

# Homework1

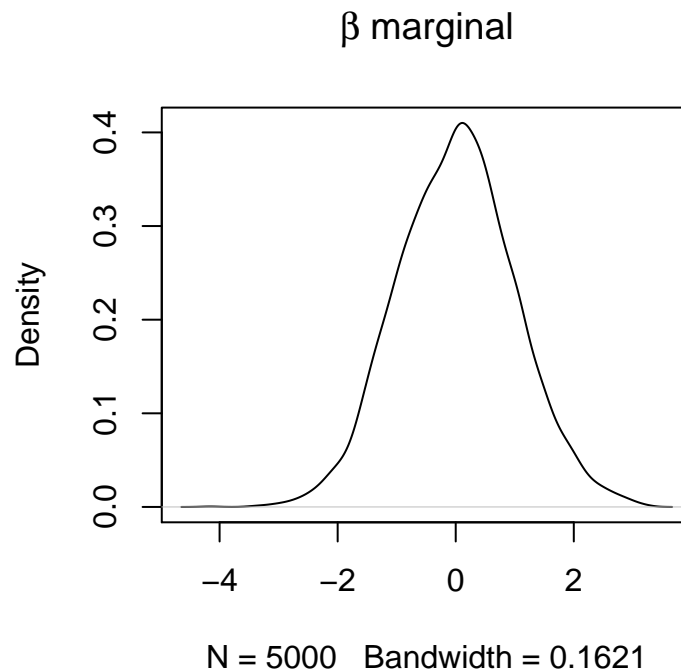
Ian Frankenburg

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## Bayesian Adaptive Lasso

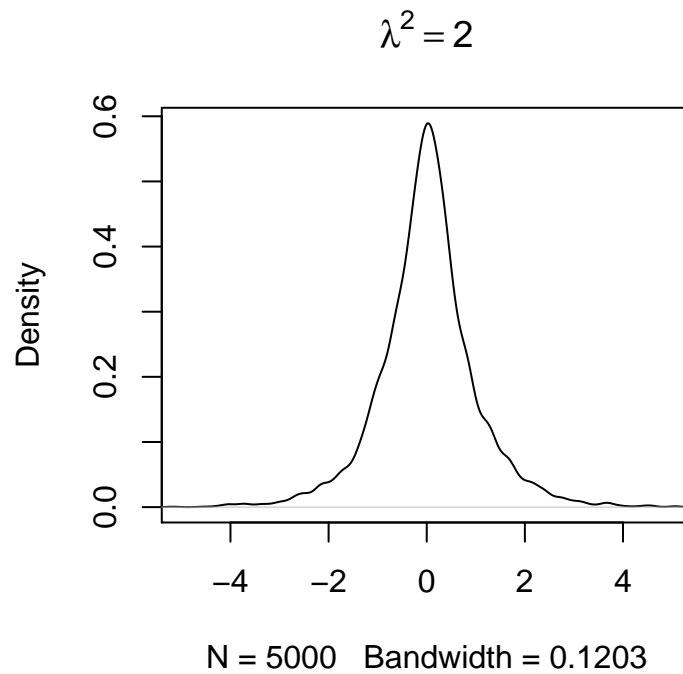
### Part a)

```
n <- 5000  
plot(density(rnorm(n,0,1)), main=TeX(paste("$\\beta$", "marginal")))
```



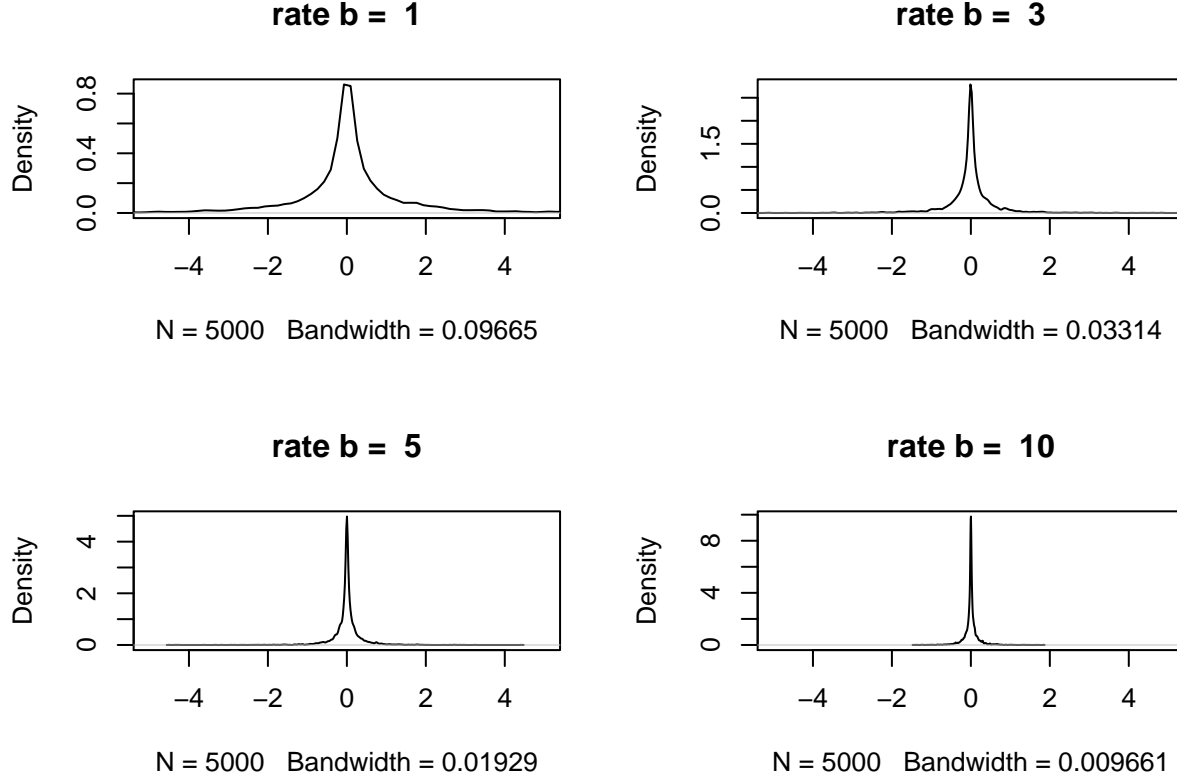
### Part b)

```
lambda <- sqrt(2)  
tau.sq <- rgamma(n,shape=1,rate = lambda^2/2)  
beta.marginal <- rnorm(n,0,sqrt(tau.sq))  
plot(density(beta.marginal), main=TeX(paste("$\\lambda^2 = 2$")), xlim=c(-5,5))
```



Part c)

```
set.seed(1)
par(mfrow=c(2,2))
rates <- c(1,3,5,10)
for(b in rates){
  lambda <- 1/rgamma(n,1,b)
  tau.sq <- rgamma(n,shape=1,rate = lambda^2/2)
  beta.marginal <- rnorm(n,0,sqrt(tau.sq))
  plot(density(beta.marginal), main=paste("rate b = ",b),xlim=c(-5,5))
}
```



### Part d) and e)

I will implement a Gibbs Sampler. The model is

$$\begin{aligned}
 \mathbf{Y}|\boldsymbol{\beta}, \sigma^2 &\sim N(\mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{I}) \\
 \beta_j|\tau_j^2 &\sim N(0, \tau_j^2) \\
 \tau_j^2 &\sim \text{Gamma}(1, \frac{\lambda^2}{2}) \\
 \lambda &\sim \text{Inverse-Gamma}(a, 1/b) \\
 \sigma^2 &\sim \text{Inverse-Gamma}(0.1, 0.1).
 \end{aligned}$$

I need the full conditionals

$$\{\beta_j|\mathbf{Y}, \tau_j^2, \sigma^2, \lambda\} \text{ and } \{\sigma^2|\mathbf{Y}, \tau_j^2, \beta_j^2, \lambda\}.$$

I'll start with the posterior

$$\begin{aligned}
 p(\beta_1, \dots, \beta_p, \tau_1^2, \dots, \tau_p^2, \sigma^2, \lambda|\mathbf{Y}) &\propto p(\mathbf{Y}|\beta_1, \dots, \beta_p, \tau_1^2, \dots, \tau_p^2, \sigma^2, \lambda) \\
 &\quad \times p(\beta_1, \dots, \beta_p|\tau_1^2, \dots, \tau_p^2) \\
 &\quad \times p(\tau_1^2, \dots, \tau_p^2|\lambda)p(\sigma^2).
 \end{aligned}$$

As a function of  $\boldsymbol{\beta}$  and  $\sigma^2$ , this is proportional to

$$\begin{aligned}
 &p(\mathbf{Y}|\beta_1, \dots, \beta_p, \tau_1^2, \dots, \tau_p^2, \sigma^2, \lambda)p(\beta_1, \dots, \beta_p|\tau_1^2, \dots, \tau_p^2)p(\sigma^2) \\
 &= N(\mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{I})N(0, \Sigma)IG(a, b) \\
 &=.
 \end{aligned}$$

Similarly, I can get the full conditional of  $\sigma^2$  since it's proportional to

$$\begin{aligned}
 &p(\mathbf{Y}|\beta_1, \dots, \beta_p, \tau_1^2, \dots, \tau_p^2, \sigma^2, \lambda)p(\sigma^2) \\
 &= N(\mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{I})IG(a, b).
 \end{aligned}$$

Now that I have the full conditionals, a Gibbs Sampling routine will follow

$i \leftarrow 10$

**for**  $s$  in  $niter$  **do**

$\boldsymbol{\beta}^{(s+1)} \sim p(\boldsymbol{\beta} | \sigma^{2(s)}, )$

$\sigma^{2(s+1)} \sim p(\sigma^2 | \boldsymbol{\beta}^{(s+1)}, )$

**end for**