November 26, 2018

Empirical Methods HA 5

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2018

Problem 1 Log-likelihood is equal to -1257.1

Problem 2 Log-likelihood is equal to -1259.8

Problem 3 See the code.

Problem 4 See the code.

Problem 5 Starting values for estimation in Problem 3: (2; 1; 0);

For GQ-20 $(\hat{\beta}_0, \hat{\sigma}_\beta, \hat{\gamma}) = (2.4823; 1.4055; -0.5056);$

GQ-20 maximal value of Log-likelihood is equal to 536.2378;

For MC-100 $(\hat{\beta}_0, \hat{\sigma}_\beta, \hat{\gamma}) = (2.5140; 1.2972; -0.5029);$

MC-100 maximal value of Log-likelihood is equal to 538.3832;

Starting values for estimation in Problem 4: (3; 1, 5; 2; 1; 2; -0.5);

For MC-100 $(\hat{\beta}_0, \hat{u}_0, \hat{\sigma}_{\beta}, \hat{\sigma}_{\beta u}, \hat{\sigma}_u \hat{\gamma}) = (3.2223; 1.4286; 1.9100; 0.6473; 1.8390; -0.6929);$

MC-100 maximal value of Log-likelihood is equal to 462.0722;

```
clear;
  load ('hw5.mat')
  rng(2);
  beta0 = 0.1;
  sig_beta=1;
6
  F=@(eps) (1+exp(-eps)).^(-1);
  % Likelihoods in vector form
  LH_i=0(b,g,u)...
       prod ((F(data.X*diag(b)+data.Z*diag(g)+ones(20,100)*diag(u)).^
10
          data.Y) .*...
       (1-F(data.X*diag(b)+data.Z*diag(g)+ones(20,100)*diag(u))).^(1-
11
          data.Y));
  % Problem 1
13
  global x20 w20
   [x20, w20] = GaussHermite_2(20);
15
16
  int1 = zeros(1, data.N);
17
  for k=1:20
18
       int1=int1+w20(k)*LH_i(beta0+sqrt(2*sig_beta)*x20(k),0,0)/sqrt(pi
19
          );
  end
  % Log-likelihood
  LLH1=sum(log(int1));
23
  % Problem 2
24
25
  U=normrnd(beta0, sqrt(sig_beta), 100, 100);
27
  int2 = zeros(1, data.N);
28
  for k=1:100
29
       int2 = int2 + (1/100) * LH_i(U(k,:), 0, 0);
30
  end
31
```

```
% Log-likelihood
  LLH2=sum(log(int2));
33
34
  % Problem 3
36
   st_val1 = [2;1;0];
37
  \% GQ
38
   fun1=@(x) -LLH_1(data.N, x(1), x(2), x(3), LH_i, 1);
   [\text{estimate1}, \text{function1}] = \text{fmincon}(\text{fun1}, \text{st\_val1}, \text{diag}([0, -1, 0]), \text{zeros}(3, 1))
      );
  \% MC
42
   fun2=@(x) -LLH_1(data.N, x(1), x(2), x(3), LH_i, 2);
   [\text{estimate2}, \text{function2}] = \text{fmincon}(\text{fun2}, \text{st\_val1}, \text{diag}([0, -1, 0]), \text{zeros}(3, 1))
44
      );
45
  % Problem 4
46
   fun3=@(x) -LLH_2(data.N, x(1), x(2), x(3), x(4), x(5), x(6), LH_i);
47
49
   st_val2 = [3; 1.5; 2; 1; 2; -0.5];
50
  A=diag([0,0,-1,0,-1,0]);
  b = zeros(6,1);
52
   [estimate3, function3] = fmincon(fun3, st_val2, A, b, [], [], [], [], @PSD);
54
  % Problem 5
56
   display (LLH1, 'log-likelihood GQ 20')
57
   display (LLH2, 'log-likelihood MC 100')
   display (st_val1, 'starting value for estimation in 3')
59
   display (estimate1, 'GQ 20 estimates of beta0, sigma_beta, gamma')
60
   display (function1, 'GQ 20 max val of LLH')
61
   display (estimate2, 'MC 100 estimates of beta0, sigma_beta, gamma')
   display (function 2, 'MC 100 max val of LLH')
63
   display (st_val2, 'starting value for estimation in 4')
```

```
display (estimate 3, 'MC 100 estimates of beta 0, u0, s_b, s_bu, su, gamma')
```

6 display (function 3, 'MC 100 max val of LLH')

```
function [x, w] = GaussHermite_2(n)
  % This function determines the abscisas (x) and weights (w) for the
4 % Gauss-Hermite quadrature of order n>1, on the interval [-INF, +INF
     ].
      % This function is valid for any degree n>=2, as the companion
5
         matrix
      % (of the n'th degree Hermite polynomial) is constructed as a
      \% symmetrical matrix, guaranteeing that all the eigenvalues (
         roots)
      % will be real.
9
10
     Geert Van Damme
  % geert@vandamme-iliano.be
  \% February 21, 2010
14
15
16
  \% Building the companion matrix CM
17
      % CM is such that det(xI-CM)=L_n(x), with L_n the Hermite
18
         polynomial
      \% under consideration. Moreover, CM will be constructed in such
19
         a way
      % that it is symmetrical.
      = 1:n-1;
21
      = \mathbf{sqrt}(i/2);
22
  CM = diag(a,1) + diag(a,-1);
23
  % Determining the abscissas (x) and weights (w)
25
      \% - since det(xI-CM)=L_n(x), the abscissas are the roots of the
26
           characteristic polynomial, i.d. the eigenvalues of CM;
      \% - the weights can be derived from the corresponding
         eigenvectors.
```

```
\begin{array}{lll} _{29} & [V\ L] & = \ eig\,(C\!M)\,; \\ _{30} & [x\ ind] = \ sort\,(\ diag\,(L)\,)\,; \\ _{31} & V & = \ V(:\,,ind)\,\,\dot{}\,\,; \\ _{32} & w & = \ sqrt\,(\,pi\,)\,\,*\,\,V(:\,,1\,)\,\,.\,\,\dot{}\,\,2\,; \end{array}
```

```
function llh = LLH_1(N, b0, s_b, g, LH_i, method)
2
  % Method corresponds to MC and GQ
  rng(2);
  global x20 w20
  x=x20;
  w=w20;
   if method==2 % MC method
       U=normrnd(b0, sqrt(s_b),100,100);
10
       int=zeros(1,N);
11
       for k=1:100
12
           int=int+(1/100)*LH_{-i}(U(k,:),g,0);
13
       end
14
       llh = sum(log(int));
15
  else % GQ method
16
       int=zeros(1,N);
17
       for k=1:20
18
           int=int+w(k)*LH_{-i}(b0+sqrt(2*s_{-}b)*x(k),g,0)/sqrt(pi);
19
20
       llh=sum(log(int));
21
  end
22
```

```
function 11h = LLH_2(N, b0, u0, s_b, s_bu, s_u, g, LH_i)
2
  % Here we use Monte Carlo method with 100 nodes
4
  rng(2);
  Mu=[b0; u0];
  for t=1:100
       if s_b>=0 & s_u>=0 & s_b*s_u-s_bu^2>=0
            Sigma = [s_b, s_bu; s_bu, s_u];
10
            break
11
       else
12
            s_bu = sqrt(0.5 * abs(s_b * s_u));
13
            s_b=s_b*(s_b>=0)+1*(s_b<0);
14
            s_u=s_u*(s_u>=0)+1*(s_u<0);
            Sigma = [1, s_bu; s_bu, 1];
16
       end
17
  end
18
19
20
  X=(mvnrnd(Mu, Sigma, 100*100));
  int3 = zeros(1,N);
   for k=1:100
23
       int3 = int3 + (1/100) * ...
24
            LH_{-i}(X(1,(k-1)*100+1:k*100),g,X(2,(k-1)*100+1:k*100));
  end
26
  11h = sum(log(int3));
```

```
function [c, ceq] = PSD(x)

% Check on PSD of 2-by-2 x matrix

ceq = [];

V=[x(3), x(4); x(4), x(5)]

ce—det([x(3), x(4); x(4), x(5)]);

end
```