Lecture 11: More Gibbs: Regression and Data Augmentation

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September 30

Normal Linear Regression Example

Model

$$
\begin{aligned}
Y \mid \beta, \phi &\sim \mathsf{N}(X\beta, \phi^{-1} I_n) \\
\beta &\sim \mathsf{N}(b_0, \Phi_0^{-1}) \\
\phi &\sim \mathsf{Gamma}(v_0/2, s_0/2)
\end{aligned}
$$

- Full Conditional for β

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\begin{aligned}
\beta \mid \phi, y_1, \ldots, y_n &\sim \mathsf{N}(b_n, \Phi_n^{-1}) \\
b_n &= (\Phi_0 + \phi X^T X)^{-1}(\Phi_0 b_0 + \phi X^T X \hat{\beta}) \\
\Phi_n &= \Phi_0 + \phi X^T X
\end{aligned}
$$

- Full Conditional for ϕ

$$
\phi \mid \beta, y_1, \ldots, y_n \sim \mathsf{Gamma}((v_0 + n)/2, (s_0 + \sum_i (y_i - x_i^T \beta)))
$$

- Choice of Prior Precision Φ_0

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- What if we transform the X matrix by $\tilde{X} = XH$ where H is $p \times p$ and invertible
- obtain the posterior for $\tilde{\beta}$ using Y and $\tilde{X}$

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- invariance suggests that since $\tilde{X}\tilde{\beta} = XH\tilde{\beta} = X\beta$ the posterior for β and $H\tilde{\beta}$ should be the same (or the posterior of $H^{-1}\beta$ and $\tilde{\beta}$ should be the same)

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- with some linear algebra we can show that this is true if $b_0 = 0$ and Φ_0 is $kX^T X$ for some k (show!)

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Popular choice is to take $k = \phi/g$ which is a special case of Zellner's g-prior

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Conjugate so we could skip Gibbs sampling and sample directly from gamma and then conditional normal!

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Posterior for β (conjugate case)

$$\beta \mid \phi, \lambda, y_1, \ldots, y_n \sim \mathsf{N}\left((\lambda I_p + X^T X)^{-1} X^T Y, \frac{1}{\phi}(\lambda I_p + X^T X)^{-1}\right)$$

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- Bayes Regression and choice of Φ_0 in general is a very important problem and provides the foundation for many variations on shrinkage estimators, variable selection, hierarchical models, nonparameteric regression and more!

- Be sure that you can derive the full conditional posteriors for β and ϕ as well as the joint posterior in the conjugate case!

Binary Regression

$$Y_i \mid \beta \sim \mathsf{Ber}(p(x_i^T \beta))$$

where $\Pr(Y_i = 1 \mid \beta) = p(x_i^T \beta))$ and linear predictor $x_i^T \beta = \lambda_i$

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- probit link

$$p(x_i^T\beta) = \Phi(x_i^T\beta)$$

- $\Phi()$ is the Normal cdf

Likelihood and Posterior

Likelihood:

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seemingly no, but there is a trick!

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Augmentation Strategy

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- $Z_i = x_i^T \beta + \epsilon_i \qquad \epsilon_i \overset{iid}{\sim}$ N(0,1)
- Relationship to probit model:

$$\begin{aligned}
\Pr(y = 1 \mid \beta) &= P(Z_i > 0 \mid \beta) \\
&= P(Z_i - x_i^T \beta > -x^T \beta) \\
&= P(\epsilon_i > -x^T \beta) \\
&= 1 - \Phi(-x_i^T \beta) \\
&= \Phi(x_i^T \beta)
\end{aligned}$$

Augmented Posterior & Gibbs

$$\pi(Z_1, \ldots, Z_n, \beta \mid y) \propto$$
$$\mathsf{N}(\beta; b_0, \phi_0) \left\{ \prod_{i=1}^{n} \mathsf{N}(Z_i; x_i^T \beta, 1) \right\} \left\{ \prod_{i=1}^{n} y_i 1(Z_i > 0) + (1 - y_i) 1(Z_i < 0) \right\}$$

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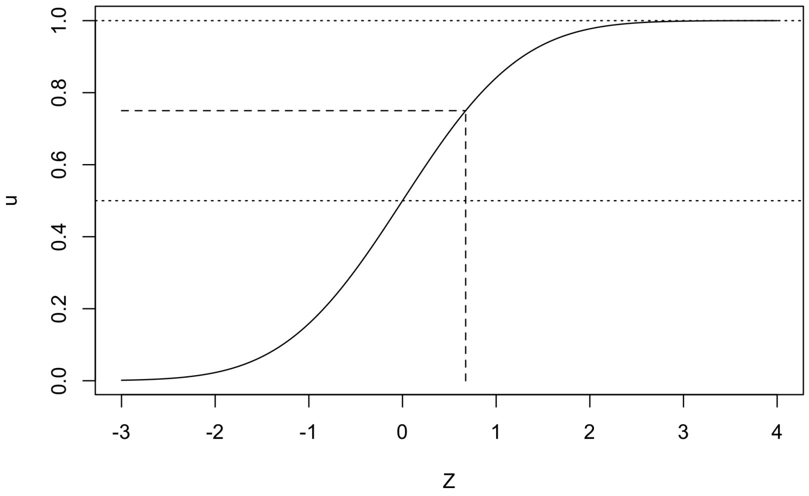
- sample from independent truncated normal distributions !
- two block Gibbs sampler $\theta_{[1]} = \beta$ and $\theta_{[2]} = (Z_1, \ldots, Z_n)^T$

Truncated Normal Sampling

- Use inverse cdf method for cdf F
- If $u \sim U(0,1)$ set $z = F^{-1}(u)$



- if $Z \in (a,b)$, Draw $u \sim U(F(a), F(b))$ and set $z = F^{-1}(u)$

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- Modeling heavy tailed distributions such as t errors in regression

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- latent variables to allow Gibbs steps but not always better!