

assignment09

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0.0.1 Binary classifier using linear regression

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```
In [ ]: import matplotlib.pyplot as plt
import numpy as np
import random

file_data = "mnist_train.csv"
file_test_data = "mnist_test.csv"
handle_file = open(file_data, "r")
handle_test_file = open(file_test_data, "r")
data = handle_file.readlines()
test_data = handle_test_file.readlines()
handle_file.close()
handle_test_file.close()

size_row = 28 # height of the image
size_col = 28 # width of the image
num_image = len(data)
num_test_image = len(test_data)
count = 0 # count for the number of images
numOfZero = 0
numOfNonZero = 0
test_numOfZero = 0
test_numOfNonZero = 0

#
# normalize the values of the input data to be [0, 1]
#
def normalize(data):

    data_normalized = (data - min(data)) / (max(data) - min(data))

    return(data_normalized)
```

```

list_image = np.empty((num_image, size_row * size_col + 1), dtype=float)
list_test_image = np.empty((num_test_image, size_row * size_col + 1), dtype=float)
list_label = np.empty(num_image, dtype=int)
list_test_label = np.empty(num_test_image, dtype=int)
classification = np.empty(num_image, dtype=float)
test_classification = np.empty(num_test_image, dtype=float)

for line in data:
    line_data = line.split(',')
    if line_data[0] == '0':
        label = 1
        numOfZero = numOfZero + 1
    else:
        label = -1
        numOfNonZero = numOfNonZero + 1

    im_vector = np.asfarray(line_data[1:])
    im_vector = normalize(im_vector)
    list_label[count] = label
    list_image[count, 0] = 1
    list_image[count, 1:] = im_vector
    count = count + 1

count = 0
for line in test_data:
    line_test_data = line.split(',')
    if line_test_data[0] == '0':
        label = 1
        test_numOfZero = test_numOfZero + 1
    else:
        label = -1
        test_numOfNonZero = test_numOfNonZero + 1

    im_vector = np.asfarray(line_test_data[1:])
    im_vector = normalize(im_vector)
    list_test_label[count] = label
    list_test_image[count, 0] = 1
    list_test_image[count, 1:] = im_vector
    count = count + 1

```

0.0.4 Compute optimal model parameter

```

In [21]: d = 28 * 28
         X = np.zeros(d+1)
         X = np.dot(np.linalg.pinv(list_image), list_label)
         print(X)

```

```

[-6.84406870e-01  2.37849111e-12  9.77649619e-13 -7.55606562e-13
 4.65302804e-13 -2.72493104e-12 -3.42955075e-12  2.44608609e-12
 1.46186912e-12  1.54540945e-12  2.34367809e-12 -3.67131030e-13
 1.68286852e-12  1.53458664e-01  1.98220986e-01 -1.53345669e-01
-6.38940289e-03  4.36666199e-13  2.27434452e-13  3.19672081e-13
-2.79285881e-13 -1.86745735e-12  2.64320482e-12 -9.20819970e-14
 8.40131115e-13 -4.18773815e-13  3.10040223e-12 -1.20469402e-12
 2.18646697e-13  1.46863171e-13  1.98674311e-12  8.17567744e-13
-1.55858501e-13 -4.06289060e+00  1.05099744e+00  1.23101922e-01
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 3.58333722e-02  3.33915605e-13  2.40022670e-12  2.57644850e-14
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 9.77593181e+00  5.34144080e-01 -7.99936568e-01 -1.89682766e-01
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-1.79359733e+00 -8.68499683e-02 -8.20073230e-02 -6.32433515e-02
-1.82101353e-03  2.33142466e-02 -6.21453144e-02 -3.36839292e-02
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-4.58517277e-02 -1.08105115e-01 -1.05007043e-01 -6.90997253e-02
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-1.06494634e-02 -1.71309113e-03  2.28669380e-02  2.94280678e-03
-5.01942060e-03  1.20090491e-02 -1.13210503e-03  1.50315298e-02
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```

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2.14089830e-02	2.56670589e-02	3.40819846e-03	3.02783250e-02
3.78463391e-02	2.17140210e-02	2.12289652e-02	-1.79607760e-02
-2.20404529e-02	-1.11672821e-02	-5.30621084e-02	9.34300821e-03
1.83625686e-03	1.66758756e-02	-1.47400731e-01	-6.10764180e-01
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1.67844952e-01	2.25941586e-02	-8.85053906e-02	7.25145926e-02
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-1.37951641e-02	-4.01226467e-03	4.11089472e-03	3.87584387e-02
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-2.69727298e-02	-6.47967538e-02	-3.07931417e-02	-4.40256645e-02
-1.10227227e-02	-3.02929742e-02	-3.42579844e-02	-2.18200615e-02
1.09956572e-02	-7.18229144e-02	8.45752821e-03	1.42200871e-01
-1.70038171e-01	-1.81931548e-01	-4.97548713e-01	-4.23939234e+00
0.00000000e+00	0.00000000e+00	0.00000000e+00	0.00000000e+00
-9.25135496e-01	2.61352157e-01	-2.06542730e-01	7.77944182e-03
-9.17599613e-02	-4.73427311e-02	-1.16567776e-01	-4.30764643e-02
-1.01269701e-01	-3.37441281e-02	-9.01871025e-02	-4.68745660e-02
-9.76980636e-02	-5.40824984e-02	-3.27357791e-02	-7.45309295e-02
-7.49540276e-03	8.34344478e-03	-1.55967392e-01	-6.34283335e-02
-2.63607005e-01	2.06109092e+00	-2.73970042e-01	0.00000000e+00
0.00000000e+00	0.00000000e+00	0.00000000e+00	0.00000000e+00
0.00000000e+00	8.04406795e-01	2.37610340e-02	-3.77192111e-01
6.07099203e-02	-1.29168168e-01	-1.13140632e-01	-3.49107977e-02

```
-1.77844159e-02 -1.36109932e-01 -7.60964262e-03 -1.35766440e-01
-2.44375949e-02 -4.33457087e-02 -1.14834013e-01 -4.48240493e-02
 1.13894563e-02 -1.02555619e-01  1.83726663e-01 -3.49763778e-01
-2.08560473e+00  0.00000000e+00  0.00000000e+00  0.00000000e+00
 0.00000000e+00]
```

0.05 Compute tp,fp,tn,fn on training set

```
In [23]: for i in range(num_image):
        if np.dot(list_image[i], X) > 0:
            classification[i] = 1
        else:
            classification[i] = -1

        tp = 0
        fp = 0
        fn = 0
        tn = 0

        for i in range(num_image):
            if list_label[i] == 1:
                if classification[i] == 1:
                    tp = tp + 1
                else:
                    fn = fn + 1

            if list_label[i] != 1:
                if classification[i] == 1:
                    fp = fp + 1
                else:
                    tn = tn + 1

        print('tp : ', tp / numOfZero)
        print('fp : ', fp / numOfNonZero)
        print('fn : ', fn / numOfZero)
        print('tn : ', tn / numOfNonZero)
```

```
tp :  0.8723619787269965
fp :  0.003310094864729922
fn :  0.12763802127300355
tn :  0.9966899051352701
```

0.06 Compute tp,fp,tn,fn on testing set

```
In [24]: for i in range(num_test_image):
        if np.dot(list_test_image[i], X) > 0:
```

```

        test_classification[i] = 1
    else:
        test_classification[i] = -1

tp = 0
fp = 0
fn = 0
tn = 0

for i in range(num_test_image):
    if list_test_label[i] == 1:
        if test_classification[i] == 1:
            tp = tp + 1
        else:
            fn = fn + 1

    if list_test_label[i] != 1:
        if test_classification[i] == 1:
            fp = fp + 1
        else:
            tn = tn + 1

print('tp : ', tp / test_numOfZero)
print('fp : ', fp / test_numOfNonZero)
print('fn : ', fn / test_numOfZero)
print('tn : ', tn / test_numOfNonZero)

tp : 0.8836734693877552
fp : 0.004767184035476719
fn : 0.11632653061224489
tn : 0.9952328159645233

```

In []: