

# STA 601 - Homework 7

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1. Data:

We generate,  $y_i \sim \mathcal{N}_2 \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0.8 \\ 0.8 & 1 \end{bmatrix} \right)$ ,  $i = 1, 2, \dots, 100$ .

We can calculate  $\mu_{MLE}$  and  $\Sigma_{MLE}$ , from this generated data.

Then we run Gibbs Sampler and estimate  $\mu_{Bayes}$  and  $\Sigma_{Bayes}$ .

2. Predictive Density:

For prediction, we will generate 50 new samples  $(y_1, y_2)$ , and predict  $y_1|y_2$ , using the given density,  $(y_{j1}|y_{j2} = a) \sim \mathcal{N} \left( \mu_1 + \frac{\sigma_1}{\sigma_2} \rho(a - \mu_2), (1 - \rho^2) \sigma_1^2 \right)$ .

Prediction Estimate,  $E_{True}(y_1|y_2) = 0.0608$ .

95% Credible Intervals: [-1.8264 2.0562].

3. Mean Square Errors:

We will then use MLE and Bayes estimates, and predict  $(y_{j1}|y_{j2} = a)$ . Then we will compute  $E(y_1|y_2)$ , for each of the two predictors and compare their performance with the Truth predictor using Mean Squared Error.

$$[E_{True}(y_1|y_2) - E_{MLE}(y_1|y_2)]^2 = 0.0807.$$

$$[E_{True}(y_1|y_2) - E_{Bayes}(y_1|y_2)]^2 = 0.0039.$$

4. Comparison:

$$\overline{E_{MLE}(y_1|y_2)} = 0.3448.$$

$$E_{Joint}(y_1|y_2) = 0.0667. \text{ Here, } (y_1, y_2) \sim \mathcal{N}_2(\mu_{MLE}, \Sigma_{MLE}).$$

Hence, the results are indeed quite different.

5. Confidence Intervals: Following are the Predictive Intervals for the Bayes and MLE Predictors.

Interval for  $E_{MLE}(y_1|y_2)$  : [-1.7668 2.9977].

Interval for  $E_{Bayes}(y_1|y_2)$  : [-2.1768 2.5306].

## Appendix:

```
1 %% STA 601 — Homework 7
2 % Author: Kedar Prabhudesai
3 % Created on: 9/24/2013
4
5 close all;
6 clear all;
7
8 %% Setup Data and Distributions
9 % Create Bivariate Distribution
10 nSamples = 100;
11 rho = 0.8;
12 mu = [0 0];
13 SIGMA = [1 rho; rho 1];
14 y1 = -3:0.1:3; y2 = -3:0.1:3;
15 [Y1,Y2] = meshgrid(y1,y2);
16 yPDF = mvnpdf([Y1(:) Y2(:)],mu,SIGMA);
17 yPDF = reshape(yPDF,length(Y2),length(Y1));
18
19 % Get Data
20 rng('shuffle');
21 rSamples = mvnrnd(mu,SIGMA,nSamples);
22
23 % Find MLE
24 muMLE = mean(rSamples);
25 sigmaMLE = cov(rSamples);
26
27 %% Gibbs Sampler
28 nGibbs = 10000;
29 ySamples = rSamples';
30 ybar = mean(rSamples)';
31 mu0 = [0.2 0.2]';
32 L0 = [1.25 0.6; 0.6 1.25];
33
34 nu0 = 4;
35 S0 = [1.2 0.4; 0.4 1.3];
36
37 thetaSamples = zeros(2,nGibbs);
38 sigmaSamples = zeros(2,2,nGibbs);
39 sigmaSamples(:,:,1) = S0;
40
41 for iSample = 2:nGibbs
42     % Update theta
43     Ln = inv(inv(L0) + nSamples.*inv(sigmaSamples(:,:,iSample-1)));
44     mun = Ln*(inv(L0)*mu0 + nSamples.*inv(sigmaSamples(:,:,iSample-1))*ybar);
45     thetaSamples(:,iSample) = mvnrnd(mun,Ln);
46
47     % Update Sigma
48     Sn = S0 + (bsxfun(@minus,ySamples,thetaSamples(:,iSample)))*(bsxfun(@minus,ySamples,...
49         thetaSamples(:,iSample)))';
50     Z = mvnrnd([0 0],inv(Sn),nu0+nSamples);
51     sigmaSamples(:,:,iSample) = inv(Z'*Z);
52 end
53
54 % Burn-In
55 thetaSamples(:,1:1000) = [];
56 sigmaSamples(:,:,1:1000) = [];
57
58 % Estimate mu and Sigma
59 muBayes = mean(thetaSamples,2)';
60 sigmaBayes = mean(sigmaSamples,3);
```

```

60
61 %% Prediction
62 nPred = 50;
63 rng('shuffle');
64
65 muPred = mu;
66 sigmaPred = SIGMA;
67
68 yTruth = mvnrnd(mu, SIGMA, nPred);
69
70 y1PredTruth = zeros(nPred, 1);
71 y1PredMLE = zeros(nPred, 1);
72 y1PredBayes = zeros(nPred, 1);
73
74 % Estimate (y1|y2) using truth
75 for iPred = 1:nPred
76     y1PredTruth(iPred, 1) = normrnd(muPred(1) + (sigmaPred(1,1)*sigmaPred(1,2)*(yTruth(iPred...
77         , 2)-muPred(2)))/sigmaPred(2,2), sqrt((1-sigmaPred(1,2)^2)*sigmaPred(1,1)^2));
78 end
79 E1Giveny2Truth = mean(y1PredTruth)
80
81 % Estimate (y1|y2) using MLE
82 for iPred = 1:nPred
83     y1PredMLE(iPred, 1) = normrnd(muMLE(1) + (sigmaMLE(1,1)*sigmaMLE(1,2)*(yTruth(iPred,2)-...
84         muMLE(2)))/sigmaMLE(2,2), sqrt((1-sigmaMLE(1,2)^2)*sigmaMLE(1,1)^2));
85 end
86 E1Giveny2MLE = mean(y1PredMLE)
87
88 % Estimate (y1|y2) using Bayes Estimates
89 for iPred = 1:nPred
90     y1PredBayes(iPred, 1) = normrnd(muBayes(1) + (sigmaBayes(1,1)*sigmaBayes(1,2)*(yTruth(...
91         iPred, 2)-muBayes(2)))/sigmaBayes(2,2), sqrt((1-sigmaBayes(1,2)^2)*sigmaBayes(1,1)^2)...
92         );
93 end
94 E1Giveny2Bayes = mean(y1PredBayes);
95
96 MSPredErrMLE = (E1Giveny2Truth - E1Giveny2MLE).^2
97 MSPredErrBayes = (E1Giveny2Truth - E1Giveny2Bayes).^2
98
99 %% MLE Comparison
100 rng('shuffle');
101 yTruthMLEJoint = mvnrnd(muMLE, sigmaMLE, nPred);
102 EyTruthMLEJoint = mean(yTruthMLEJoint(:, 1))
103
104 %% Confidence intervals for different predictors
105 ConfIntervalsTruth = quantile(y1PredTruth, [0.025 0.975])
106 ConfIntervalsMLE = quantile(y1PredMLE, [0.025 0.975])
107 ConfIntervalsBayes = quantile(y1PredBayes, [0.025 0.975])

```