# Pattern Recognition Assignment 1

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## Question 1

```
close all
  clear all
  clc
  % load dataset
  load('Example_MNIST_digits.mat');
  % loop over 10 digits
  for i = 1: 10
      \% 3/4 subplots
     subplot(3,4,i)
     % Get the average of each digit, convert it 8bit integers,
10
     % Reshape the row into a matrix and show the resulting image
11
     imshow(reshape(uint8(mean(b(labb = i, :), 1)), 28, 28));
     % Show the title for the subplot
     title(i-1)
14
15
```

For output please see figure 1

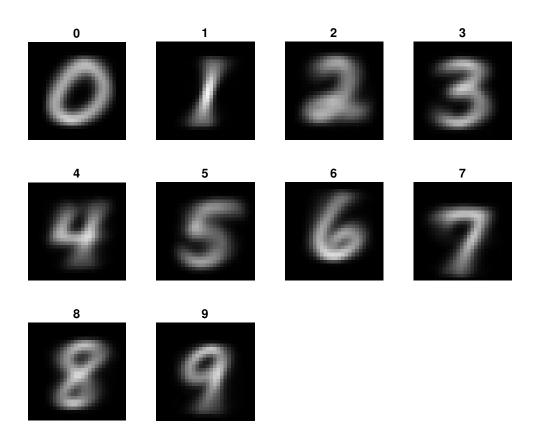


Figure 1: Average digit visualisation

```
close all
  clear all
  clc
  load('Example_MNIST_digits.mat');
  \% create D and Z variables
  D = zeros(size(b));
  Z = zeros(size(b,1), 2);
  % 1 to number of rows in b
  for i = 1: size(b, 1)
     % apply treshold
11
     D(\,i\;,\;\;:)\;=\;(\,b\,(\,i\;,\;\;:)\;<=\;120\,)\,;
12
     \% transform each row into a 28X28 matrix
13
      c = reshape(D(i, :), 28, 28);
14
     \% find all values in c that are 0
15
      [row, col] = find(~c);
16
     % find aspect ratio
17
      Z(i, 1) = (\max(row) - \min(row)) / \dots
18
            (\max(col)-\min(col));
19
     % find proportion
     Z(i, 2) = numel(row)/numel(D(i, :));
  end
```

```
close all
   clear all
   clc
   load('Example_MNIST_digits.mat');
  D = b \le 120;
   Z = zeros(size(b,1), 2);
   % 1 to number of rows in b
   for i = 1: size(b, 1)
       c = reshape(D(i, :), 28, 28);
10
       [row, col] = find(~c);
11
      % find aspect ratio
12
       Z(i, 1) = (\max(row) - \min(row)) / \dots
13
             (\max(\operatorname{col}) - \min(\operatorname{col}));
14
      % find proportion
15
   end
17
   Z(:,2) = \operatorname{mean}(^{\sim}D, 2);
18
19
   % part A
   % Variable to hold errors
   ers = zeros(9,1);
   % Loop over 10 digits
23
   for i = 0:9
      % use suplied classifier with the data and save the labels in nl
25
       nl = classifier(Z, labb == i + 1);
26
      \% count the errors in the new labels
27
       ers(i + 1) = 1 - sum(nl = (labb = i + 1)) / size(nl,1);
   end
29
   figure
30
   % plot the errors for the 10 digits for comparison further down
   plot (0:9, ers, 'r-');
   xlabel('Digit')
   ylabel('Error rate')
34
   print -depsc 3a
36
   % part c
37
   % Variable to hold errors
   err = zeros(numel(unique(labb)), 1);
   % Loop over 10 digits
40
   for i = 1:10
        % current label(digit) is positive (1) everything else is negative(0)
42
        labba = labb == i;
43
        % lables array
44
        labels = zeros(size(Z,1),1);
45
        %loop over all data in Z
46
        for j = 1 : size(Z,1)
47
           % assign label for the left out element
            \mbox{labels} \, (\, j \, ) \, \, = \, \mbox{MyNMC} (\, Z \, (\, [\, 1 \, : \, j \, \, , \, \, \, j \, + 1 \, : \, \mbox{end} \, ] \, \, , \, \, : \, ) \, \, , \, \, \, \ldots \, \,
49
                 labba ([1:j, j+1:end]), Z(j, :);
50
51
        \% calculate the error rate
```

```
err(i) = mean(labels ~= labba);
53
  end
54
  % plot the error rate for comparison
55
   figure
   plot(0:9, err, 'b-');
57
   xlabel('Digit')
   vlabel('Error rate')
59
   print -depsc 3c
   function NewLabels = MyNMC(Ztr, Ytr, Zts)
       % Get a variable holding the unique labels
2
       labels = unique(Ytr);
3
       \% grpstats gets mean grouped by the labels
4
       mean = grpstats(Ztr, Ytr);
5
       for i = 1 : size(Zts, 1);
          % Assign label index by getting the smallest distance when comparing
          % the current element with the means
          [, NewLabels(i)] = \min(\text{pdist2}(\text{mean}, \text{Zts}(i,:)));
       end
10
       % Assign label values by indexing the unique labels with
11
       % the supplied indeces
12
       NewLabels = labels (NewLabels);
13
  end
14
```

Using the given classifier indicates that the digit 1 is a more distinct as it will have a lower aspect ratio and lower proportion of black as seen by figure 2

In task 3c we use the MyNMC classifier to classify the data and we notice that the error plot (figure 3) it very similar to that of the given classifier which leads to the conclusion that it is an NMC classifier. THe slight differences in error is down to the fact that in figure 3 a leaveone out NMC is being used, whereas in figure 2 the classifier is being trained on all of the data.

Actual error rates below.

```
3a
                   3c
       0.3338
                   0.3338
2
       0.1894
                   0.1894
       0.3058
                   0.3058
4
       0.4680
                   0.4680
       0.4600
                   0.4600
       0.3324
                   0.3324
       0.4654
                   0.4654
       0.4068
                   0.4068
       0.4882
                   0.4882
10
       0.4138
                   0.4138
11
```

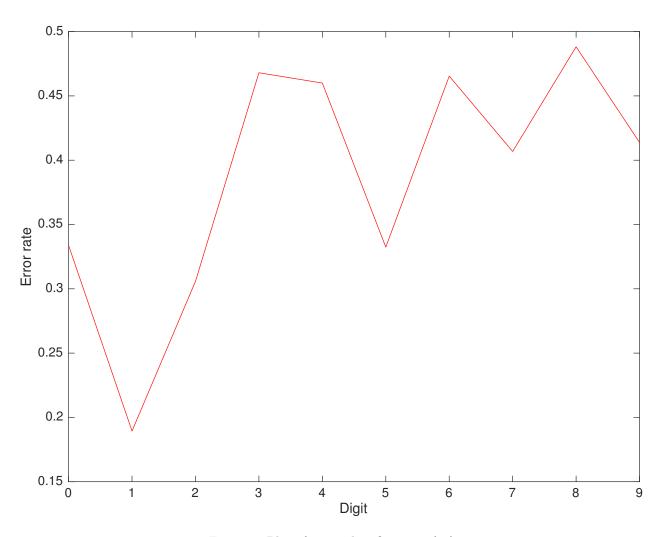


Figure 2: Plot of given classifier error (3a)

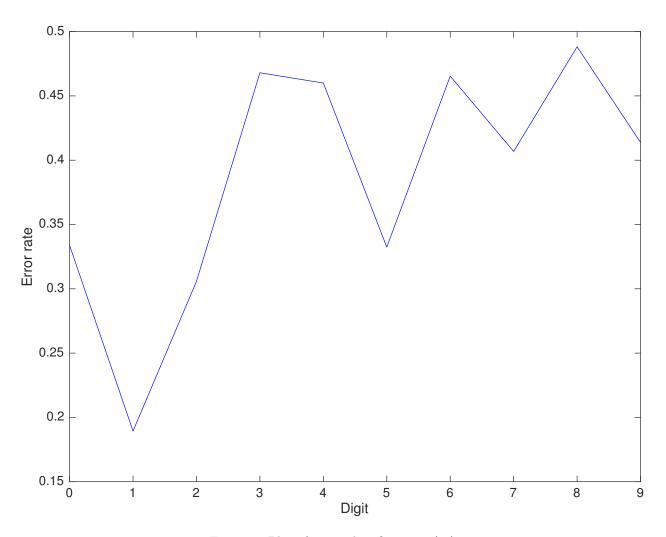


Figure 3: Plot of given classifier error (3c)

```
close all
  clear all
   clc
  load ( 'Example_MNIST_digits.mat');
  D = b \le 120;
  % part a
10
   ers = zeros(9,1);
11
   for i = 1:10
12
      nl= classifier (b, labb == i);
13
      ers(i) = 1 - sum(nl = (labb = i)) / size(nl,1);
14
15
  ers2 = zeros(9,1);
17
   for i = 0:9
18
      nl = classifier(double(D), labb = i + 1);
19
      ers2(i + 1) = 1 - sum(nl = (labb = i + 1)) / size(nl,1);
  end
21
22
  figure
23
  hold on
  % plot the error rates for both classifier with Original Data and D
  plot(0:9, ers, 'r-');
  plot (0:9, ers2, 'b-');
  xlabel('Digit')
  ylabel('Error rate')
  print -depsc plot4
```

When not considering aspect ratio and ink amount the NMC classifier returns different results in terms of error rate, there are differing peaks but better overall error rate as seen in figure 4

Error rates

```
Original
                   Threshold
       0.0522
                   0.0528
2
       0.0646
                   0.0636
       0.0786
                   0.0770
       0.1002
                   0.0974
       0.1268
                   0.1262
       0.1780
                   0.1774
       0.0666
                   0.0660
       0.0784
                   0.0780
       0.1206
                   0.1220
10
       0.1828
                   0.1816
11
```

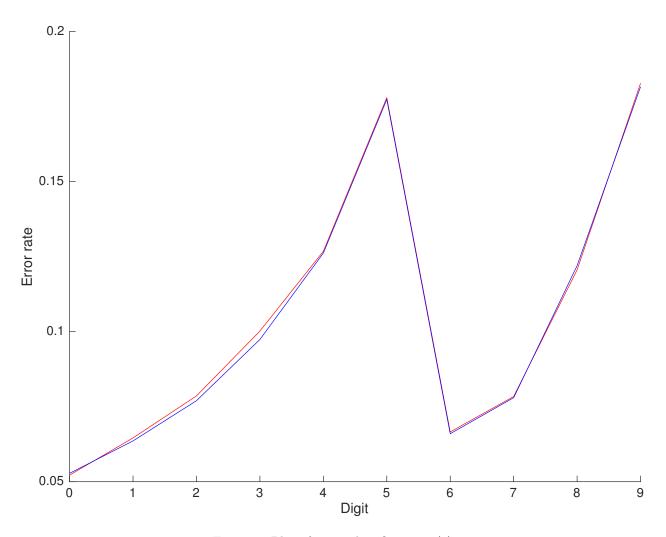


Figure 4: Plot of given classifier error (4)

```
function [RocMatrix, Closest] = myRoc(data, labels)
   [\tilde{\ }, ind] = sort(data);
   d = labels(ind);
   RocMatrix = zeros(numel(d), 2);
        for i = 1:numel(d)
6
            % Get current position in the data (split)
            dstart = d(1:i);
            dend = d(i+1:end);
            % Find all the:
10
                 \% True Positives and Negatives and
11
                 % False Positives and Negatives
12
            tPos = sum(dend == 2);
13
            tNeg = sum(dstart == 1);
            fPos = sum(dend == 1);
15
            fNeg = sum(dstart == 2);
            % Put the Sensitivity and specificity for each split
17
            \% into the roc matrix in columns 1 and 2 respectively
18
            RocMatrix(i, 1) = tNeg/(tNeg+fPos);
19
            RocMatrix(i, 2) = tPos/(tPos+fNeg);
20
        end
21
        \begin{bmatrix} \tilde{\phantom{a}}, & \text{ind} \end{bmatrix} = \min(\text{pdist2}([1 - \text{RocMatrix}(:,1) | \text{RocMatrix}(:,2)], [0 \ 1]));
        Closest = RocMatrix(ind,:);
23
   end
```

```
close all
   clear all
   clc
  load ( 'Example_MNIST_digits.mat');
  D = b \le 120;
   Z = zeros(size(b,1), 2);
  Z(:,2) = \operatorname{mean}(\tilde{D}, 2);
  % 1 to number of rows in b
   for i = 1: size(b, 1)
      c = reshape(D(i, :), 28, 28);
11
      [row, col] = find(~c);
12
      % find aspect ratio
13
      Z(i, 1) = (\max(row) - \min(row)) / \dots
14
            (\max(\operatorname{col}) - \min(\operatorname{col}));
15
      % find proportion
17
   end
18
19
   labbs = labb == 2;
   % Use the MyRoc function to compare the Aspect Ratio
  % and Proportion
   [rocMatrixAspect, aClosest] = MyRoc(Z(:,1), ~labbs + 1);
   [rocMatrixProportion, pClosest] = MyRoc(Z(:,2), ~labbs + 1);
   figure
25
   hold on
26
   grid on
27
   axis square
   set (gca, 'ytick', 0:0.2:1)
   plot(1 - rocMatrixAspect(:,1), rocMatrixAspect(:,2), 'r-');
   plot(1 - rocMatrixProportion(:,1), rocMatrixProportion(:,2), 'b-');
   xlabel('1-specifictiy')
   ylabel('sensitivity')
   legend ('Aspect Ratio', 'Proportion Black')
34
   print -depsc plot6
   For output, see plot in figure 5 The closest points to [0,1] in each case are
       Aspect Ratio
1
                   0.8633
       0.8315
2
       Proportion
       0.8763
                   0.8204
```

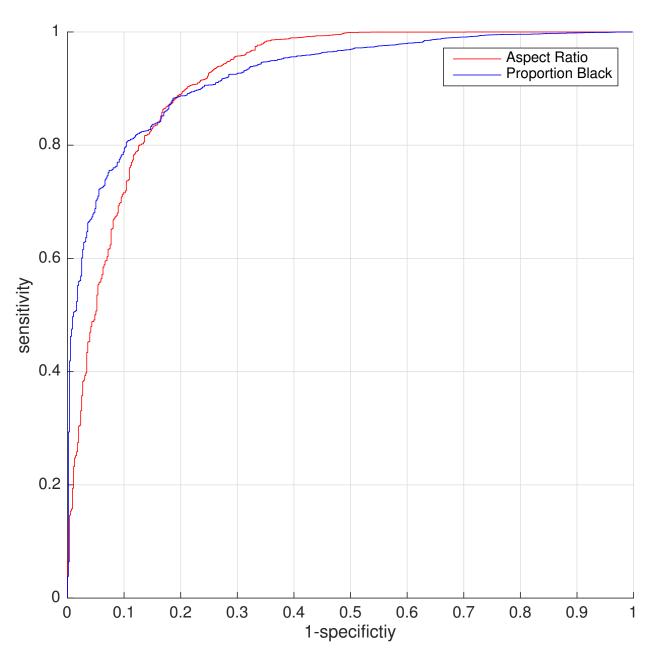


Figure 5: Plot rock curve for aspect ratio and proportion (6)

```
close all
   clear all
   clc
  load('Example_MNIST_digits.mat');
  % create variable to hold all assigned labels in bagging
   assignedLabs = zeros(5000,9);
   for i = 1 : 9
      \% Build an index of 5000 values with repitition
      % in the range 1 to length of dataset
10
       ind = randi(size(b, 1), size(b, 1), 1);
11
       % pass the indexed dataset to the MyNMC function
12
      % as well as the full dataset for testing
13
       assignedLabs(:,i) = MyNMC(b(ind, :), labb(ind), b);
14
15
  % Get the assigned label by selecting the most assigned
  % label from the output for each value
  alabb = mode(assignedLabs, 2);
  % calculate the accuracy of the classifier ensemble
   acc = mean(alabb = labb);
21
  % construct the confusion matrix
  c = zeros(10);
23
  % loop over the rows in the
   for i = 1 : size(alabb, 1);
    % increment the value at the position representing where the
26
    % assigned label is
27
     c(labb(i), alabb(i)) = c(labb(i), alabb(i)) + 1;
  end
29
30
  % used to test accuracy of confusion matrix
  % con = confusionmat(labb, avgLabs);
32
  \% \text{ mean}(c(:) = con(:))
33
34
  % run single nmc on the data and output the accuracy
  snmc = MvNMC(b, labb, b);
  snmcAcc = mean(snmc=labb)
```

Confusion matrix

1	424	0	2	1	0	46	16	1	2	2
2	0	537	2	3	0	6	2	0	8	0
3	10	32	422	17	20	3	15	9	15	2
4	4	16	13	375	1	29	4	3	25	10
5	0	7	2	0	393	0	4	1	4	66
6	7	37	4	56	5	320	11	3	7	19
7	9	16	6	0	15	17	450	0	3	0
8	1	28	4	0	9	2	1	422	6	33
9	4	21	4	48	3	15	4	1	358	19
10	6	11	3	9	48	4	1	19	8	369

The accuracy for the ensemble is around 0.81 and the single NMC has a similar accuracy at around 0.81.