

07-claret-2

November 5, 2018

1 Partical Work 07 - Classification with Support Vector Machines (SVM)

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- Due-date: *05.11.2018*

1.1 Exercice 1 Digit classification system using different SVM classifiers

1.1.1 a) Getting the training and test sample sets from the MNIST database

a) Load MNIST

```
In [1]: import pandas as pd
import os
import numpy as np

# This is a method to read the MNIST dataset from a ROOT directory
def load_MNIST(ROOT):
    train_nrows = 5000
    test_nrows = 1000
    '''load all of mnist training set first'''
    Xtr = []
    #train = pd.read_csv(os.path.join(ROOT, 'mnist_train.csv'), nrows = train_nrows)
    train = pd.read_csv(os.path.join(ROOT, 'mnist_train.csv'))
    X = np.array(train.drop('label', axis=1))
    Ytr = np.array(train['label'])
    # With this for-loop we give the data a shape of the acctual image (28x28)
    # instead of the shape in file (1x784)
    for row in X:
        Xtr.append(row.reshape(28,28))
    # load test set second
    Xte = []
    #test = pd.read_csv(os.path.join(ROOT, 'mnist_test.csv'), nrows = test_nrows)
    test = pd.read_csv(os.path.join(ROOT, 'mnist_test.csv'))
    X = np.array(test.drop('label', axis=1))
    Yte = np.array(test['label'])
    # same reshaping
    for row in X:
```

```

Xte.append(row.reshape(28,28))

return np.array(Xtr), np.array(Ytr), np.array(Xte), np.array(Yte)

# Load the raw MNIST data.
mnist_dir = './mnist' # TODO: update this dir information to your own dir
X_train, y_train, X_test, y_test = load_MNIST(mnist_dir)

# As a sanity check, we print out the size of the training and test data.
print('Training data shape: ', X_train.shape)
print('Training labels shape: ', y_train.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)

Training data shape: (60000, 28, 28)
Training labels shape: (60000,)
Test data shape: (10000, 28, 28)
Test labels shape: (10000,)

```

```

In [2]: #from sklearn import svm
        #clf_svm = svm.LinearSVC()
        #clf_svm.fit(X_train, y_train)
        #y_pred_svm = clf_svm.predict(X_test)
        #acc_svm = accuracy_score(y_test, y_pred_svm)
        #print("Linear SVM accuracy: ",acc_svm)

```

b) Visualize (plot)

```

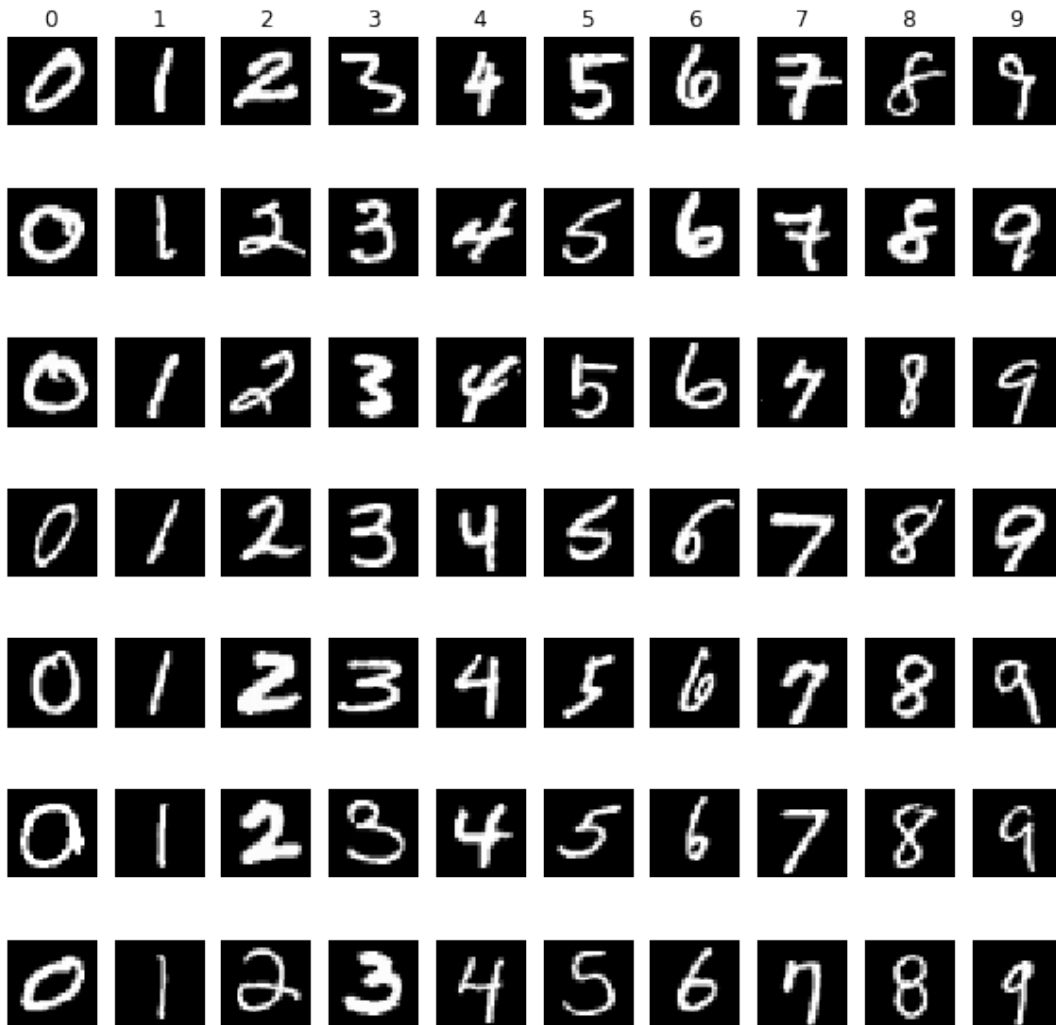
In [3]: import matplotlib.pyplot as plt

# This is a bit of magic to make matplotlib figures appear inline in the notebook
# rather than in a new window. Also setting some parameters for display.
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 10.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# Now let's visualise some of the images
classes = ['0', '1', '2', '3', '4', '5', '6', '7', '8', '9']
num_classes = len(classes)
samples_per_class = 7
for y, cls in enumerate(classes): # y and cls takes values from 0-9
    idxs = np.flatnonzero(y_train == y) # gets the indices of samples that corresponds
    idxs = np.random.choice(idxs, samples_per_class, replace=False) # picks randomly s
    for i, idx in enumerate(idxs):
        plt_idx = i * num_classes + y + 1 # determines the sub-plot index
        plt.subplot(samples_per_class, num_classes, plt_idx)
        plt.imshow(X_train[idx].astype('uint8'))

```

```
plt.axis('off')
if i == 0:
    plt.title(cls)
plt.show()
```



c) Build the final training and test sets

```
In [4]: # Subsample the data for more efficient code execution in this exercise. We do this to
# When you will have completed the whole notebook, you can run it again on a larger (o
# and observe the difference in terms of accuracy (and speedup).
#X_train, y_train, X_test, y_test
#num_training = 200
#mask = range(num_training)
#X_train = X_train[mask]
```

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#y_train = y_train[mask]

#num_test = 100
#mask = range(num_test)
#X_test = X_test[mask]
#y_test = y_test[mask]

#print('Training subsampled data shape: ', X_train.shape)
#print('Training subsampled labels shape: ', y_train.shape)
#print('Test subsampled data shape: ', X_test.shape)
#print('Test subsampled labels shape: ', y_test.shape)

from collections import defaultdict

def balance(X_data, y_data, samples=0):

    blanced_truth_min = samples
    if samples == 0:
        truth_count = int()
        for y in range(len(y_data)):
            truth_count[y_data[y]] = truth_count[y_data[y]] + 1
        blanced_truth_min = truth_count[min(truth_count, key=truth_count.get)]

    index_list = defaultdict(list)
    index = []

    y_mask = list(range(len(y_data)))
    np.random.shuffle(y_mask)
    for y in y_mask:
        if len(index_list[y_data[y]]) < blanced_truth_min:
            index_list[y_data[y]].append(y)
            index.append(y)

    return index, blanced_truth_min

train_balanced_indices, n1 = balance(X_train, y_train, 200)
test_balanced_indices, n2 = balance(X_test, y_test, 100)

def X_train_balance():
    return [X_train[i] for i in train_balanced_indices]

def y_train_balance():
    return [y_train[i] for i in train_balanced_indices]

def X_test_balance():
    return [X_test[i] for i in test_balanced_indices]

def y_test_balance():

```

```
return [y_test[i] for i in test_balanced_indices]
```

1.1.2 b) Classification of digits based on raw pixel values using SVM and different kernels

a) <http://scikit-learn.org/stable/modules/svm.html>

```
In [6]: from sklearn import svm
        from sklearn.model_selection import cross_val_score
        from sklearn.metrics import confusion_matrix

        y_train_balanced = y_train_balance()

        X_train_balanced_dim_2 = []
        X_train_balanced_dim_2_labels = []
        for x in X_train_balance():
            X_tmp = []
            sorted_labels = sorted(x, key=lambda x: x[1], reverse=True)
            X_train_balanced_dim_2_labels.append(sorted_labels[0][0])
            for tmp in x:
                X_tmp.append(tmp[1])
            X_train_balanced_dim_2.append(X_tmp)

        fold_size = 10

        Cs = [10, 100, 1000]
        gammas = [0.001, 0.01, 0.1, 1]
        degrees = [1, 2, 3, 4]

        linear_measures = []
        linear_measures_cm = []
        linear_measures_score = []

        linear_cvs_measures = []
        linear_cvs_measures_cm = []
        linear_cvs_measures_score = []

        rbf_measures = []
        rbf_measures_cm = []
        rbf_measures_score = []

        poly_measures = []
        poly_measures_cm = []
        poly_measures_score = []

        for c in Cs:
            # linear
            model = svm.SVC(kernel='linear', C=c, gamma='auto')
            model.fit(X_train_balanced_dim_2, y_train_balanced)
```

```

res = np.mean(cross_val_score(model,
                              X_train_balanced_dim_2,
                              y_train_balanced,
                              cv=fold_size))

linear_measures.append(res)
y_pred = model.predict(X_train_balanced_dim_2)
linear_measures_cm.append(confusion_matrix(y_train_balanced, y_pred))
linear_measures_score.append(model.score(X_train_balanced_dim_2, y_train_balanced))

# linear cvs
#model = svm.LinearSVC(C=1.0)
model = svm.LinearSVC(C=c)
model.fit(X_train_balanced_dim_2, y_train_balanced)
res = np.mean(cross_val_score(model,
                              X_train_balanced_dim_2,
                              y_train_balanced,
                              cv=fold_size))

linear_cvs_measures.append(res)
y_pred = model.predict(X_train_balanced_dim_2)
linear_cvs_measures_cm.append(confusion_matrix(y_train_balanced, y_pred))
linear_cvs_measures_score.append(model.score(X_train_balanced_dim_2, y_train_balanced))

# rbf
res = []
for gamma in gammas:
    model = svm.SVC(kernel='rbf', gamma=gamma, C=c)
    res.append(np.mean(cross_val_score(model,
                                       X_train_balanced_dim_2,
                                       y_train_balanced,
                                       cv=fold_size)))

    #y_pred = model.predict(X_train_balanced_dim_2)
    #rbf_measures_cm.append(confusion_matrix(y_train_balanced, y_pred))
    #rbf_measures_score.append(model.score(X_train_balanced_dim_2, y_train_balanced))
rbf_measures.append(res)

# poly
res = []
for degree in degrees:
    model = svm.SVC(kernel='poly', degree=degree, C=c, gamma='auto')
    res.append(np.mean(cross_val_score(model,
                                       X_train_balanced_dim_2,
                                       y_train_balanced,
                                       cv=fold_size)))

    #y_pred = model.predict(X_train_balanced_dim_2)
    #poly_measures_cm.append(confusion_matrix(y_train_balanced, y_pred))
    #poly_measures.append(model.score(X_train_balanced_dim_2, y_train_balanced))
poly_measures.append(res)

```

[illegible]

```

    "the number of iterations.", ConvergenceWarning)
/anaconda3/envs/MachLe/lib/python3.6/site-packages/sklearn/svm/base.py:922: ConvergenceWarning
    "the number of iterations.", ConvergenceWarning)
/anaconda3/envs/MachLe/lib/python3.6/site-packages/sklearn/svm/base.py:922: ConvergenceWarning
    "the number of iterations.", ConvergenceWarning)
/anaconda3/envs/MachLe/lib/python3.6/site-packages/sklearn/svm/base.py:922: ConvergenceWarning
    "the number of iterations.", ConvergenceWarning)

```

```

Cs: [10, 100, 1000]
gammas: [0.001, 0.01, 0.1, 1]
degrees: [1, 2, 3, 4]
linear_measures: [0.101, 0.101, 0.101]
linear_measures_score: [0.1025, 0.1025, 0.1025]
linear_cvs_measures: [0.101, 0.101, 0.101]
linear_measures_score: [0.1025, 0.1025, 0.1025]
rbf_measures: [[0.101, 0.101, 0.1015, 0.1015], [0.1015, 0.101, 0.1015, 0.1015], [0.101, 0.101, 0.1015, 0.1015], [0.1015, 0.1015, 0.101, 0.1015]]
poly_measures: [[0.101, 0.1005, 0.1005, 0.1005], [0.101, 0.1005, 0.1005, 0.1005], [0.101, 0.1005, 0.1005, 0.1005], [0.101, 0.1005, 0.1005, 0.1005]]

```

- b) <http://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html>
- c) http://scikit-learn.org/stable/modules/grid_search.html
- d) http://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html
- e) http://scikit-learn.org/stable/modules/model_evaluation.html#confusion-matrix and
...#classification-report
- f) <http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf>

```

In [ ]: c = 1000
        gamma = 0.001
        degree = 1

        model = svm.SVC(kernel='linear', C=c)
        model.fit(X_train_balanced_dim_2, y_train_balanced)
        y_pred = model.predict(X_train_balanced_dim_2)
        cm = confusion_matrix(y_train_balanced, y_pred)
        score = model.score(X_train_balanced_dim_2, y_train_balanced)
        print("linear score: ", score)
        print("linear confusion_matrix:\n", cm)

        model = svm.LinearSVC(C=c)
        model.fit(X_train_balanced_dim_2, y_train_balanced)
        y_pred = model.predict(X_train_balanced_dim_2)
        cm = confusion_matrix(y_train_balanced, y_pred)
        score = model.score(X_train_balanced_dim_2, y_train_balanced)
        print("SVC score: ", score)

```



```

print("SVC confusion_matrix:\n", cm)

# RBF
model = svm.SVC(kernel='rbf', gamma=gamma, C=c)
model.fit(X_train_balanced_dim_2, y_train_balanced)
y_pred = model.predict(X_train_balanced_dim_2)
cm = confusion_matrix(y_train_balanced, y_pred)
score = model.score(X_train_balanced_dim_2, y_train_balanced)
print("RBF score: ", score)
print("RBF confusion_matrix:\n", cm)

# Poly
model = svm.SVC(kernel='poly', degree=degree, C=c, gamma='auto')
model.fit(X_train_balanced_dim_2, y_train_balanced)
y_pred = model.predict(X_train_balanced_dim_2)
cm = confusion_matrix(y_train_balanced, y_pred)
score = model.score(X_train_balanced_dim_2, y_train_balanced)
print("Poly score: ", score)
print("Poly confusion_matrix:\n", cm)

```

1.1.3 c. (Optional) Impact of preprocessing and feature extraction

1.1.4 d. Analysis of the results

a) Which kernel and parameters were used ? Not sure.. Didn't have time to run a good amount batches. The results are all similar with a measure at 0.101 and a score at 0.101ish. Not looking that good.

b) Which digit classes are the best/worse recognized against which ? Why ? Not sure...

c) What is the impact of the sizes of the training and test sets on the classification performance ?
 The calculation time. Based on the features wanted, the training set have to increase dramatically.
 PS: Sorry again for this screw up...