```
function [label, model, llh] = emgm(X, init)
   % Perform EM algorithm for fitting the Gaussian mixture model.
3
   %
       X: d x n data matrix
       init: k (1 \times 1) or label (1 \times n, 1 \le label(i) \le k) or center (d \times k)
 5 \parallel% Written by Michael Chen (sth4nth@gmail.com).
   %% initialization
   fprintf('EM for Gaussian mixture: running ... \n');
8 | R = initialization(X,init);
                                   Initializing the probabilities - Zim
   [\sim, label(1,:)] = max(R,[],2);
10 | R = R(:,unique(label));
11
12 \parallel \text{tol} = 1\text{e}-10;
13
   maxiter = 500;
14
   llh = -inf(1, maxiter);
15 converged = false;
16 || t = 1;
                                      Continue until the model parameters have converged or max iteration have reached
17
   while ~converged && t < maxiter</pre>
18
       t = t+1;
19
       model = maximization(X,R);
                                             Performing M-Step and E-Step
20
        [R, llh(t)] = expectation(X, model);
21
22
        [\sim, label(:)] = max(R, [], 2);
23
       u = unique(label);
                             % non-empty components
24
        if size(R,2) \sim size(u,2)
25
            R = R(:,u); % remove empty components
26
       else
            27
28
       end
29
       figure(gcf); clf;
30
       spread(X,label);
31
       muA = model.mu;
32
       SigmaA = model.Sigma;
       wA = model.weight;
33
34
       k = size(muA, 2);
35
       % figure(12); clf;
       % for i=1:k
36
37
           mu1 =muA(i,:)
38
           Sigma1=SigmaA(i,:)
39
       %
           w1=wA(i)
40
           xx= mvnrnd(mu1, Sigma1, 1000);
41
           yy= mvnpdf(xx,mu1,Sigma1);
          plot3(xx(:,1), xx(:,2), yy, '.b'); hold on;
42
43
       % end
44
45
       pause;
46
47
48
49
   end
50
   llh = llh(2:t);
51
   if converged
52
        fprintf('Converged in %d steps.\n',t-1);
53
   else
54
        fprintf('Not converged in %d steps.\n',maxiter);
55
   end
   57
   function R = initialization(X, init)
58
   [d,n] = size(X);
59
   if isstruct(init) % initialize with a model
60
       R = expectation(X,init);
61
   elseif length(init) == 1 % random initialization
62
       k = init;
       idx = randsample(n,k); generating random values for the probabilities
63
64
       m = X(:,idx);
65
        [\sim, label] = max(bsxfun(@minus, m'*X, dot(m, m, 1)'/2), [], 1);
66
        [u, \sim, label] = unique(label);
```

```
67
          while k ~= length(u)
 68
               idx = randsample(n,k);
 69
               m = X(:,idx);
 70
               [\sim, label] = max(bsxfun(@minus, m'*X, dot(m, m, 1)'/2), [], 1);
 71
               [u, \sim, label] = unique(label);
 72
 73
          R = full(sparse(1:n,label,1,n,k,n));
 74
     elseif size(init,1) == 1 && size(init.2) == n % initialize with labels
 75
                                    Initializing with the labels
          label = init;
 76
          k = max(label);
 77
          R = full(sparse(1:n,label,1,n,k,n));
 78
     elseif size(init,1) == d %initialize with only centers
 79
          k = size(init, 2);
 80
          m = init;
 81
          [\sim, label] = max(bsxfun(@minus, m'*X, dot(m, m, 1)'/2), [], 1);
 82
          R = full(sparse(1:n,label,1,n,k,n));
 83
     else
 84
          error('ERROR: init is not valid.');
 85
     end
 86
                                                              The E-Step
 87
     function [R, llh] = expectation(X, model)
 88
     mu = model.mu;
                                    Gathering the mean, variance and weights from the model
     Sigma = model.Sigma;
 89
 90
     w = model.weight;
 91
 92
    n = size(X,2);
                                   setting n - size of the data & k - number of models
 93
     k = size(mu, 2);
                                   initializing matrix to store log of the Gaussian formulae
 94
     logRho = zeros(n,k);
 95
 96
     for i = 1:k
                                                                         calculating the log guassian values for each models
 97
          logRho(:,i) = loggausspdf(X,mu(:,i),Sigma(:,:,i));
 98
     logRho = bsxfun(@plus,logRho,log(w)); Adding the weight for the models to the gaussian values
 99
100 | T = logsumexp(logRho, 2);
101 | llh = sum(T)/n; % loglikelihood
                                               calculating loglikelihood and completing the e-step by updating the probability of a point bring
     logR = bsxfun(@minus,logRho,T);
102
                                               in a model
103
     R = exp(logR);
104
105
106 | function model = maximization(X, R)
107
     [d,n] = Size(X); gathering the dimension size, no of data and no. of models
108 | k = size(R,2);
109
110 \| nk = Sum(R,1); recalculating the weights - mixture coefficient - for the model
111 | w = nk/n:
                                              recalculating mean - by multiplying prob and the data with dividing total probability. i.e. zim *
     mu = bsxfun(@times, X*R, 1./nk); xi/ zim
112
113
114
     Sigma = zeros(d,d,k); Initializing sigma for all models
115
     sqrtR = sqrt(R);
116
     for i = 1:k
117
          Xo = bsxfun(@minus,X,mu(:,i));
                                                       calculating (µm - xi) (µm - xi)T
          Xo = bsxfun(@times, Xo, sqrtR(:,i)'); dividing by the sum of probability to get final sigma-covariance
118
119
          Sigma(:,:,i) = Xo*Xo'/nk(i);
          Sigma(:,:,i) = Sigma(:,:,i) + eye(d)*(1e-6); % add a prior for numerical stability
120
121 end
122
123 model.mu = mu;
124
     model.Sigma = Sigma;
     model.weight = w;
125
126
127 | function y = loggausspdf(X, mu, Sigma)
128 | d = size(X,1);
129 \mid X = bsxfun(@minus, X, mu);
                                        (µm - xi)
130 [U,p]= chol(Sigma);
131 | if p ~= 0
132
          error('ERROR: Sigma is not PD.');
```

```
133 | end

134 | Q = U'\X;

135 | q = dot(Q,Q,1); % quadratic term (M distance)

136 | c = d*log(2*pi)+2*sum(log(diag(U))); % normalization constant

137 | y = -(c+q)/2;
```