## Spike-and-Slab Priors for Linear Models

- In regression, the priors on the regression coefficients are crucial.
- Whether or not $\beta_{j}=0$ defines whether $X_{j}$ is "important" in the regression.
- For any $j$, a useful prior for $\beta_{j}$ is:



## Spike-and-Slab Priors for Linear Models

- Here: $P\left(\beta_{j}=0\right)=h_{0 j}$ ( $=$ prior probability that $X_{j}$ is not needed in the model)
- $P\left(\beta_{j} \neq 0\right)=1-h_{0 j}=h_{1 j}\left(f_{j}-\left(-f_{j}\right)\right)=2 f_{j} h_{1 j}$ (where $\left[-f_{j}, f_{j}\right]$ contains all "reasonable" values for $\beta_{j}$ )
- To include $X_{j}$ in the model with certainty, set $h_{0 j}=0$.
- To reflect more doubt that $X_{j}$ should be in the model, increase the ratio

$$
\frac{h_{0 j}}{h_{1 j}}=\frac{h_{0 j}}{\left(1-h_{0 j}\right) / 2 f_{j}}=2 f_{j} \frac{h_{0 j}}{1-h_{0 j}}
$$

- Recently, "nonparametric priors" have become popular, typically involving a mixture of Dirichet processes.

CHAPTER 6(a) SLIDES BEGIN HERE

## The Monte Carlo Method

- The Monte Carlo method involves studying a distribution (e.g., a posterior) and its characteristics by generating many random observations having that distribution.
- If $\theta^{(1)}, \ldots, \theta^{(S)} \stackrel{\text { iid }}{\sim} \pi(\theta \mid \mathbf{x})$, then the empirical distribution of $\left\{\theta^{(1)}, \ldots, \theta^{(S)}\right\}$ approximates the posterior, when $S$ is large.
- By the law of large numbers,

$$
\frac{1}{S} \sum_{s=1}^{S} g\left(\theta^{(s)}\right) \rightarrow E[g(\theta) \mid \mathbf{x}]
$$

as $S \rightarrow \infty$.

## The Monte Carlo Method

So as $S \rightarrow \infty$ :

$$
\begin{aligned}
\bar{\theta}=\frac{1}{S} \sum_{s=1}^{S} \theta^{(s)} & \rightarrow \text { posterior mean } \\
\frac{1}{S-1} \sum_{s=1}^{S}\left(\theta^{(s)}-\bar{\theta}\right)^{2} & \rightarrow \text { posterior variance } \\
\frac{\#\left\{\theta^{(s)} \leq c\right\}}{S} & \rightarrow P[\theta \leq c \mid \mathbf{x}]
\end{aligned}
$$

$\operatorname{median}\left\{\theta^{(1)}, \ldots, \theta^{(S)}\right\} \rightarrow$ posterior median
(and similarly for any posterior quantile).

## The Monte Carlo Method

- If the posterior is a "common" distribution, as in many conjugate analyses, we could draw samples from the posterior using $R$ functions.


## Example 1: (General Social Survey)

- Sample 1: \# of children for women age 40+, no bachelor's degree.
- Sample 2: \# of children for women age 40+, bachelor's degree or higher.
- Assume Poisson $\left(\theta_{1}\right)$ and Poisson $\left(\theta_{2}\right)$ models for the data.
- We use gamma $(2,1)$ priors for $\theta_{1}$ and for $\theta_{2}$.


## The Monte Carlo Method

- Data: $n_{1}=111, \sum_{i} x_{i 1}=217$
- Data: $n_{2}=44, \sum_{i} x_{i 2}=66$
- $\Rightarrow$ Posterior for $\theta_{1}$ is gamma $(219,112)$.
- $\Rightarrow$ Posterior for $\theta_{2}$ is gamma $(68,45)$.
- Find $P\left[\theta_{1}>\theta_{2} \mid \mathbf{x}_{1}, \mathbf{x}_{2}\right]$.
- Find posterior distribution of the ratio $\frac{\theta_{1}}{\theta_{2}}$.
- See R example using Monte Carlo method on course web page.

