## **Q-3 MNIST Classification**

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# Classificaton using linear SVM

```
In [0]:
             from sklearn import datasets, svm, metrics
          2
             from sklearn.model_selection import train_test_split
          3
          4
            digits = datasets.load digits()
          5
          6
            images_and_labels = list(zip(digits.images, digits.target))
          8
             n samples = len(digits.images)
          9
            data = digits.images.reshape((n samples, -1))
         10
            classifier = svm.SVC(gamma=0.001)
         11
         12
         13
            X_train, X_test, y_train, y_test = train_test_split(
         14
                 data, digits.target, test size=0.5, shuffle=False)
         15
         16
            classifier.fit(X train, y train)
         17
         18
            predicted = classifier.predict(X test)
         19
         20
            images_and_predictions = list(zip(digits.images[n_samples // 2:], predicted
         21
            print("Classification report for classifier %s:\n%s\n"
         22
         23
                   % (classifier, metrics.classification_report(y_test, predicted)))
         24
            disp = metrics.plot_confusion_matrix(classifier, X_test, y_test)
         25
            disp.figure_.suptitle("Confusion Matrix")
         26
            print("Confusion matrix:\n%s" % disp.confusion_matrix)
        Classification report for classifier SVC(C=1.0, break ties=False, cache size=2
        00, class weight=None, coef0=0.0,
             decision_function_shape='ovr', degree=3, gamma=0.001, kernel='rbf',
            max_iter=-1, probability=False, random_state=None, shrinking=True,
             tol=0.001, verbose=False):
                       precision
                                     recall f1-score
                                                         support
                    0
                                       0.99
                            1.00
                                                  0.99
                                                              88
                    1
                            0.99
                                       0.97
                                                  0.98
                                                              91
                    2
                            0.99
                                       0 99
                                                  0 99
                                                              86
                    3
                            0.98
                                       0.87
                                                  0.92
                                                              91
                    4
                            0.99
                                       0.96
                                                  0.97
                                                              92
                    5
                                       0.97
                                                              91
                            0.95
                                                  0.96
                    6
                            0.99
                                       0.99
                                                  0.99
                                                              91
                    7
                            0.96
                                       0.99
                                                  0.97
                                                              89
                    8
                            0.94
                                       1.00
                                                  0.97
                                                              88
                            0.93
                                       0.98
                                                  0.95
                    9
                                                              92
                                                             899
             accuracy
                                                  0.97
                            0.97
                                       0.97
                                                             899
                                                  0.97
            macro avg
        weighted avg
                            0.97
                                       0.97
                                                  0.97
                                                             899
        Confusion matrix:
        [[87 0
                  0 0
                       1
                           0
                              0
                                  0
                                        01
          88 0 ]
                  1
                     0
                        0
                           0
                              0
                                  0
                                     1
                                        1]
           0
              0 85
                     1
                        0
                           0
                              0
                                  0
                                     0
                                        0]
          [
                  0 79
                                     5
          [ 0
              0
                        0
                           3
                              0
                                  4
                                        0]
           0
              0
                  0
                     0 88
                           0
                              0
                                  0
                                     0
                                        4]
           0
              0
                  0
                          88
                                        2]
                     0
                        0
                              1
                                  Θ
                                     0
          [ 0
              1
                  0
                     0
                        0
                           0 90
                                  0
                                     0
                                        01
          [ 0
              0
                  0
                     0
                        0
                           1
                              0 88
                                     0
                                        01
                                 0 88
           0
              0
                  0
                     0
                        0
                           0
                              0
                                        01
          0
              0
                  0
                        0
                                 0
                                    0 9011
                     1
                           1
                              0
                    Confusion Matrix
                                            90
                                            80
                88
           1
```

## Read binary file of the dataset

```
In [0]:
             import time
             stime = time.time()
          3
             import struct as st
             import numpy as np
             filename = {'images' : 'dataset/train-images-idx3-ubyte' ,'labels' : 'datas
          8
             labels array = np.array([])
         10
             data_types = {
                     0x08: ('ubyte', 'B', 1),

0x09: ('byte', 'b', 1),

0x0B: ('>i2', 'h', 2),

0x0C: ('>i4', 'i', 4),

0x0D: ('>f4', 'f', 4),

0x0E: ('>f8', 'd', 8)}
         11
         12
         13
         14
         15
         16
         17
         18
             for name in filename.keys():
                 if name == 'images':
         19
         20
                      imagesfile = open(filename[name],'rb')
         21
                 if name == 'labels':
                      labelsfile = open(filename[name],'rb')
         22
         23
         24 imagesfile.seek(0)
             magic = st.unpack('>4B',imagesfile.read(4))
         25
             if(magic[0] and magic[1])or(magic[2] not in data_types):
         26
         27
                 raise ValueError("File Format not correct")
         28
         29
            nDim = magic[3]
         30 print ("Data is ",nDim,"-D")
         31
         32
             #offset = 0004 for number of images
         33 #offset = 0008 for number of rows
             #offset = 0012 for number of columns
         34
         35
             #32-bit integer (32 bits = 4 bytes)
         36 imagesfile.seek(4)
         37 nImg = st.unpack('>I',imagesfile.read(4))[0] #num of images/labels
         38 nR = st.unpack('>I',imagesfile.read(4))[0] #num of rows
         39 nC = st.unpack('>I',imagesfile.read(4))[0] #num of columns
         40 nBytes = nImg*nR*nC
             labelsfile.seek(8) #Since no. of items = no. of images and is already read
         42 print ("no. of images :: ",nImg)
         43 print ("no. of rows :: ",nR)
         44 print ("no. of columns :: ",nC)
         45
         46 #Read all data bytes at once and then reshape
             images array = 255 - np.asarray(st.unpack('>'+'B'*nBytes,imagesfile.read(nB
         47
             labels_array = np.asarray(st.unpack('>'+'B'*nImg,labelsfile.read(nImg))).re
         48
         49
         50 print (labels_array)
         51 print (labels array.shape)
         52 nrint (images array shape)
         Data is 3 -D
         no. of images :: 60000
         no. of rows :: 28
         no. of columns ::
         [[5]
          [0]
          [4]
          [5]
          [6]
          [8]]
         (60000, 1)
         (60000, 28, 28)
```

#### Read data using MNIST library

```
In [2]: 1 from mnist import MNIST
2 import numpy as np
3 mndata = MNIST('./dataset')
4 images_array, labels_array = mndata.load_training()
5 print(nn_shape(images_array))
(60000, 784)
```

#### **Classification using CNN**

```
Import Pytorch libraries
```

```
In [3]: 1 import torch
2 import torch.nn as nn
3 import torch.nn.functional as F
4 import torch optim as optim
```

Define class for CNN

```
In [13]:
           1
             class Net(nn.Module):
                  def __init__(self):
           3
                      super(Net, self).__init__()
           4
           5
                      self.conv1 = nn.Conv2d(\overline{1}, 10, kernel\_size=5)
           6
                      self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
           7
                      self.conv2_drop = nn.Dropout2d()
           8
                      self.fcl = nn.Linear(320, 50)
           9
                      self.fc2 = nn.Linear(50, 10)
          10
          11
                  def forward(self, x):
          12
                      x = F.relu(F.max_pool2d(self.conv1(x), 2))
          13
                      x = F.relu(F.max_pool2d(self.conv2_drop(self.conv2(x)), 2))
                      x = x.view(-1, 320)
          14
          15
                      x = F.relu(self.fc1(x))
          16
                      x = F.dropout(x, training=self.training)
          17
                      x = self.fc2(x)
          18
                      return F log softmax(x)
```

Define parameters for training

```
Initialize network
```

Prepare train and test data

Number of images in  $x\_{test}$  12000

```
In [15]:
              from sklearn.model_selection import train_test_split
           3
              BATCH SIZE = 32
           4
              X_train, X_test, y_train, y_test = train_test_split(np.asarray(images_array
           6
           7
              ################
              X_{\text{train}} = X_{\text{train.reshape}}(X_{\text{train.shape}}[0], 1, 28, 28)
             X \text{ test} = X \text{ test.reshape}(X \text{ test.shape}[0], 1, 28, 28)
          10 | y_train = y_train.reshape(y_train.shape[0])
          11 y_test = y_test.reshape(y_test.shape[0])
          12
              input\_shape = (28, 28, 1)
          13
          14 X_train = X_train.astype('float32')
          15 X test = X test.astype('float32')
          16
          17 X train /= 255
          18 X_test /= 255
          19 print('x_train shape:', X_train.shape)
          20 print('Number of images in x_train', X_train.shape[0])
21 print('Number of images in x_test', X_test.shape[0])
          22
              ###############
          23
          24
          25
              torch_X_train = torch.from_numpy(X_train).type(torch.FloatTensor)
          26
              torch_y_train = torch.from_numpy(y_train).type(torch.LongTensor)
          27
          28
              torch X test = torch.from numpy(X test).type(torch.FloatTensor)
          29
              torch y test = torch.from numpy(y test).type(torch.LongTensor)
          30
          31
              train = torch.utils.data.TensorDataset(torch X train,torch y train)
          32
              test = torch.utils.data.TensorDataset(torch_X_test,torch_y_test)
          33
          34
          35
          36 train_loader = torch.utils.data.DataLoader(train, batch_size = BATCH_SIZE,
              test_loader = torch.utils.data.DataLoader(test, batch_size = BATCH_SIZE, sh
          37
          38
          x train shape: (48000, 1, 28, 28)
          Number of images in x_train 48000
```

```
In [16]: 1 train_losses = []
2 train_counter = []
3 test_losses = []
4 test_counter = [i*len(images_array) for i in range(n_enochs + 1)]
```

```
In [17]:
            1
               def train(epoch):
                 network.train()
            2
            3
                 for batch_idx, (data, target) in enumerate(train_loader):
            4
                    optimizer.zero grad()
            5
                    output = network(data)
            6
                    loss = F.nll_loss(output, target)
                    loss.backward()
            7
            8
                    optimizer.step()
            a
                    if batch idx % log interval == 0:
                      print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
           10
                        epoch, batch_idx * len(data), len(train_loader.dataset),
100. * batch_idx / len(train_loader), loss.item()))
           11
           12
           13
                      train_losses.append(loss.item())
                      train_counter append(
           14
                        (hatch idx*64) + ((enoch-1)*len(train loader dataset)))
           15
In [22]:
            1
               def test():
            2
                 network.eval()
            3
                 test_loss = 0
                 correct = 0
            4
                 with torch.no_grad():
            5
            6
                    for data, target in test loader:
            7
                      #print(data.shape)
            8
                      #print(np.shape(target))
            9
                      #print(data)
           10
                      output = network(data)
                      test_loss += F.nll_loss(output, target, size_average=False).item()
           11
           12
                      pred = output.data.max(1, keepdim=True)[1]
           13
                      #print(pred)
           14
                      correct += pred.eq(target.data.view_as(pred)).sum()
                 test_loss /= len(test_loader.dataset)
           15
                 test_losses.append(test_loss)
print('\nTest set: Avg. loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)\n'.format
  test_loss, correct, len(test_loader.dataset),
           16
           17
           18
           19
                    100 * correct / len(test loader dataset)))
```

In [0]: 1

```
In [25]:
            for epoch in range(1, n epochs + 1):
          1
          2
              train(epoch)
         /usr/lib/python3/dist-packages/ipykernel_launcher.py:18: UserWarning: Implicit
         dimension choice for log softmax has been deprecated. Change the call to inclu
         de dim=X as an argument.
         Train Epoch: 1 [0/48000 (0%)] Loss: 0.712653
         Train Epoch: 1 [32000/48000 (67%)]
                                                Loss: 0.404447
         Test set: Avg. loss: 0.1710, Accuracy: 11416/12000 (95%)
         Train Epoch: 2 [0/48000 (0%)] Loss: 0.818281
         Train Epoch: 2 [32000/48000 (67%)]
                                                Loss: 0.493597
         Test set: Avg. loss: 0.1632, Accuracy: 11432/12000 (95%)
         Train Epoch: 3 [0/48000 (0%)]
                                       Loss: 0.682777
         Train Epoch: 3 [32000/48000 (67%)]
                                             Loss: 0.365860
         Test set: Avg. loss: 0.1592, Accuracy: 11438/12000 (95%)
         Train Epoch: 4 [0/48000 (0%)] Loss: 1.049464
         Train Epoch: 4 [32000/48000 (67%)]
                                                Loss: 0.418026
         Test set: Avg. loss: 0.1582, Accuracy: 11428/12000 (95%)
         Train Epoch: 5 [0/48000 (0%)] Loss: 0.775062
         Train Epoch: 5 [32000/48000 (67%)]
                                                Loss: 0.609121
         Test set: Avg. loss: 0.1514, Accuracy: 11471/12000 (96%)
         Train Epoch: 6 [0/48000 (0%)] Loss: 0.769052
         Train Epoch: 6 [32000/48000 (67%)]
                                                Loss: 0.510075
         Test set: Avg. loss: 0.1495, Accuracy: 11476/12000 (96%)
         Train Epoch: 7 [0/48000 (0%)] Loss: 0.743701
         Train Epoch: 7 [32000/48000 (67%)]
                                               Loss: 0.468539
         Test set: Avg. loss: 0.1452, Accuracy: 11492/12000 (96%)
         Train Epoch: 8 [0/48000 (0%)]
                                        Loss: 0.347850
         Train Epoch: 8 [32000/48000 (67%)]
                                               Loss: 0.464340
         Test set: Avg. loss: 0.1411, Accuracy: 11506/12000 (96%)
```