

# Homework Assignment 5

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Statistical Learning I - Fall 2021

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**Problem Quiz.** This week we use the cheetah image to evaluate the performance of a classifier based on mixture models estimated with EM. Once again we use the decomposition into  $8 \times 8$  image blocks, compute the DCT of each block, and zig-zag scan. For this (using the data in *TrainingSamplesDCT\_new\_8.mat*) we fit a mixture of Gaussians of diagonal covariance to each class, i.e.

$$P_{X|Y}(x|i) = \sum_{c=1}^C \pi_c G(x, \mu_c, \Sigma_c)$$

- (a) For each class, learn 5 mixtures of  $C = 8$  components, using a random initialization (recall that the mixture weights must add up to one). Plot the probability of error vs. dimension for each of the 25 classifiers obtained with all possible mixture pairs. Comment the dependence of the probability of error on the initialization.

*Sol.* The probability of error vs. dimension result is as follow. Note that the codes are attached at the last of the report.

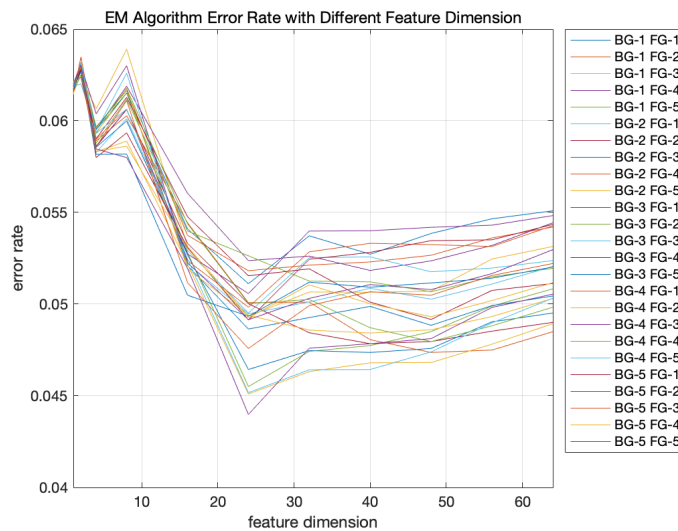


Figure 1: EM Algorithm Test with Different Feature Dimension

### Comments:

- (a) **Dependence of probability of error on the initialization:** Using different initialization (randomly initialized every time) is really important for EM algorithm. We can find that distinct initialization may result in higher or lower probability error. That's telling us that some of them are falling into the local optimum of the result. Some of them is smaller than the others and some of them are bigger while all of them are the same algorithm process. However, it's also important to see that the trend of the error with respect to dimension is not changing with different initialization. That's because it's determined by the feature dimension.
- (b) **Comment on Feature Dimension:** We can see that when the feature dimension is getting higher, the probability of error may go up or down. We've shown in the previous homework, it's better when we choose the best features rather than directly use the 64 dimensional feature. Thus this is also an reasonable interpretation of the result we got before.

□

- (b) For each class, learn mixtures with  $C \in \{1, 2, 4, 8, 16, 32\}$ . Plot the probability of error vs. dimension for each number of mixture components. What is the effect of the number of mixture components on the probability of error?

*Sol.* The probability of error vs. dimension result for each number of mixture components is as follow.

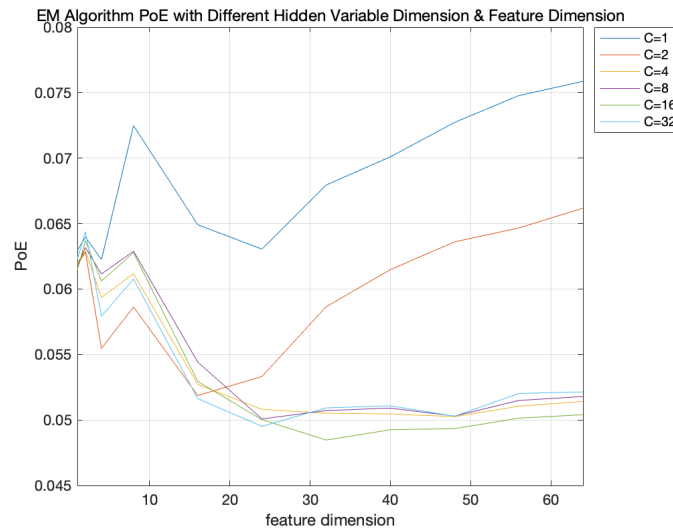


Figure 2: EM Algorithm Test with Different Feature Dimension for Different Hidden Dimension

When  $C = 1$  or  $C = 2$  the plot is really different from the others. That's reasonable because when  $C$  is small, it may lead to bias of estimation. Notice that when  $C = 32$  it's worse than the result of  $C = 16$ . That's also reasonable because maybe there are overfitting by too many hidden dimension. For the others, the error decreases as  $C$  increases. Note that the initialization will also disturb the result.  $\square$

Codes are attached as follow.

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```

1 % EM.M
2 load('/Users/quan/Documents/MATLAB/SL/5/TrainingSamplesDCT_8_new.mat')
3
4 [rg, cg] = size(TrainsampleDCT_BG);
5 [rc, cc] = size(TrainsampleDCT_FG);
6
7 % READING IMAGE
8 img = imread('cheetah.bmp');
9 img = im2double(img);
10 [rows,cols] = size(img);
11 img_mask = imread('cheetah_mask.bmp');
12 img_mask = img_mask / 255;
13
14 % USING MATRIX REPRESENTATION
15 zigzags = zeros(rows,cols,64);
16 for row = 1:rows-7
17     for col = 1:cols-7
18         DCT = (dct2(img(row:row+7,col:col+7)));
19         zigzag_matrix = zigzag(DCT);
20         zigzag_matrix = zigzag_matrix';
21         zigzags(row,col,:) = zigzag_matrix;
22     end
23 end
24
25 BG_m = containers.Map();
26 BG_s = containers.Map();
27 BG_p = containers.Map();
28 FG_m = containers.Map();
29 FG_s = containers.Map();
30 FG_p = containers.Map();
31 C = 8;
32
33 % EM TRAINING PHASE
34 tic;
35 for i = 1:5
36     [mu_grass, sigma_grass, pi_grass] = EM_learn(TrainsampleDCT_BG, C);
37     [mu_cheetah, sigma_cheetah, pi_cheetah] = EM_learn(TrainsampleDCT_FG, C);
38     BG_m(num2str(i)) = mu_grass;
39     BG_s(num2str(i)) = sigma_grass;
40     BG_p(num2str(i)) = pi_grass;
41     FG_m(num2str(i)) = mu_cheetah;
42     FG_s(num2str(i)) = sigma_cheetah;
43     FG_p(num2str(i)) = pi_cheetah;
44 end

```

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45 toc
46
47 % COMPUTE ERROR
48 dim = [1, 2, 4, 8, 16, 24, 32, 40, 48, 56, 64];
49 errors = zeros(5, 5, 11);
50 for i = 1:5
51     for j = 1:5
52         res = zeros(rows, cols);
53         for di = 1:size(dim, 2)
54             d = dim(di);
55             mu_BG = BG_m(num2str(i));
56             mu_BG = mu_BG(:, 1:d);
57             mu_FG = FG_m(num2str(j));
58             mu_FG = mu_FG(:, 1:d);
59             sigma_BG = BG_s(num2str(i));
60             sigma_BG = sigma_BG(1:d, 1:d, :);
61             sigma_FG = FG_s(num2str(j));
62             sigma_FG = sigma_FG(1:d, 1:d, :);
63             pi_BG = BG_p(num2str(i));
64             pi_FG = FG_p(num2str(j));
65
66             % PRIOR
67             prior_BG = rg / (rc + rg);
68             prior_FG = rc / (rc + rg);
69
70             inv_BG = zeros(d, d, C);
71             inv_FG = zeros(d, d, C);
72             alpha_BG = zeros(1, C);
73             alpha_FG = zeros(1, C);
74
75             % CALCULATE INVERSE AHEAD
76             for c = 1:C
77                 inv_BG(:, :, c) = pinv(sigma_BG(:, :, c));
78                 inv_FG(:, :, c) = pinv(sigma_FG(:, :, c));
79                 alpha_BG(1, c) = sum(log(diag(sigma_BG(:, :, c))));
80                 alpha_FG(1, c) = sum(log(diag(sigma_FG(:, :, c))));
81             end
82
83             % CALCULATE ERROR
84             for row = 1:rows-7
85                 for col = 1:cols-7
86                     zigzag_matrix = zigzags(row, col, :);
87                     zigzag_matrix = zigzag_matrix(:);
88                     zigzag_matrix = zigzag_matrix(1:d);
89                     pBG = 0;
90                     pFG = 0;
91                     for c = 1:C
92                         cur_mu_FG = mu_FG(c, :)' ;
93                         cur_mu_BG = mu_BG(c, :)' ;
94                         X_FG = zigzag_matrix - cur_mu_FG;
95                         X_BG = zigzag_matrix - cur_mu_BG;
96                         pBG = pBG + exp(log(pi_BG(c)) - 0.5 * X_BG' * inv_BG(:, :, c) *
97                             X_BG - 0.5 * alpha_BG(c));
98                         pFG = pFG + exp(log(pi_FG(c)) - 0.5 * X_FG' * inv_FG(:, :, c) *

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                                X_FG - 0.5 * alpha_FG(c));
98         end
99         pFG = log(pFG) + log(prior_FG);
100        pBG = log(pBG) + log(prior_BG);
101        if pFG >= pBG
102            res(row, col) = 1;
103        end
104    end
105    end
106    err = sum(sum(res ~= img_mask)) / (rows*cols)
107    errors(i, j, di) = err;
108    end
109    end
110    end

```

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```

1  % EM_LEARN.M
2  function [mu, sigma, pi] = EM_learn(dataset, C)
3      [N, d] = size(dataset);
4
5      % RANDOMIZED INITIALIZATION
6      mu0 = zeros(C, d);
7      sigma0 = zeros(d, d, C);
8      index = randi(N, 1, C);
9      for i = 1:C
10         sigma0(:, :, i) = diag(ones(1, d) .* rand(1, d) + 1e-5);
11         mu0(i, :) = dataset(index(i), :);
12     end
13
14     % EM PROCEDURE
15     pi0 = ones(1, C) / C;
16     mu = mu0;
17     sigma = sigma0;
18     pi = pi0;
19     pm = mu0(:, 1);
20     for i = 1:5000
21         % E-STEP SOLVE H MATRIX
22         H = zeros(N, C);
23         for c = 1:C
24             mu_c = mu0(c, :);
25             sigma_c = sigma0(:, :, c);
26             H(:, c) = mvnpdf(dataset, mu_c, sigma_c);
27             H(:, c) = H(:, c) * pi0(c);
28         end
29         H = H ./ sum(H, 2);
30
31         % M-STEP GETTING NEW PARAMETERS
32         pi = sum(H) / N;
33         for c = 1:C
34             mu(c, :) = sum(H(:, c) .* dataset) / (sum(H(:, c))));
35             x_c = dataset - mu0(c, :);
36             s = sum((x_c .* x_c) .* H(:, c) / (sum(H(:, c))))) + 1e-5;
37             sigma(:, :, c) = diag(s);

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38         end
39
40         % EARLY STOPPING
41         if sum(abs(mu(:, 1) - pm ./ pm)) < 1e-2
42             break;
43         end
44
45         mu0 = mu;
46         sigma0 = sigma;
47         pi0 = pi;
48     end
49 end

```

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```

1 % EM2.M
2 load('/Users/quan/Documents/MATLAB/SL/5/TrainingSamplesDCT_8_new.mat')
3
4 [rg, cg] = size(TrainsampleDCT_BG);
5 [rc, cc] = size(TrainsampleDCT_FG);
6
7 % READING IMAGE
8 img = imread('cheetah.bmp');
9 img = im2double(img);
10 [rows,cols] = size(img);
11 img_mask = imread('cheetah_mask.bmp');
12 img_mask = img_mask / 255;
13
14 % USING MATRIX REPRESENTATION
15 zigzags = zeros(rows,cols,64);
16 for row = 1:rows-7
17     for col = 1:cols-7
18         DCT = (dct2(img(row:row+7,col:col+7)));
19         zigzag_matrix = zigzag(DCT);
20         zigzag_matrix = zigzag_matrix';
21         zigzags(row,col,:) = zigzag_matrix;
22     end
23 end
24
25 BG_m = containers.Map();
26 BG_s = containers.Map();
27 BG_p = containers.Map();
28 FG_m = containers.Map();
29 FG_s = containers.Map();
30 FG_p = containers.Map();
31 Cs = [1, 2, 4, 8, 16, 32];
32
33 % EM TRAINING PHASE
34 tic;
35 for C = Cs
36     [mu_grass, sigma_grass, pi_grass] = EM_learn(TrainsampleDCT_BG, C);
37     [mu_cheetah, sigma_cheetah, pi_cheetah] = EM_learn(TrainsampleDCT_FG, C);
38     BG_m(num2str(C)) = mu_grass;
39     BG_s(num2str(C)) = sigma_grass;

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40     BG_p(num2str(C)) = pi_grass;
41     FG_m(num2str(C)) = mu_cheetah;
42     FG_s(num2str(C)) = sigma_cheetah;
43     FG_p(num2str(C)) = pi_cheetah;
44 end
45 toc
46
47 % COMPUTE ERROR
48 dim = [1, 2, 4, 8, 16, 24, 32, 40, 48, 56, 64];
49 errors = zeros(6, 11);
50 for C = Cs
51     for di = 1:size(dim, 2)
52         res = zeros(rows, cols);
53         d = dim(di);
54         mu_BG = BG_m(num2str(C));
55         mu_BG = mu_BG(:, 1:d);
56         mu_FG = FG_m(num2str(C));
57         mu_FG = mu_FG(:, 1:d);
58         sigma_BG = BG_s(num2str(C));
59         sigma_BG = sigma_BG(1:d, 1:d, :);
60         sigma_FG = FG_s(num2str(C));
61         sigma_FG = sigma_FG(1:d, 1:d, :);
62         pi_BG = BG_p(num2str(C));
63         pi_FG = FG_p(num2str(C));
64
65         % PRIOR
66         prior_BG = rg / (rc + rg);
67         prior_FG = rc / (rc + rg);
68
69         inv_BG = zeros(d, d, C);
70         inv_FG = zeros(d, d, C);
71         alpha_BG = zeros(1, C);
72         alpha_FG = zeros(1, C);
73
74         % CALCULATE INVERSE AHEAD
75         for c = 1:C
76             inv_BG(:, :, c) = inv(sigma_BG(:, :, c));
77             inv_FG(:, :, c) = inv(sigma_FG(:, :, c));
78             alpha_BG(1, c) = sum(log(diag(sigma_BG(:, :, c))));
79             alpha_FG(1, c) = sum(log(diag(sigma_FG(:, :, c))));
80         end
81
82         % CALCULATE ERROR
83         for row = 1:rows-7
84             for col = 1:cols-7
85                 zigzag_matrix = zigzags(row, col, :);
86                 zigzag_matrix = zigzag_matrix(:);
87                 zigzag_matrix = zigzag_matrix(1:d);
88                 pBG = 0;
89                 pFG = 0;
90                 for c = 1:C
91                     cur_mu_FG = mu_FG(c, :)';
92                     cur_mu_BG = mu_BG(c, :)';
93                     X_FG = zigzag_matrix - cur_mu_FG;

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94         X_BG = zigzag_matrix - cur_mu_BG;
95         pBG = pBG + exp(log(pi_BG(c)) - 0.5 * X_BG' * inv_BG(:, :, c) *
96             X_BG - 0.5 * alpha_BG(c));
97         pFG = pFG + exp(log(pi_FG(c)) - 0.5 * X_FG' * inv_FG(:, :, c) *
98             X_FG - 0.5 * alpha_FG(c));
99     end
100     pFG = log(pFG) + log(prior_FG);
101     pBG = log(pBG) + log(prior_BG);
102     if pFG >= pBG
103         res(row, col) = 1;
104     end
105 end
106 err = sum(sum(res ~= img_mask)) / (rows*cols)
107 errors(C, di) = err;
108 end

```

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