CS189_Hw1

February 9, 2016

1 Homework 1 Writeup and Code

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In [1]:
```
%matplotlib inline
```

In [7]:
```
from sklearn import svm
from sklearn.metrics import confusion_matrix
from sklearn.utils import shuffle
import matplotlib.pyplot as plt
import numpy as np
from scipy import io
```

In [ ]:
```
cd data/digit-dataset/
```

In [11]:
```
#import data
training_digits = io.loadmat("train.mat")
train_images_digits = training_digits['train_images']
train_images_digits = train_images_digits.reshape((28*28,-1)) #reshape so features are flatten
train_images_digits = train_images_digits.transpose() #transpose so sample number is first dim

train_labels_digits = training_digits['train_labels']

test_digits = io.loadmat('test.mat')
test_image_digits = test_digits['test_images']
test_image_digits = test_image_digits.transpose() #test images are tranpose of training images
test_image_digits = test_image_digits.reshape((28*28,-1))
test_image_digits = test_image_digits.transpose()
```

In [ ]:
```
cd ..
```

In [ ]:
```
cd spam-dataset
```

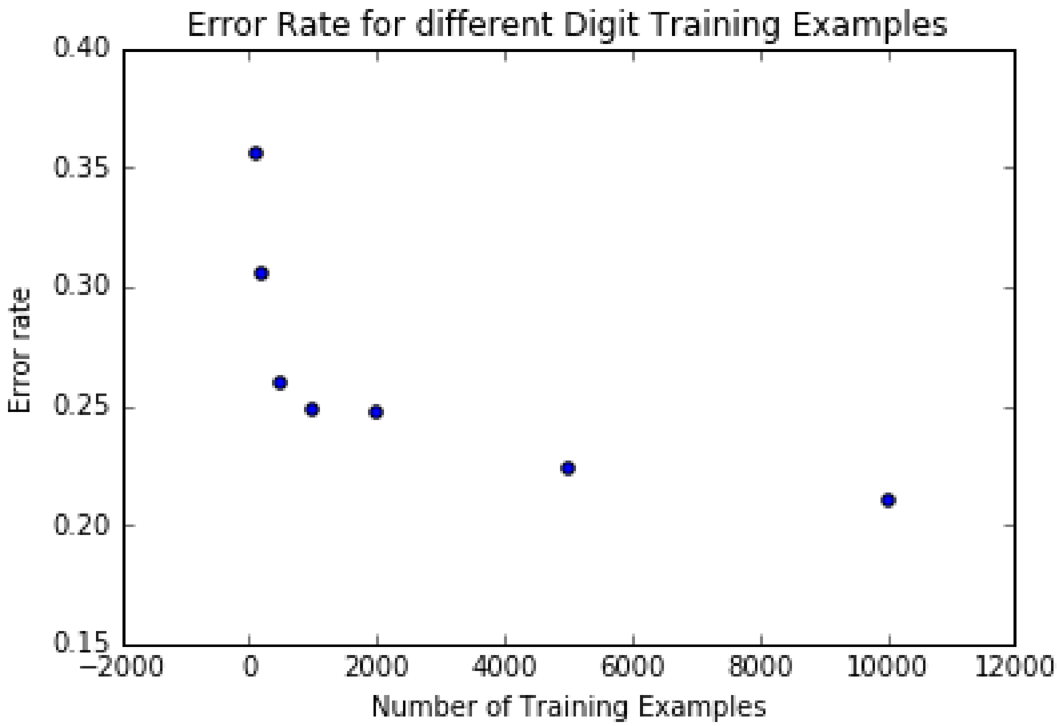
In [15]:
```
spam_data = io.loadmat('spam_data.mat')
spam_training = spam_data['training_data']
spam_training_labels = spam_data['training_labels']
spam_training_labels = spam_training_labels.transpose() #Tranpose so (number, label) shape

spam_test = spam_data['test_data']
```

In [16]:
```
import math

#benchmark.m, converted
def benchmark(pred_labels, true_labels):
    errors = pred_labels != true_labels
```

```
        err_rate = sum(errors) / float(len(true_labels))
        indices = errors.nonzero()
        return err_rate #, indices
```

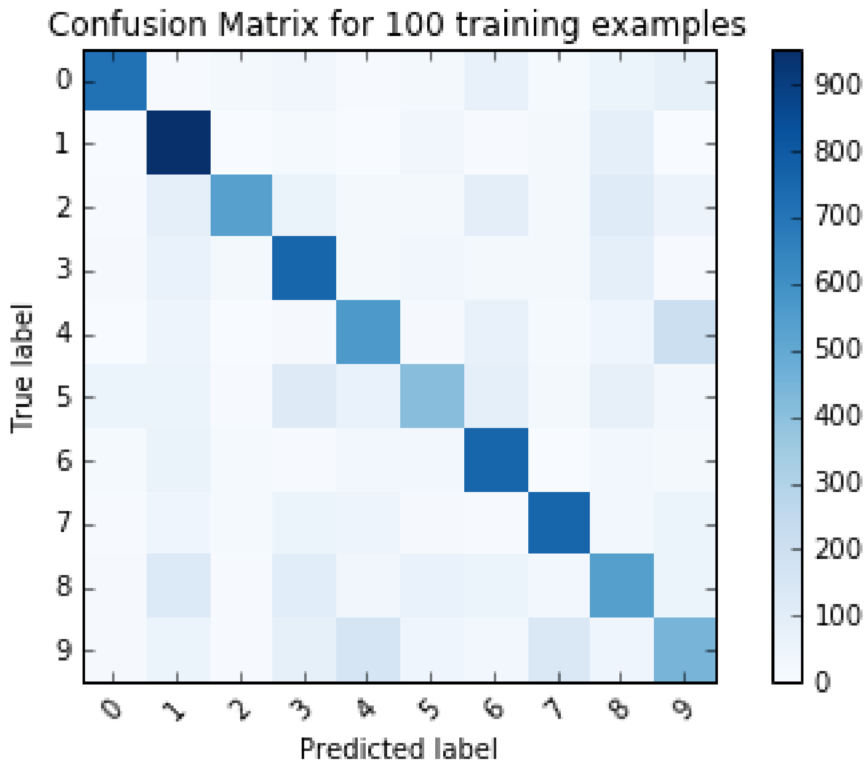
```
In [17]: def problem1(training_digits, training_digit_labels):
             #Inputs are the training digits (correctly flattened and transposed as above) and the corr
             training_numbers = [100, 200, 500, 1000, 2000, 5000,10000]
             digit_shuffled, digit_labels_shuffled = shuffle(training_digits,training_digit_labels)
             validation_digits = digit_shuffled[10000:20000, :]
             validation_digits_labels = digit_labels_shuffled[10000:20000,0]

             digit_prediction_list = []
             validation_errors = []

             for number in training_numbers:
                 digits_train = digit_shuffled[0:number,:]
                 digits_labels = digit_labels_shuffled[0:number, 0]
                 digit_classifier = svm.LinearSVC()
                 digit_classifier.fit(digits_train, digits_labels)

                 prediction_labels = digit_classifier.predict(validation_digits)
                 digit_prediction_list.append(prediction_labels)

                 validation_errors.append(benchmark(prediction_labels, validation_digits_labels))

             plt.scatter(training_numbers, validation_errors)
             plt.xlabel('Number of Training Examples')
             plt.ylabel('Error rate')
             plt.title('Error Rate for different Digit Training Examples')
             return digit_prediction_list, validation_digits_labels
```

```
In [18]: digit_predictions, validation_digit_labels = problem1(train_images_digits, train_labels_digits
```

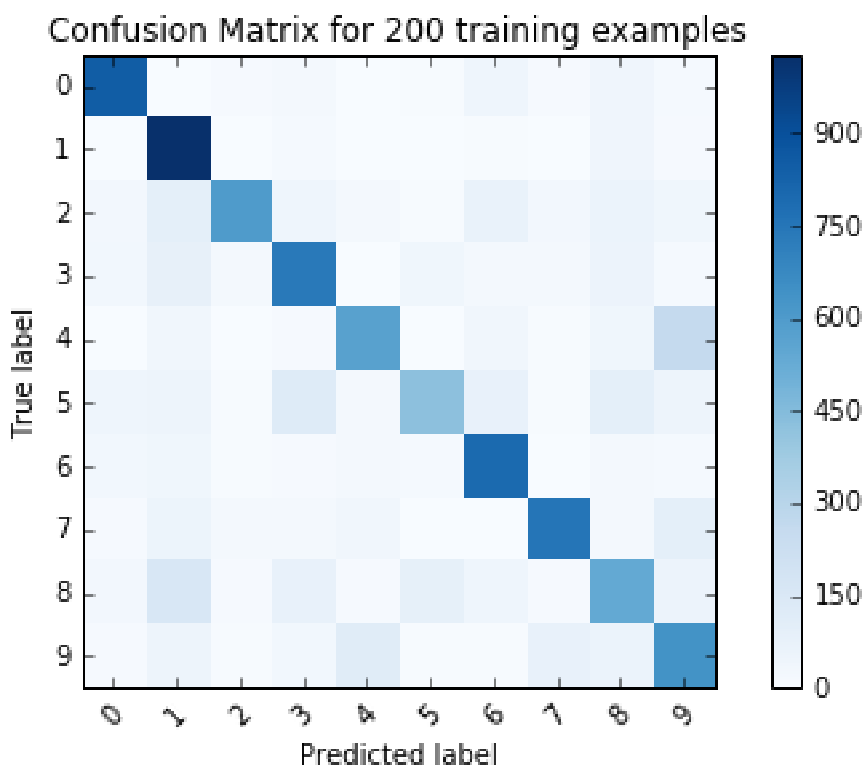


Training the linear classifier with increasing number of training examples, the error rate clearly goes down.

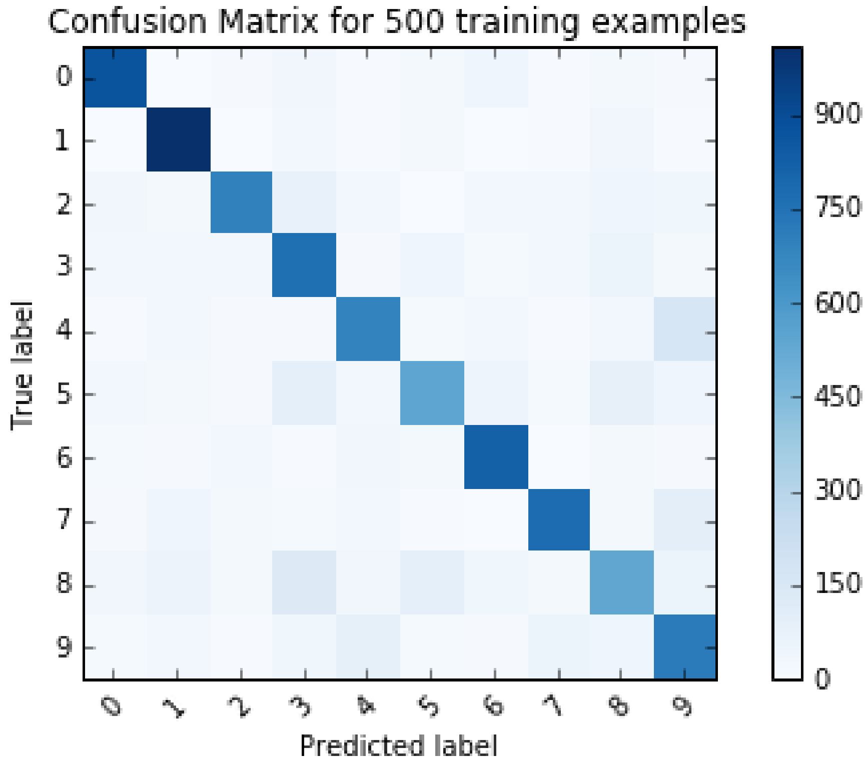
```
In [19]: def problem2(digit_predictions, true_labels, training_number):
             #inputs are prediction labels from problem1 and their corresponding true labels, and lastl
             c_matrix = confusion_matrix(true_labels, digit_predictions)
             #print(c_matrix)
             digit_strings = ['0', '1', '2', '3', '4', '5','6', '7','8','9'] #Number in string format t

             def plot_confusion_matrix(cm, title='Confusion matrix', cmap=plt.cm.Blues):
                 #function modified from scikitlearn documentation
                 plt.imshow(cm, interpolation='nearest', cmap=cmap)
                 plt.title('Confusion Matrix for ' + str(training_number) + ' training examples')
                 plt.colorbar()
                 tick_marks = np.arange(len(range(10)))
                 plt.xticks(tick_marks, digit_strings, rotation=45)
                 plt.yticks(tick_marks, digit_strings)
                 plt.tight_layout()
                 plt.ylabel('True label')
                 plt.xlabel('Predicted label')

             plt.figure()
             plot_confusion_matrix(c_matrix)

         training_numbers = [100, 200, 500, 1000, 2000, 5000,10000]

In [20]: for i in range(len(digit_predictions)):
             problem2(digit_predictions[i], validation_digit_labels, training_numbers[i])
```

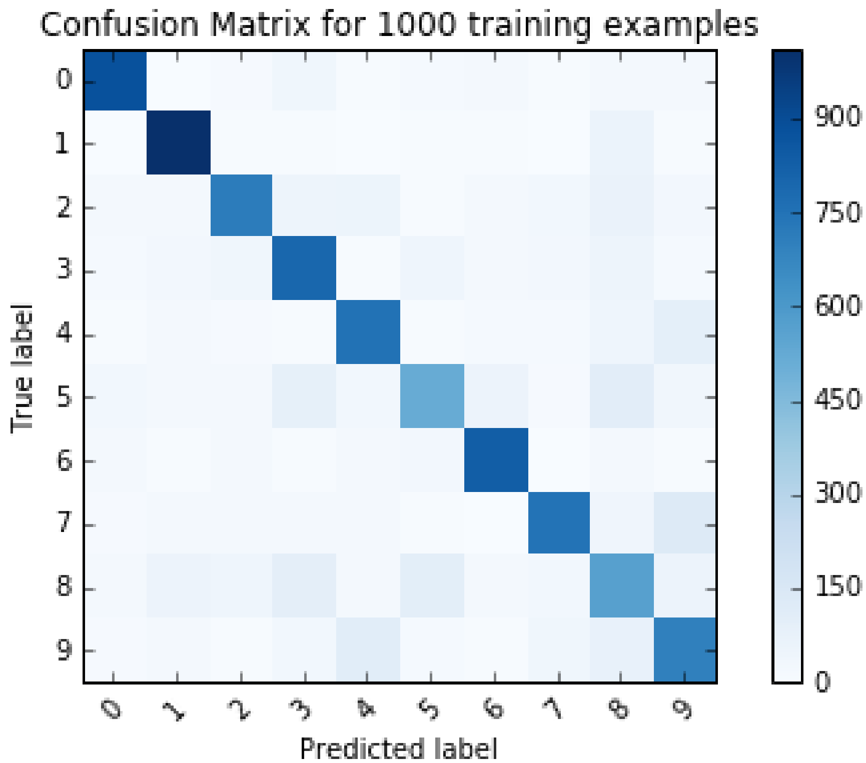


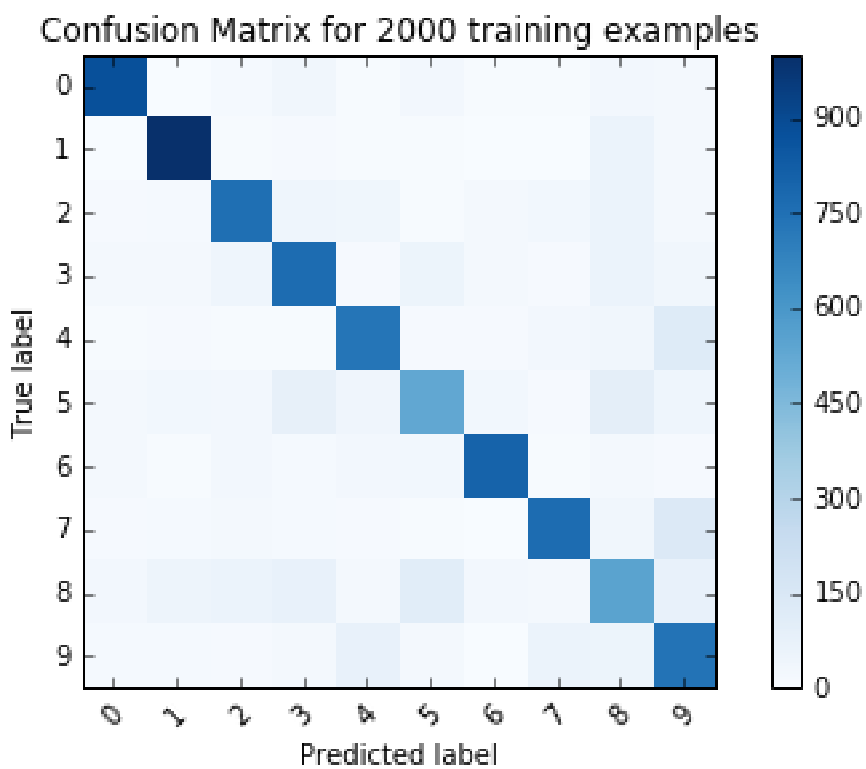
Confusion Matrix for 100 training examples
True label
Predicted label
0
1
2
3
4
5
6
7
8
9
900
800
700
600
500
400
300
200
100

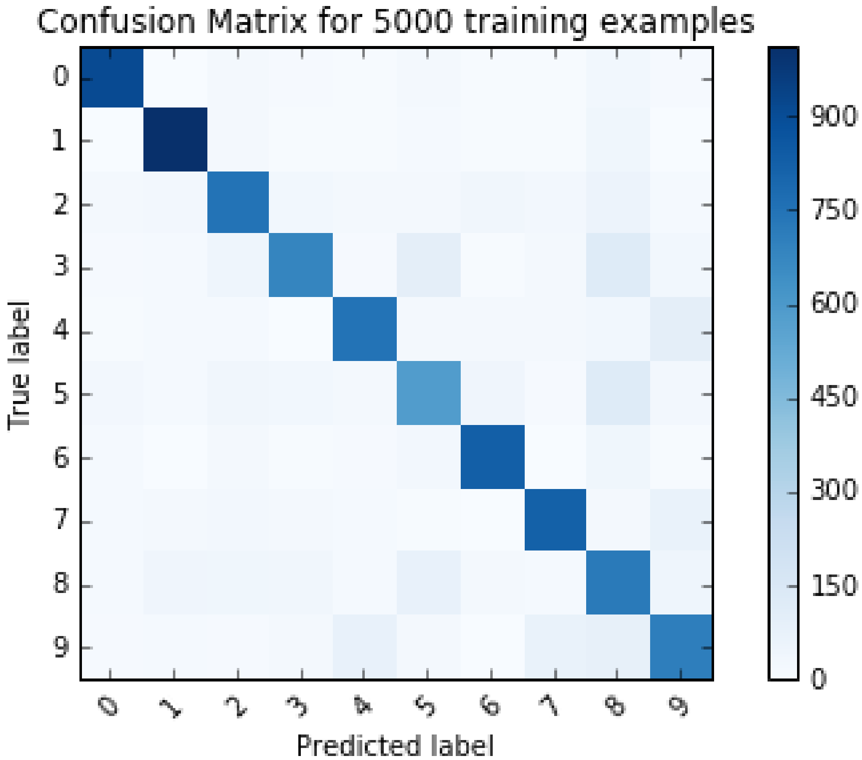


Confusion Matrix for 200 training examples
True label
Predicted label
0
1
2
3
4
5
6
7
8
9
900
750
600
450
300
150

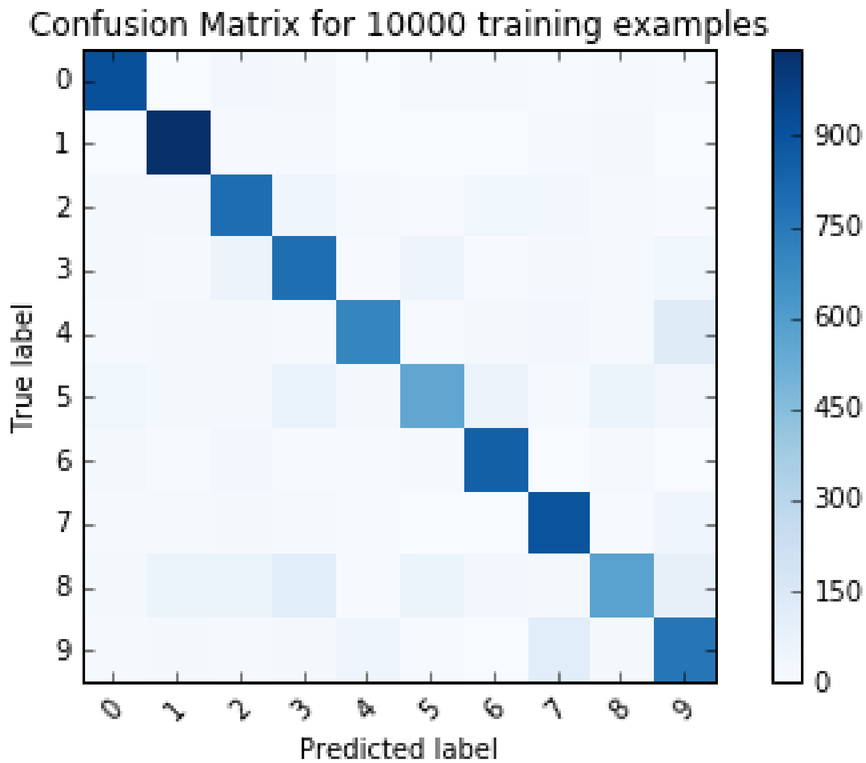

Confusion Matrix for 500 training examples
True label
0
1
2
3
4
5
6
7
8
9
Predicted label
0
150
300
450
600
750
900


Confusion Matrix for 1000 training examples
True label
Predicted label
0
1
2
3
4
5
6
7
8
9
900
750
600
450
300
150


Confusion Matrix for 2000 training examples
True label
Predicted label
0
1
2
3
4
5
6
7
8
9
900
750
600
450
300
150



Confusion Matrix for 5000 training examples
True label
Predicted label
0
1
2
3
4
5
6
7
8
9
900
750
600
450
300
150
0



While hard to see along the diagonal, looking at the off diagonal elements we can clearly see a decrease in color indicating a decrease in incorrect prediction. Thus as expected there is a general increase in performance across the board as training examples increase. Some interesting features are that 5 and 8 seem to be the least accurate in general. Looking at the off diagonal terms we can see that it is actually due to them being classified as the other which is due to the close similarities in representation.

```
In [21]: def cross_validation(k_fold, train_images_input, train_labels_input, C_parameter=1):
             clf_cross_validation = svm.LinearSVC(C=C_parameter)
             train_images_shuffled, train_labels_shuffled = shuffle(train_images_input,train_labels_inpu
             reduced_training_images = train_images_shuffled[0:10000,:]
             reduced_training_labels = train_labels_shuffled[0:10000]
             #print(reduced_training_labels)
             partition_size = len(reduced_training_labels)/k_fold
             #print(partition_size)
             validation_accuracy = 0
             for i in range(k_fold):
                 validation_set = reduced_training_images[i*partition_size:((i+1)*partition_size),:]
                 validation_labels = reduced_training_labels[i*partition_size:((i+1)*partition_size),0]
                 #print(validation_set.shape)
                 training_set = reduced_training_images[0:i*partition_size,:]
                 training_set = np.append(training_set,reduced_training_images[((i+1)*partition_size):,
                 #print(training_set.shape)
                 training_labels = reduced_training_labels[0:i*partition_size,0]
                 training_labels = np.append(training_labels,reduced_training_labels[((i+1)*partition_si
                 #print(len(training_set),len(training_labels))
                 clf_cross_validation.fit(training_set, training_labels)
                 predicted_labels = clf_cross_validation.predict(validation_set)
```

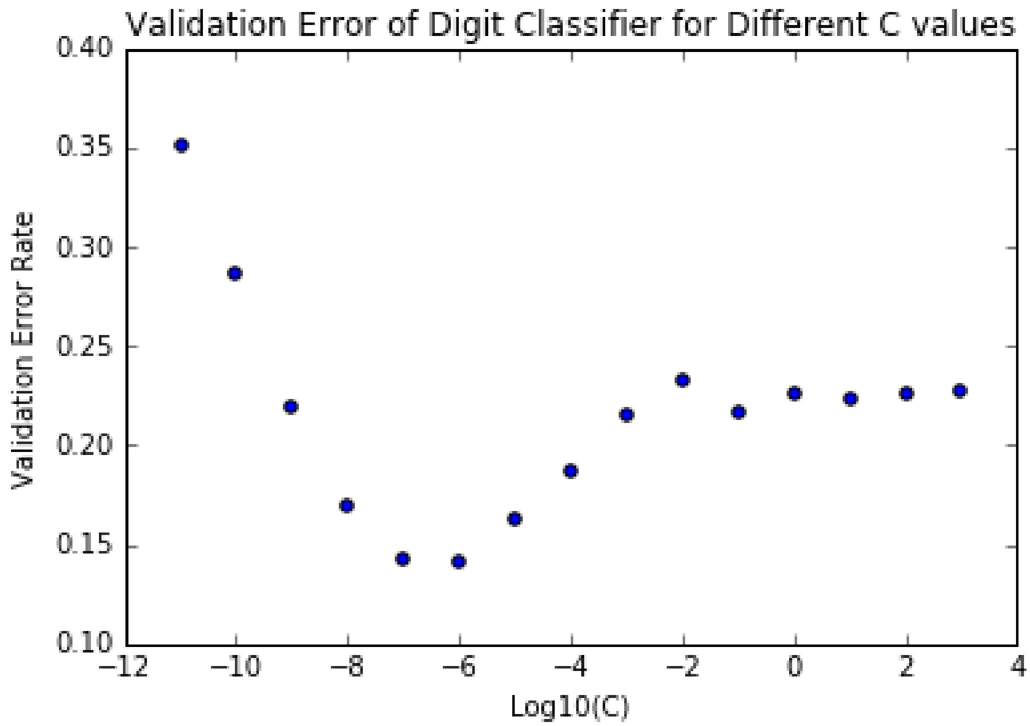
```
            err_rate=benchmark(predicted_labels, validation_labels)
            #print(err_rate)
            validation_accuracy += err_rate
        return validation_accuracy/k_fold
```

In [26]:
```
def write2csv(filename, prediction_labels):
    #Writes an array of labels to a csv file in format specified on Kaggle
    #Example:
    # Id,Category
    # 1,2
    # 2,4
    # ..
    import csv
    with open(filename, 'wb') as csvfile:
        label_writer = csv.writer(csvfile, delimiter = ',')
        label_writer.writerow(['Id','Category'])
        for i in range(len(prediction_labels)):
            label_writer.writerow([i+1,prediction_labels[i]])
```

In [24]:
```
def problem3(training_digits, training_digit_labels, test_digits):
    #inputs are fully formatted training digit images and labels as well as the testing images
    #Important that test digits are correctly formatted (need to tranpose before flattening to
    C_values = [1E-11, 1E-10, 1E-9,1E-8,1E-7,1E-6,1E-5,1E-4,1E-3,1E-2,1E-1,1, 10, 100, 1000]
    error_rates = []
    for C in C_values:
        error_rates.append(cross_validation(10,training_digits, training_digit_labels, C))

    plt.scatter(np.log10(C_values), error_rates)
    plt.xlabel('Log10(C)')
    plt.ylabel('Validation Error Rate')
    plt.title('Validation Error of Digit Classifier for Different C values')
    C_optimal = C_values[error_rates.index(min(error_rates))]


    train_images_shuffled, train_labels_shuffled = shuffle(training_digits,training_digit_label
    reduced_training_images = train_images_shuffled[0:10000,:]
    reduced_training_labels = train_labels_shuffled[0:10000,0]

    optimal_digit_clf = svm.LinearSVC(C=C_optimal)
    optimal_digit_clf.fit(reduced_training_images, reduced_training_labels)

    digit_predictions = optimal_digit_clf.predict(test_digits)
    print('The optimal C value is ' +str(C_optimal) + ' with a validation error rate of ' +str
    return digit_predictions
```

In [25]:
```
digit_predictions = problem3(train_images_digits, train_labels_digits, test_image_digits)
write2csv('digit_predictions.csv', digit_predictions)
```

```
The optimal C value is 1e-06 with a validation error rate of 0.1416
```



Cross validation is useful since ideally we train on as many datasets as possible, but we still want to test our classifier. By partitioning the training data and cycling through the validation set, we maintain a large training data size, while ultimately testing on all the training data to ensure that the small validation data set is not biased in someway which affects the accuracy rate.

Training an SVM with varying C values, we see from above that the optimal C value is 1E-6 with a cross validation error rate of .1416. Creating an SVM with this optimal C value and using the test data set, the Kaggle Score is an accuracy of .875 .

```
In [37]: def problem4(spam_data, spam_data_labels, testing_spam):
             #Inputs are spam data and labels provided by spam_data.mat
             C_values = [1E-11, 1E-10, 1E-9,1E-8,1E-7,1E-6,1E-5,1E-4,1E-3,1E-2,1E-1,1, 10, 100, 1000]
             spam_error_rates = []
             for C in C_values:
                 spam_error_rates.append(cross_validation(6,spam_data,spam_data_labels,C))

             C_optimal = C_values[spam_error_rates.index(min(spam_error_rates))]
             print('The optimal C value is ' +str(C_optimal) + ' with a validation error rate of ' +str
             optimal_spam_clf = svm.LinearSVC(C=C_optimal)
             optimal_spam_clf.fit(spam_data, spam_data_labels[:,0])

             predicted_spam = optimal_spam_clf.predict(testing_spam)
             return predicted_spam

In [38]: predicted_spam = problem4(spam_training, spam_training_labels, spam_test)
         write2csv('spam_predictions.csv', predicted_spam)

The optimal C value is 100 with a validation error rate of 0.187161639598
```

Using cross validation for the spam dataset, the optimal C value is 100 with a validation error rate of .187 . Creating a linear SVM with this C value and using it to predict the test dataset, the resulting Kaggle score is an accuracy of .78 .

```
In [ ]:
```