
           11
                57
                    11 5450 28
                                      40
                                          27
                                               621
     [ 14
                6
                    54
                         0 4995
                                 37
                                          15
                                              7]
     [ 31
                57
                   18
                                          26
            3
                         45
                            58 5763
                                               4]
            10
                    42
                             5
                                 1 5837
                                         0
               48
                         4
                                               341
     [ 47
            15 101
                    43
                             59
                                 38 18 5419 30]
                          6
                    57 291
     [ 11
           16
               19
                            73
                                 1 224 103 569511
    digit: 0 precision: 0.9805841634306939 recall:
    0.9662285809349526 digit: 1 precision: 0.9829427469593592
    recall: 0.9518816432059753 digit: 2 precision:
```

[4.] 4 0.966594439838561

```
0.9100369251426653 recall: 0.974303683737646 digit: 3
precision: 0.9491110748654379 recall: 0.9132140615191463 digit:
4 precision: 0.9328996918863403 recall: 0.9548002803083392
digit: 5 precision: 0.9214167127836193 recall:
0.9744440109246976 digit: 6 precision: 0.973808719161879
recall: 0.9590614078881677 digit: 7 precision:
0.931683958499601 recall: 0.9759237585688012 digit: 8
precision: 0.9261664672705521 recall: 0.9381925207756233 digit:
9 precision: 0.9573037485291646 recall: 0.8775038520801233
```