## Assignment 4

March 4, 2018

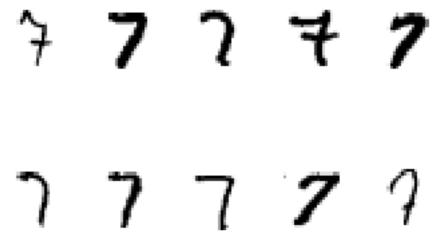
## 1 Load the entire MNIST digit dataset

```
In [82]: # Reference: https://github.com/aferriss/mnist2image/blob/master/mnist.py
         import os, struct
         from array import array as pyarray
         from numpy import append, array, int8, uint8, zeros
         from pylab import *
         from numpy import *
         from PIL import Image
         import math
         def load_mnist(dataset="training", digits=np.arange(10), path=".", size = 60000):
             if dataset == "training":
                 fname_img = os.path.join(path, 'train-images-idx3-ubyte')
                 fname_lbl = os.path.join(path, 'train-labels-idx1-ubyte')
             elif dataset == "testing":
                 fname_img = os.path.join(path, 't10k-images-idx3-ubyte')
                 fname_lbl = os.path.join(path, 't10k-labels-idx1-ubyte')
             else:
                 raise ValueError("dataset must be 'testing' or 'training'")
             flbl = open(fname_lbl, 'rb')
             magic_nr, size = struct.unpack(">II", flbl.read(8))
             lbl = pyarray("b", flbl.read())
             flbl.close()
             fimg = open(fname_img, 'rb')
             magic_nr, size, rows, cols = struct.unpack(">IIII", fimg.read(16))
             img = pyarray("B", fimg.read())
             fimg.close()
             ind = [ k for k in range(size) if lbl[k] in digits ]
             N = size #int(len(ind) * size/100.)
             images = zeros((N, rows, cols), dtype=uint8)
             labels = zeros((N, 1), dtype=int8)
             for i in range(N): #int(len(ind) * size/100.)):
```

## 2 Choose two digit classes (e.g 7s and 3s) from the training data, and plot some of the examples.

```
3 3 3 3
```

```
In [70]: plot_random(train_images_7)
```



## 3 Train a support vector classifier using each of the following kernels: Linear, Poly, RBF

```
In [71]: # Prepare training data; combine and shuffle
         from random import shuffle
         data = zip(train_images_7, [1]*len(train_images_7))+zip(train_images_3, [0]*len(train_i
         shuffle(data)
         X, y = zip(*data)
         X = np.array(X).reshape(len(y),28*28)
In [80]: # Measure training time
         from sklearn.svm import SVC, LinearSVC
         from time import time
         kernels = {k:SVC(kernel=k) for k in ["linear", "poly", "rbf"]}
         times = {}
         for name, model in kernels.items():
             start_time = time()
             model.fit(X,y)
             times[name] = time() - start_time
         print times
{'rbf': 378.7521810531616, 'linear': 10.659451007843018, 'poly': 6.508466005325317}
In [84]: # Load test data
         test_images, test_labels = load_mnist(dataset="testing")
         test_images_3 = test_images[test_labels==3]
```

```
test_images_7 = test_images[test_labels==7]
         print "Picked {} images of digit 3 \nand {} images of digit 7".format(len(test_images_3
         test_data = zip(test_images_7, [1]*len(test_images_7))+zip(test_images_3, [0]*len(test_
         shuffle(test_data)
         test_X, test_y = zip(*test_data)
         test_X = np.array(test_X).reshape(len(test_y),28*28)
Picked 1010 images of digit 3
and 1028 images of digit 7
In [85]: # Measure error rates
        error_rates = {}
         for name, model in kernels.items():
             error_rates[name] = 1 - (model.predict(test_X)==test_y).sum()/float(len(test_y))
In [86]: error_rates
Out[86]: {'linear': 0.023552502453385693,
          'poly': 0.0044160942100097689,
          'rbf': 0.49558390578999023}
```

It is interesting to observe that although RBF kernel takes the longest training time, its performance is the worst. This might be because the RBF kernel has high degress of freedom in its transformed topology and therefore likely to overfit. Of course, since I only used the default RBF hyperparameters, there is still possibilities that RBF could potentially work better with different regularization and (lower) gamma parameters.

Since our data is very high dimensional (784), using non-linear kernels can lead to the slow down of training process and also potential overfitting problems. (I don't know if this is correct at all, but) I suspect that first using dimensional reduction (to remove redundancy) and then applying non-linear SVM might produce better results.