ECE 5470 Computer Vision Lab7 report

Part A

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Hand written numbers:

To get started, I created a new set of 60 images of characters:
50 of these are the digits 0-9 handwritten and 10 of these are English characters. I photographed these hand written characters and convert them from png files to vx files to further process the images. The images are processed in the following way. First, I threshold the image with vit.c which gives us the figures in black background. After thresholding, I cut the characters from the image by find the leftmost, rightmost, upmost and downmost white pixels in the image, and these four coordinates give us the boundary of the character. We now have , and I used vimag command to shrink the size down to 20*20*1, last but not least, the images were centered in a 28x28 image by computing the center of mass of the pixels, and translating the image so as to position this point at the center of the 28x28 field.

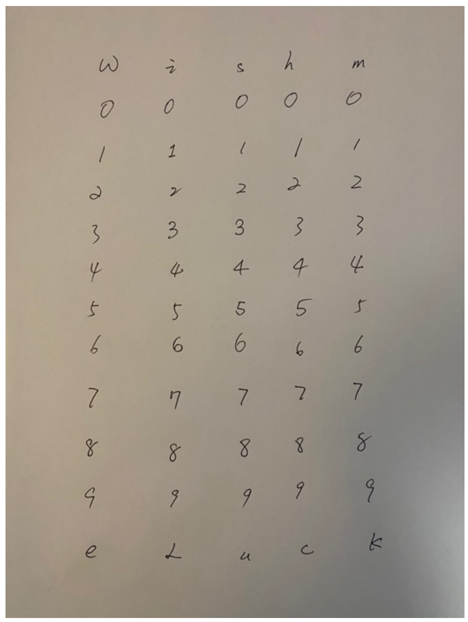


Fig1. Hand written characters

To perform these data process, I created a bash script to run all the c program and command for each of the image. As you can see vfmt is to convert a image from png to vx, vits is to threshold the image, boundary is the c program cutting the characters from the background. Add is the center of mass program embedding a 20*20 image to 28*28. And the evolution of the image can be seen in fig2, fig3, fig4.

```
#!/bin/sh
for i in {1..60}
do
vfmt if=p$i.png of=$i.vx -g -png
vits if=$i.vx of=$i.vx
boundary if=$i.vx of=$i.vx
vimag if=$i.vx of=$i.vx s=20,20,1
vitss if=$i.vx of=$i.vx
add if=$i.vx of=$i.vx
vxport if=$i.vx of=$i.png -png
done
```

Fig2. image before & after thresholding

Fig3. image rescaling

Fig4. Image center of mass

Fig5. Hand written dataset

Experiments with logistic regression classifier

After acquiring hand written dataset, we are really to train logistic regression classifier and test the result with testing dataset and hand written dataset that was created.

In [38]:
```
import time
import io
import matplotlib.pyplot as plt
import numpy as np
from scipy.io.arff import loadarff
from sklearn.datasets import get_data_home
from sklearn.externals.joblib import Memory
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.utils import check_random_state
from urllib.request import urlopen
```

In [39]:
```
#2.  read the NMIST dataset
memory = Memory(get_data_home())
@memory.cache()
def fetch_mnist():
    content = urlopen(
        'https://www.openml.org/data/download/52667/mnist_784.arff').read()
    data, meta = loadarff(io.StringIO(content.decode('utf8')))
    data = data.view([('pixels', '<f8', 784), ('class', '|S1')])
    return data['pixels'], data['class']
X, y = fetch_mnist()
```

In [40]:
```
#plt.imshow(X[12].reshape(28, 28), interpolation='nearest',cmap=plt.cm.gray)
```

In [41]:
```
# rescale the data, use the traditional train/test split

X = X / 255.
y_new = []
for i in range(len(y)):
    y_new.append(int(y[i]))
y = np.asarray(y_new)

X_train, X_test = X[:60000], X[60000:]
y_train, y_test = y[:60000], y[60000:]
```

In [24]:
```
for i in range(50):
    l1_plot = plt.subplot(5, 10, i + 1)
    l1_plot.imshow(255 * X_test[i].reshape(28, 28), interpolation='nearest',
                   cmap=plt.cm.gray)
    l1_plot.set_xticks(())
    l1_plot.set_yticks(())
    #l1_plot.set_xlabel('Class %s' % y_test[i].decode())
    l1_plot.set_xlabel('%i' % int(y_test[i]))
plt.suptitle('Test image Examples')
plt.show()
```

In [25]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [26]:
```
X_train.shape
```

Out[26]:
```
(60000, 784)
```

In [27]:
```python
#train and test classifier
# Turn up tolerance for faster convergence
clf = LogisticRegression(C=50. / 1000,
                         multi_class='multinomial',
                         penalty='l1', solver='saga', tol=0.1)
# Train the classifier
clf.fit(X_train, y_train)

#Evaluate the classifier
sparsity = np.mean(clf.coef_ == 0) * 100
score = clf.score(X_test, y_test)
# print('Best C % .4f' % clf.C_)
print("Sparsity with L1 penalty: %.2f%%" % sparsity)
print("Test score with L1 penalty: %.4f" % score)
```

```
Sparsity with L1 penalty: 16.47%
Test score with L1 penalty: 0.8913
```

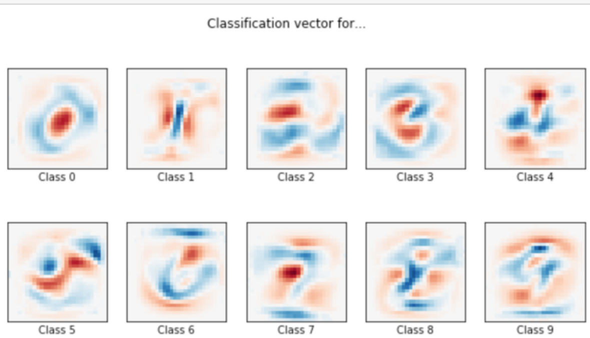
In [28]:
```python
y_train
```

Out[28]:
```
array([5, 0, 4, ..., 5, 6, 8])
```

In [29]:
```python
## For analysis show also the confusion matrix

from sklearn.metrics import confusion_matrix
y_predict = clf.predict(X_test)
cfm = confusion_matrix(y_test, y_predict)
print (cfm)
```

```
[[ 952    0    1    2    0   10   11    1    3    0]
 [    0 1103    3    3    1    1    4    0   20    0]
 [   16   21  870   23   19    0   17   23   40    3]
 [    5    8   20  891    1   31    8   19   19    8]
 [    2   10    4    0  903    2   13    2    3   43]
 [   14    9    6   44   23  724   20   14   23   15]
 [   16    9    9    0   11   19  889    1    4    0]
 [    1   34   18    5   12    0    1  916    1   40]
 [   10   30    9   29   20   37    9   17  796   17]
 [   18   10    4   13   55    5    0   32    3  869]]
```

In [30]:
```python
# Bonus 2: Visualization of the weights
# This is only possible for simple classifiers

coef = clf.coef_.copy()
plt.figure(figsize=(10, 5))
scale = np.abs(coef).max()
for i in range(10):
    l1_plot = plt.subplot(2, 5, i + 1)
    l1_plot.imshow(coef[i].reshape(28, 28), interpolation='nearest',
                   cmap=plt.cm.RdBu, vmin=-scale, vmax=scale)
    l1_plot.set_xticks(())
    l1_plot.set_yticks(())
    l1_plot.set_xlabel('Class %i' % i)
plt.suptitle('Classification vector for...')
plt.show()
```

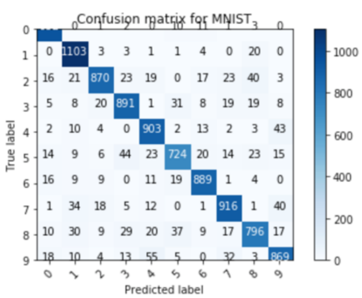


In [31]:
```python
import itertools
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    #print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
```

In [32]:
```python
plot_confusion_matrix(cfm, classes=range(10),
                      title='Confusion matrix for MNIST')
```

```
Confusion matrix, without normalization
```

Confusion matrix, without normalization



In [44]:
```python
import pandas as pd
import imageio

class SimpleDataset():
    def __init__(self, data_path, csv_name, transform = None ):


        data_path = '/Users/wang/Desktop/Course 2019 fall/Computer Vision/lab7/out/'
        csv_name ='label.csv'

        # Set path
        self.data_path = data_path
        # Read the csv file
        self.data_info = pd.read_csv(data_path + csv_name, header=None)
        # First column contains the image paths
        self.image_arr = np.asarray(self.data_info.iloc[:, 0])
        # Second column is the labels
        self.label_arr = np.asarray(self.data_info.iloc[:, 1])
        # Calculate len
        self.data_len = len(self.data_info.index)

    def __getitem__(self, index):
        # Get image name from the pandas df
        single_image_name = self.image_arr[index]
        # Open image
        img_as_img = imageio.imread(self.data_path + single_image_name)

        # Get label(class) of the image based on the cropped pandas column
        single_image_label = self.label_arr[index]

        return (img_as_img, single_image_label)

    def __len__(self):
        return self.data_len
```

In [45]:
```
mydata = SimpleDataset( "./idata/", "labels.csv")

#splitting into images and labels
X = []
y = []
for i in range(len(mydata)):
    X.append(mydata[i][0])
    y.append((mydata[i][1]))

#converting into numpy arrays to enable easy reshaping and other array operations

X = np.asarray(X)
print("Shape of the input image", X.shape)
y= np.asarray(y)
```

```
Shape of the input image (50, 28, 28)
```

In [35]:
```
import warnings
warnings.filterwarnings('ignore')
#l1_plot = plt.subplot(1, 4, i + 1)
for i in range(50):
    l1_plot = plt.subplot(5, 10, i + 1)
    l1_plot.imshow(X[i], interpolation='nearest',
                   cmap=plt.cm.gray)
    l1_plot.set_xticks(())
    l1_plot.set_yticks(())
    l1_plot.set_xlabel('%i' % int(y[i]))
plt.suptitle('Generated New Test image Examples')
plt.show()
```

In [36]:
```
#reshaping the array into flattened 784 array as an input for prediciton by the logistic regression classifier
X = X.reshape(X.shape[0], 784)
X = X / 255.
#data standardiation with the training set statistics is required for this clasifier
X = scaler.transform(X)

y_pred = clf.predict(X)

score = clf.score(X, y)

print("Test score with L1 penalty: %.4f" % score)
print("y_predicted_values", y_pred)
print("y_labels", y)
```

```
Test score with L1 penalty: 0.4200
y_predicted_values [0 0 0 0 0 1 1 1 1 1 0 8 2 2 1 1 3 3 1 1 5 1 6 1 1 1 5 5 1 1 1 6 5 6 8 1 7
 1 3 1 5 5 8 1 3 9 1 1 1 5]
y_labels [0 0 0 0 0 1 1 1 1 1 2 2 2 2 2 3 3 3 3 3 4 4 4 4 4 5 5 5 5 5 6 6 6 6 6 7 7
 7 7 7 8 8 8 8 8 9 9 9 9 9]
```

As the result shown above, the accuracy of the classifier on my handwritten dataset is 42%. which I think is not bad. To improve the testing accuracy, I tried to modify several parameters in the logistic regression classifier, I changed the solver to newton-cg, lbfgs and sag, but in my case none of them beat saga. I also changed the penalty term to further avoid overfitting. Last but not least, I added a max_iter term and set it to 100 iteration. It gives a better testing result of 44%

In [42]:
```
clf = LogisticRegression(C=50. / 3000,
                         multi_class='multinomial',
                         penalty='l1', solver='saga', max_iter=100, tol=0.1)
# Train the classifier
clf.fit(X_train, y_train)

#Evaluate the classifier
sparsity = np.mean(clf.coef_ == 0) * 100
score = clf.score(X_test, y_test)
# print('Best C % .4f' % clf.C_)
print("Sparsity with L1 penalty: %.2f%%" % sparsity)
print("Test score with L1 penalty: %.4f" % score)
```

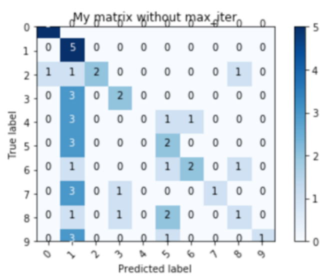
```
Sparsity with L1 penalty: 53.99%
Test score with L1 penalty: 0.9165
```

In [46]:
```
#reshaping the array into flattened 784 array as an input for prediciton by the logistic regression classifier
X = X.reshape(X.shape[0], 784)
X = X / 255.
#data standardiation with the training set statistics is required for this clasifier
X = scaler.transform(X)

y_pred = clf.predict(X)

score = clf.score(X, y)

print("Test score with L1 penalty: %.4f" % score)
print("y_predicted_values", y_pred)
print("y_labels", y)
```

```
Test score with L1 penalty: 0.4400
y_predicted_values [0 0 0 0 0 1 1 1 1 1 2 8 2 2 1 1 3 3 1 1 5 1 6 1 1 7 5 5 6 1 1 6 6 6 6 1 7
 1 3 1 5 5 1 1 5 4 1 1 1 5]
y_labels [0 0 0 0 0 1 1 1 1 1 2 2 2 2 2 3 3 3 3 3 4 4 4 4 4 5 5 5 5 5 6 6 6 6 6 7 7
 7 7 7 8 8 8 8 8 9 9 9 9 9]
```

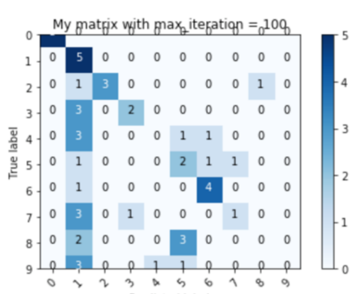
In [37]:
```
y_pred = clf.predict(X)
cfm = confusion_matrix(y, y_pred)
plot_confusion_matrix(cfm, classes=range(10),
                      title='My matrix without max_iter')
```

```
Confusion matrix, without normalization
```



In [47]:
```
y_pred = clf.predict(X)
cfm = confusion_matrix(y, y_pred)
plot_confusion_matrix(cfm, classes=range(10),
                      title='My matrix with max_iteration = 100')
```

```
Confusion matrix, without normalization
```



To better visualize the predicting result, I computed the confusion matrix, from the matrix we can see the true label and it's predicted label. we can see that the predition of character 0 and 1 are pretty good. The classifier got them 100% correct. However, the classifier does not seem to work very well with character 4,8 and 9. For some reason, most of the mispredict label is 1. So the classifier has problem diffientiate 1 and other characters.