

# STA 601 - Lab 9

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We have an additional parameter to do inference on. Let,  $W_i = 1$ , denote weekday and  $W_i = 0$  denote weekend.

$$W_i \sim \text{Bernoulli}(\theta)$$

If  $W_i = 1$ ,  $X_i \sim \log\mathcal{N}(\mu_1, \tau_1)$ , else  $X_i \sim \log\mathcal{N}(\mu_2, \tau_2)$ .

## Data Likelihood:

Let  $\tau = 1/\sigma^2$ , and  $k$  is the number of weekdays.

$$L(X^n, W^n \mid \mu_1, \tau_1, \mu_2, \tau_2, \theta) = \prod_{i=1}^n [\mathbb{1}(W_i = 1)\log\mathcal{N}(\mu_1, \tau_1) + \mathbb{1}(W_i = 0)\log\mathcal{N}(\mu_2, \tau_2)] \times \prod_{i=1}^n \binom{n}{k} \theta^k (1 - \theta)^{n-k}$$

## Priors:

We use the same priors we defined on  $\mu$  and  $\tau$  from last time.

$$\begin{aligned}\mu_j &\sim \mathcal{N}(\mu_{j0}, \tau_{j0}) \therefore p(\mu_j) \propto \exp\left[\frac{-\tau_{j0}(\mu_j - \mu_{j0})^2}{2}\right] \\ \tau_j &\sim \text{Gamma}(\alpha_j, \beta_j) \therefore p(\tau_j) \propto \tau_j^{\alpha_j-1} \exp(-\beta_j \tau_j) \\ \theta &\sim \text{Beta}(5, 2) \therefore p(\theta) \propto \theta^{5-1} (1 - \theta)^{2-1}\end{aligned}$$

## Posterior:

$$p(\mu_1, \tau_1, \mu_2, \tau_2, \theta \mid X^n, W^n) \propto L(X^n, W^n \mid \mu_1, \tau_1, \mu_2, \tau_2, \theta) \times p(\mu_1) \times p(\tau_1) \times p(\mu_2) \times p(\tau_2) \times p(\theta)$$

### Full Conditionals:

$$\begin{aligned} p(\theta \mid \dots) &\propto \theta^{5+k-1}(1-\theta)^{2+n-k-1} \\ \therefore p(\theta \mid \dots) &\propto \text{Beta}(5+k, 2+n-k) \end{aligned}$$

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$$\begin{aligned} p(\mu_1 \mid \dots) &\propto \prod_{i=1}^n \left\{ \mathbb{1}(W_i = 1) \exp \left[ \frac{-\tau_1 (\ln x_i - \mu_1)^2}{2} \right] \right\} \times \exp \left[ \frac{-\tau_{10} (\mu_1 - \mu_{10})^2}{2} \right] \\ &\propto \left\{ \mathbb{1}(W_i = 1) \exp \left[ \frac{-\tau_1}{2} \sum_{i=1}^n (\ln x_i - \mu_1)^2 \right] \right\} \times \exp \left[ \frac{-\tau_{10} (\mu_1 - \mu_{10})^2}{2} \right] \\ \therefore p(\mu_1 \mid \dots) &\propto \exp \left[ \frac{-\tau_1}{2} \sum_{i:W_i=1} (\ln x_i - \mu_1)^2 - \frac{\tau_{10} (\mu_1 - \mu_{10})^2}{2} \right] \end{aligned}$$

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$$p(\mu_2 \mid \dots) \propto \exp \left[ \frac{-\tau_2}{2} \sum_{i:W_i=0} (\ln x_i - \mu_2)^2 - \frac{\tau_{20} (\mu_2 - \mu_{20})^2}{2} \right]$$

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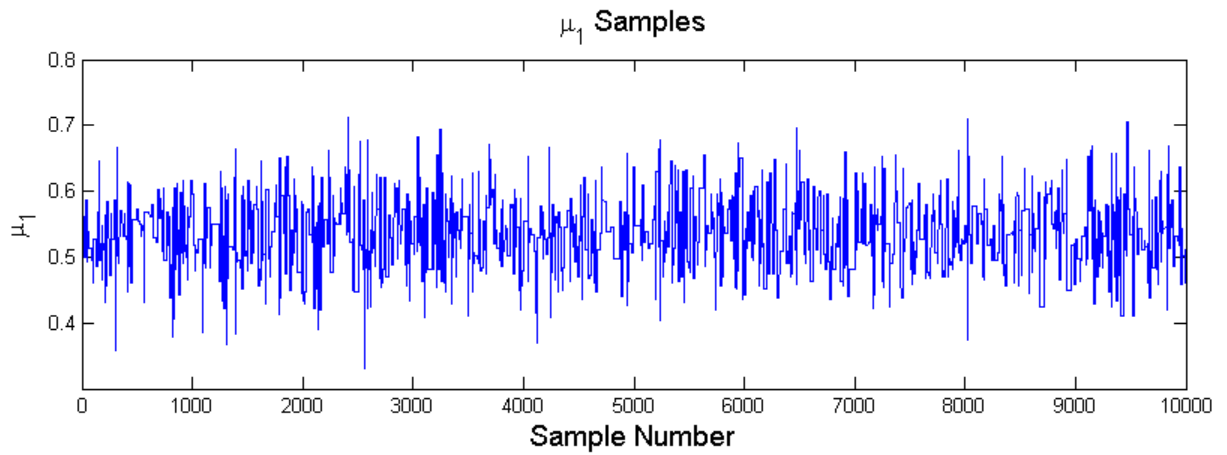
$$\begin{aligned} p(\tau_1 \mid \dots) &\propto \prod_{i=1}^n \left\{ \mathbb{1}(W_i = 1) \tau_1^{1/2} \exp \left[ \frac{-\tau_1 (\ln x_i - \mu_1)^2}{2} \right] \right\} \times \tau_1^{\alpha_1-1} \exp(-\beta_1 \tau_1) \\ &\propto \mathbb{1}(W_i = 1) \tau_1^{k/2} \exp \left[ \frac{-\tau_1}{2} \sum_{i=1}^n (\ln x_i - \mu_1)^2 \right] \times \tau_1^{\alpha_1-1} \exp(-\beta_1 \tau_1) \\ &\propto \tau_1^{\alpha_1+k/2-1} \exp \left\{ -\tau_1 \left[ \frac{\sum_{i:W_i=1} (\ln x_i - \mu_1)^2}{2} + \beta_1 \right] \right\} \\ \therefore p(\tau_1 \mid \dots) &\propto \text{Gamma} \left( \alpha_1 + \frac{k}{2}, \frac{\sum_{i:W_i=1} (\ln x_i - \mu_1)^2}{2} + \beta_1 \right) \end{aligned}$$

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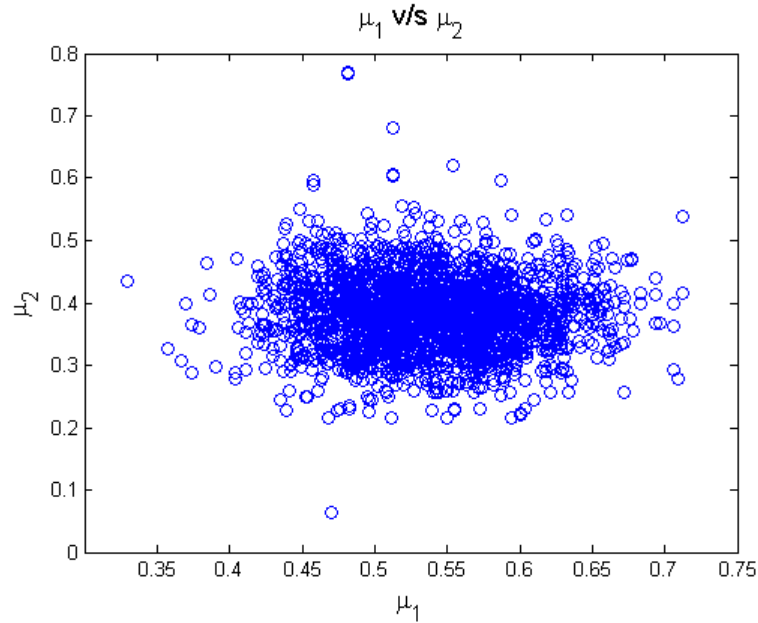
$$p(\tau_2 \mid \dots) \propto \text{Gamma} \left( \alpha_2 + \frac{n-k}{2}, \frac{\sum_{i:W_i=0} (\ln x_i - \mu_2)^2}{2} + \beta_2 \right)$$

### Results from Gibbs Sampler:

Following plot shows posterior  $\mu_1$  samples. We can see that our Gibbs Sampler has converged.



Next plot is that of  $\mu_1$  v/s  $\mu_2$ .



Point and interval estimates of number of days that were weekdays ( $k$ ):

$$k \rightarrow 72.4366 [36, 97].$$

Probability that proportion of weekends is less than  $2/7 = 0.5579$

**Point and interval estimates of all parameters:**

$$\begin{aligned}\mu_1 &\rightarrow 0.5403 \ [0.4481, 0.6373]. \\ \sigma_1^2 &\rightarrow 1.2155 \ [0.7776, 1.8222]. \\ \mu_2 &\rightarrow 0.3831 \ [0.2859, 0.4805]. \\ \sigma_2^2 &\rightarrow 1.1263 \ [0.3057, 2.3891].\end{aligned}$$

**Point and interval estimates from last time:**

$$\begin{aligned}\mu_1 &\rightarrow 0.4102 \ [0.3037, 0.5219]. \\ \sigma_1^2 &\rightarrow 0.8585 \ [0.5750, 1.2491]. \\ \mu_2 &\rightarrow 0.1533 \ [0.0462, 0.2561]. \\ \sigma_2^2 &\rightarrow 2.4503 \ [1.4273, 4.1320].\end{aligned}$$

If we compare our current estimates to estimates from last time we observe that the separation between  $\mu_1$  and  $\mu_2$  is much smaller. In fact there is a slight overlap in our credible intervals for  $\mu_1$  and  $\mu_2$  despite using priors such that  $\mu_1 > \mu_2$ . This is because this time we have added uncertainty about what type of day it is.

## Appendix:

```
1 %% STA 601: Lab 8
2 % Author: Kedar S Prabhudesai
3 % Created on: 11/22/2013
4 function sta601.ksp6_lab9
5
6 close all;
7 clear all;
8
9 %% Get Data
10 X = importdata('data.txt');
11 X = X.data;
12
13 %% Prior Parameters
14 mu10 = 0.6;mu20 = 0.4;
15 t10 = 400;t20 = 400;
16 a1 = 1;a2 = 1;
17 % Remember that 'b' parameter in matlab's gamma function is in fact '1/b'
18 b1 = 0.05;b2 = 0.05;
19 n = numel(X);
20
21 % Target Distribution for Mu1 and Mu2
22 Mu1FullCond = @(Xwd,t1,mu1) exp(-0.5*t1*sum((log(Xwd)-mu1).^2) - 0.5*t10*(mu1-mu10)^2);
23 Mu2FullCond = @(Xwe,t2,mu2) exp(-0.5*t2*sum((log(Xwe)-mu2).^2) - 0.5*t20*(mu2-mu20)^2);
24
25 %% Gibbs Sampler
26 nGibbs = 12000;
27 nBurnIn = 2000;
28 % Proposal Distribution Std Dev
29 SCand = 0.5;
30
31 % Initialize
32 ThetaSamples = zeros(1,nGibbs);
33 ThetaSamples(1) = 5/7;
34 Mu1Samples = zeros(1,nGibbs);
35 Mu2Samples = zeros(1,nGibbs);
36
37 Tau1Samples = zeros(1,nGibbs);
38 Tau2Samples = zeros(1,nGibbs);
39 Tau1Samples(1) = 0.05;
40 Tau2Samples(1) = 0.05;
41
42 kVals = zeros(1,nGibbs);
43
44 for iGibbs = 2:nGibbs
45     home;disp(iGibbs);
46     % Draw W from Binomial(n,Theta)
47     W = rand(n,1);
48     W = W < ThetaSamples(iGibbs-1);
49
50     % Split data according to weekdays/weekends
51     XWkDays = X(W == 1);
52     XWkEnds = X(W == 0);
53
54     kVals(iGibbs-1) = sum(W);
55     %% Update Theta | —
56     ThetaSamples(iGibbs) = betarnd(5+kVals(iGibbs-1),2+n-kVals(iGibbs-1));
57
58     %% Update Mu1 | — using M-H
59     % Step 1: Sample from Mu1'|Mu1(s)
60     Mu1Prime = normrnd(Mu1Samples(iGibbs-1),SCand);
```

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61
62 % Step 2: Compute Acceptance Ratio
63 r = Mu1FullCond(XWkDays, Tau1Samples(iGibbs-1), Mu1Prime) / Mu1FullCond(XWkDays, Tau1Samples...
    (iGibbs-1), Mu1Samples(iGibbs-1));
64
65 % Step 3: Accept/Reject
66 u = rand;
67 if u < r
68     Mu1Samples(iGibbs) = Mu1Prime;
69 else
70     Mu1Samples(iGibbs) = Mu1Samples(iGibbs-1);
71 end
72
73 %% Update Mu2 | — using M-H
74 % Step 1: Sample from Mu2'|Mu2(s)
75 Mu2Prime = normrnd(Mu2Samples(iGibbs-1), SCand);
76
77 % Step 2: Compute Acceptance Ratio
78 r = Mu2FullCond(XWkEnds, Tau2Samples(iGibbs-1), Mu2Prime) / Mu2FullCond(XWkEnds, Tau2Samples...
    (iGibbs-1), Mu2Samples(iGibbs-1));
79
80 % Step 3: Accept/Reject
81 u = rand;
82 if u < r
83     Mu2Samples(iGibbs) = Mu2Prime;
84 else
85     Mu2Samples(iGibbs) = Mu2Samples(iGibbs-1);
86 end
87
88 %% Update Tau1 | —
89 Tau1Samples(iGibbs) = gamrnd(a1+kVals(iGibbs-1)/2, 1/(0.5*sum((log(XWkDays)-Mu1Samples(...
    iGibbs)).^2)+b1));
90
91 %% Update Tau2 | —
92 Tau2Samples(iGibbs) = gamrnd(a2+(n-kVals(iGibbs-1))/2, 1/(0.5*sum((log(XWkEnds)-...
    Mu2Samples(iGibbs)).^2)+b2));
93 end
94
95 %% Burn-In
96 ThetaSamples(1:nBurnIn) = [];
97 Mu1Samples(1:nBurnIn) = [];
98 Mu2Samples(1:nBurnIn) = [];
99 Tau1Samples(1:nBurnIn) = [];
100 Tau2Samples(1:nBurnIn) = [];
101 kVals(1:nBurnIn) = [];
102
103 % Convert Taus to sigma^2
104 S1Samples = 1./Tau1Samples;
105 S2Samples = 1./Tau2Samples;
106 keyboard
107 end

```