Lecture 10: More MCMC: Blocked Metropolis-Hastings and Gibbs

Merlise Clyde

September 27

Blocked Metropolis-Hastings

So far all algorithms update all of the parameters simultaneously

Blocked Metropolis-Hastings

So far all algorithms update all of the parameters simultaneously

- convenient to break problems in to K blocks and update them separately

Blocked Metropolis-Hastings

So far all algorithms update all of the parameters simultaneously

- convenient to break problems in to K blocks and update them separately
- $\theta = (\theta_{[1]}, \ldots, \theta_{[K]}) = (\theta_1, \ldots, \theta_p)$

Blocked Metropolis-Hastings

So far all algorithms update all of the parameters simultaneously

- convenient to break problems in to K blocks and update them separately
- $\theta = (\theta_{[1]}, \ldots, \theta_{[K]}) = (\theta_1, \ldots, \theta_p)$

At iteration s, for $k = 1, \ldots, K$ Cycle thru blocks: (fixed order or random order)

- propose $\theta^*_{[k]} \sim q_k(\theta_{[k]} \mid \theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[>k]})$
- set $\theta^{(s)}_{[k]} = \theta^*_{[k]}$ with probability

$$\min\left\{1, \frac{\pi(\theta^{(s)}_{[<k]}, \theta^*_{[k]}, \theta^{(s-1)}_{[>k]})\mathcal{L}(\theta^{(s)}_{[<k]}, \theta^*_{[k]}, \theta^{(s-1)}_{[>k]})/q_k(\theta^*_{[k]} \mid \theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[>k]})}{\pi(\theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[k]}, \theta^{(s-1)}_{[>k]})\mathcal{L}(\theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[k]}, \theta^{(s-1)}_{[>k]})/q_k(\theta^{(s-1)}_{[k]} \mid \theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[>k]})}\right\}$$

Gibbs Sampler

special case of Blocked MH

Gibbs Sampler

special case of Blocked MH

- proposal distribution q_k for the kth block is the **full conditional** distribution for $\theta_{[k]}$

$$\pi(\theta_{[k]} \mid \theta_{[-k]}, y) = \frac{\pi(\theta_{[k]}, \theta_{[-k]} \mid y)}{\pi(\theta_{[-k]} \mid y))} \propto \pi(\theta_{[k]}, \theta_{[-k]} \mid y)$$

Gibbs Sampler

special case of Blocked MH

- proposal distribution q_k for the kth block is the **full conditional** distribution for $\theta_{[k]}$

$$\pi(\theta_{[k]} \mid \theta_{[-k]}, y) = \frac{\pi(\theta_{[k]}, \theta_{[-k]} \mid y)}{\pi(\theta_{[-k]} \mid y))} \propto \pi(\theta_{[k]}, \theta_{[-k]} \mid y)$$

$$\pi(\theta_{[k]} \mid \theta_{[-k]}, y) \propto \mathcal{L}(\theta_{[k]}, \theta_{[-k]})\pi(\theta_{[k]}, \theta_{[-k]})$$

Gibbs Sampler

special case of Blocked MH

- proposal distribution q_k for the kth block is the **full conditional** distribution for $\theta_{[k]}$

$$\pi(\theta_{[k]} \mid \theta_{[-k]}, y) = \frac{\pi(\theta_{[k]}, \theta_{[-k]} \mid y)}{\pi(\theta_{[-k]} \mid y))} \propto \pi(\theta_{[k]}, \theta_{[-k]} \mid y)$$

$$\pi(\theta_{[k]} \mid \theta_{[-k]}, y) \propto \mathcal{L}(\theta_{[k]}, \theta_{[-k]})\pi(\theta_{[k]}, \theta_{[-k]})$$

$$\min\left\{1, \frac{\pi(\theta^{(s)}_{[<k]}, \theta^*_{[k]}, \theta^{(s-1)}_{[>k]})\mathcal{L}(\theta^{(s)}_{[<k]}, \theta^*_{[k]}, \theta^{(s-1)}_{[>k]})/q_k(\theta^*_{[k]} \mid \theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[>k]})}{\pi(\theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[k]}, \theta^{(s-1)}_{[>k]})\mathcal{L}(\theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[k]}, \theta^{(s-1)}_{[>k]})/q_k(\theta^{(s-1)}_{[k]} \mid \theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[>k]})}\right\}$$

Gibbs Sampler

special case of Blocked MH

- proposal distribution q_k for the kth block is the **full conditional** distribution for $\theta_{[k]}$

$$\pi(\theta_{[k]} \mid \theta_{[-k]}, y) = \frac{\pi(\theta_{[k]}, \theta_{[-k]} \mid y)}{\pi(\theta_{[-k]} \mid y))} \propto \pi(\theta_{[k]}, \theta_{[-k]} \mid y)$$

$$\pi(\theta_{[k]} \mid \theta_{[-k]}, y) \propto \mathcal{L}(\theta_{[k]}, \theta_{[-k]})\pi(\theta_{[k]}, \theta_{[-k]})$$

$$\min\left\{1, \frac{\pi(\theta^{(s)}_{[<k]}, \theta^{*}_{[k]}, \theta^{(s-1)}_{[>k]})\mathcal{L}(\theta^{(s)}_{[<k]}, \theta^{*}_{[k]}, \theta^{(s-1)}_{[>k]})/q_k(\theta^{*}_{[k]} \mid \theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[>k]})}{\pi(\theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[k]}, \theta^{(s-1)}_{[>k]})\mathcal{L}(\theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[k]}, \theta^{(s-1)}_{[>k]})/q_k(\theta^{(s-1)}_{[k]} \mid \theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[>k]})}\right\}$$

- acceptance probability is always 1!

Gibbs Sampler

special case of Blocked MH

- proposal distribution q_k for the kth block is the **full conditional** distribution for $\theta_{[k]}$

$$\pi(\theta_{[k]} \mid \theta_{[-k]}, y) = \frac{\pi(\theta_{[k]}, \theta_{[-k]} \mid y)}{\pi(\theta_{[-k]} \mid y))} \propto \pi(\theta_{[k]}, \theta_{[-k]} \mid y)$$

$$\pi(\theta_{[k]} \mid \theta_{[-k]}, y) \propto \mathcal{L}(\theta_{[k]}, \theta_{[-k]})\pi(\theta_{[k]}, \theta_{[-k]})$$

$$\min\left\{1, \frac{\pi(\theta^{(s)}_{[<k]}, \theta^{*}_{[k]}, \theta^{(s-1)}_{[>k]})\mathcal{L}(\theta^{(s)}_{[<k]}, \theta^{*}_{[k]}, \theta^{(s-1)}_{[>k]})/q_k(\theta^{*}_{[k]} \mid \theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[>k]})}{\pi(\theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[k]}, \theta^{(s-1)}_{[>k]})\mathcal{L}(\theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[k]}, \theta^{(s-1)}_{[>k]})/q_k(\theta^{(s-1)}_{[k]} \mid \theta^{(s)}_{[<k]}, \theta^{(s-1)}_{[>k]})}\right\}$$

- acceptance probability is always 1!

- even though joint distribution is messy, full conditionals may be (conditionally) conjugate and easy to sample from!

Univariate Normal Example

Model

$$
\begin{aligned}
Y_i \mid \mu, \sigma^2 &\overset{iid}{\sim} \mathsf{N}(\mu, 1/\phi) \\
\mu &\sim \mathsf{N}(\mu_0, 1/\tau_0) \\
\phi &\sim \mathsf{Gamma}(a/2, b/2)
\end{aligned}
$$

Univariate Normal Example

Model

$$
\begin{aligned}
Y_i \mid \mu, \sigma^2 &\overset{iid}{\sim} \mathsf{N}(\mu, 1/\phi) \\
\mu &\sim \mathsf{N}(\mu_0, 1/\tau_0) \\
\phi &\sim \mathsf{Gamma}(a/2, b/2)
\end{aligned}
$$

- Joint prior is a product of independent Normal-Gamma

Univariate Normal Example

Model

$$
\begin{aligned}
Y_i \mid \mu, \sigma^2 &\overset{iid}{\sim} \mathsf{N}(\mu, 1/\phi) \\
\mu &\sim \mathsf{N}(\mu_0, 1/\tau_0) \\
\phi &\sim \mathsf{Gamma}(a/2, b/2)
\end{aligned}
$$

- Joint prior is a product of independent Normal-Gamma
- Is $\pi(\mu, \phi \mid y_1, \ldots, y_n)$ also a Normal-Gamma family?

Full Conditional for the Mean

The full conditional distributions $\mu \mid \phi, y_1, \ldots, y_n$

$$
\begin{aligned}
\mu \mid \phi, y_1, \ldots, y_n &\sim \mathsf{N}(\hat{\mu}, 1/\tau_n) \\
\hat{\mu} &= \frac{\tau_0 \mu_0 + n\phi\bar{y}}{\tau_0 + n\phi} \\
\tau_n &= \tau_0 + n\phi
\end{aligned}
$$

Full Conditional for the Precision

$$\begin{aligned}
\phi \mid \mu, y_1, \ldots, y_n &\sim \textsf{Gamma}(a_n/2, b_n/2) \\
a_n &= a + n \\
b_n &= b + \sum_i (y_i - \mu)^2
\end{aligned}$$

Full Conditional for the Precision

$$
\begin{aligned}
\phi \mid \mu, y_1, \ldots, y_n &\sim \textsf{Gamma}(a_n/2, b_n/2) \\
a_n &= a + n \\
b_n &= b + \sum_i (y_i - \mu)^2
\end{aligned}
$$

$$
\textsf{E}[\phi \mid \mu, y_1, \ldots, y_n] = \frac{(a+n)/2}{(b + \sum_i (y_i - \mu)^2)/2}
$$

Full Conditional for the Precision

$$\begin{aligned}
\phi \mid \mu, y_1, \ldots, y_n &\sim \textsf{Gamma}(a_n/2, b_n/2) \\
a_n &= a + n \\
b_n &= b + \sum_i (y_i - \mu)^2
\end{aligned}$$

$$\textsf{E}[\phi \mid \mu, y_1, \ldots, y_n] = \frac{(a+n)/2}{(b + \sum_i (y_i - \mu)^2)/2}$$

What happens with a non-informative prior i.e

$a = b = \epsilon$ as $\epsilon \to 0$?

Full Conditional for the Precision

$$
\begin{aligned}
\phi \mid \mu, y_1, \ldots, y_n &\sim \textsf{Gamma}(a_n/2, b_n/2) \\
a_n &= a + n \\
b_n &= b + \sum_i (y_i - \mu)^2
\end{aligned}
$$

$$
\textsf{E}[\phi \mid \mu, y_1, \ldots, y_n] = \frac{(a+n)/2}{(b + \sum_i (y_i - \mu)^2)/2}
$$

What happens with a non-informative prior i.e

$a = b = \epsilon$ as $\epsilon \to 0$?

Normal Linear Regression Example

Model

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

Normal Linear Regression Example

Model

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

x_i is a $p \times 1$ vector of predictors and X is $n \times p$ matrix

Normal Linear Regression Example

Model

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

x_i is a $p \times 1$ vector of predictors and X is $n \times p$ matrix

β is a $p \times 1$ vector of coefficients

Normal Linear Regression Example

Model

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

x_i is a $p \times 1$ vector of predictors and X is $n \times p$ matrix

β is a $p \times 1$ vector of coefficients

Φ_0 is a $p \times p$ prior precision matrix

Normal Linear Regression Example

Model

$$
\begin{aligned}
Y_i \mid \beta, \phi &\overset{iid}{\sim} \textsf{N}(x_i^T\beta, 1/\phi) \\
Y \mid \beta, \phi &\sim \textsf{N}(X\beta, \phi^{-1} I_n) \\
\beta &\sim \textsf{N}(b_0, \Phi_0^{-1}) \\
\phi &\sim \textsf{N}(v_0/2, s_0/2)
\end{aligned}
$$

x_i is a $p \times 1$ vector of predictors and X is $n \times p$ matrix

β is a $p \times 1$ vector of coefficients

Φ_0 is a $p \times p$ prior precision matrix

Multivariate Normal density for β

$$\pi(\beta \mid b_0, \Phi_0) = \frac{|\Phi_0|^{1/2}}{(2\pi)^{p/2}} \exp\left\{-\frac{1}{2}(\beta - b_0)^T \Phi_0 (\beta - b_0)\right\}$$

Full Conditional for β

$$\beta \mid \phi, y_1, \ldots, y_n \sim \mathsf{N}(b_n, \Phi_n^{-1})$$

$$b_n = (\Phi_0 + \phi X^T X)^{-1}(\Phi_0 b_0 + \phi X^T X \hat{\beta})$$

$$\Phi_n = \Phi_0 + \phi X^T X$$

Derivation continued

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

Non-Informative $\Phi_0 \to 0$

Choice of Prior Precision

Non-Informative $\Phi_0 \to 0$

- Formal Posterior given ϕ

$$\beta \mid \phi, y_1, \ldots, y_n \sim \mathsf{N}(\hat{\beta}, \phi^{-1}(X^T X)^{-1})$$

Choice of Prior Precision

Non-Informative $\Phi_0 \to 0$

- Formal Posterior given ϕ

$$\beta \mid \phi, y_1, \ldots, y_n \sim \mathsf{N}(\hat{\beta}, \phi^{-1}(X^T X)^{-1})$$

- needs $X^T X$ to be full rank for distribution to be unique

Invariance and Choice of Mean/Precision

- the model in vector form

$$Y \sim \mathsf{N}_n(X\beta, \phi^{-1} I_n)$$

Invariance and Choice of Mean/Precision

- the model in vector form

$$Y \sim \mathsf{N}_n(X\beta, \phi^{-1} I_n)$$

- What if we transform the X matrix by $\tilde{X} = XH$ where H is $p \times p$ and invertible

Invariance and Choice of Mean/Precision

- the model in vector form

$$Y \sim \mathsf{N}_n(X\beta, \phi^{-1} I_n)$$

- 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 $\tilde{X}$

$$Y \sim \mathsf{N}_n(\tilde{X}\tilde{\beta}, \phi^{-1} I_n)$$

- since $\tilde{X}\tilde{\beta} = XH\tilde{\beta} = X\beta$ invariance suggests that the posterior for β and $H\tilde{\beta}$ should be the same

Invariance and Choice of Mean/Precision

- the model in vector form

$$Y \sim \mathsf{N}_n(X\beta, \phi^{-1} I_n)$$

- 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 $\tilde{X}$

$$Y \sim \mathsf{N}_n(\tilde{X}\tilde{\beta}, \phi^{-1} I_n)$$

- since $\tilde{X}\tilde{\beta} = XH\tilde{\beta} = X\beta$ invariance suggests that 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

Invariance and Choice of Mean/Precision

- the model in vector form

$$Y \sim \mathsf{N}_n(X\beta, \phi^{-1} I_n)$$

- 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 $\tilde{X}$

$$Y \sim \mathsf{N}_n(\tilde{X}\tilde{\beta}, \phi^{-1} I_n)$$

- since $\tilde{X}\tilde{\beta} = XH\tilde{\beta} = X\beta$ invariance suggests that 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

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

Zellner's g-prior

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

$$\beta \mid \phi, g \sim \mathsf{N}\left(0, \frac{g}{\phi}(X^T X)^{-1}\right)$$

Zellner's g-prior

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

$$\beta \mid \phi, g \sim \mathsf{N}\left(0, \frac{g}{\phi}(X^T X)^{-1}\right)$$

- Full conditional

$$\beta \mid \phi, g \sim \mathsf{N}\left(\frac{g}{1+g}\hat{\beta}, \frac{1}{\phi}\frac{g}{1+g}(X^T X)^{-1}\right)$$

Zellner's g-prior

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

$$\beta \mid \phi, g \sim \mathsf{N}\left(0, \frac{g}{\phi}(X^T X)^{-1}\right)$$

- Full conditional

$$\beta \mid \phi, g \sim \mathsf{N}\left(\frac{g}{1+g}\hat{\beta}, \frac{1}{\phi}\frac{g}{1+g}(X^T X)^{-1}\right)$$

- one parameter g controls shrinkage

Zellner's g-prior

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

$$\beta \mid \phi, g \sim \mathsf{N}\left(0, \frac{g}{\phi}(X^T X)^{-1}\right)$$

- Full conditional

$$\beta \mid \phi, g \sim \mathsf{N}\left(\frac{g}{1+g}\hat{\beta}, \frac{1}{\phi}\frac{g}{1+g}(X^T X)^{-1}\right)$$

- one parameter g controls shrinkage

if $\phi \sim \mathsf{Gamma}(v_0/2, s_0/2)$ then posterior is

$$\phi \mid y_1, \ldots, y_n \sim \mathsf{Gamma}(v_n/2, s_n/2)$$

Zellner's g-prior

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

$$\beta \mid \phi, g \sim \mathsf{N}\left(0, \frac{g}{\phi}(X^T X)^{-1}\right)$$

- Full conditional

$$\beta \mid \phi, g \sim \mathsf{N}\left(\frac{g}{1+g}\hat{\beta}, \frac{1}{\phi}\frac{g}{1+g}(X^T X)^{-1}\right)$$

- one parameter g controls shrinkage

if $\phi \sim \mathsf{Gamma}(v_0/2, s_0/2)$ then posterior is

$$\phi \mid y_1, \ldots, y_n \sim \mathsf{Gamma}(v_n/2, s_n/2)$$

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

Ridge Regression

If $X^T X$ is nearly singular, certain elements of β or (linear combinations of β) may have huge variances under the g-prior (or flat prior) as the MLEs are highly unstable!

Ridge Regression

If $X^T X$ is nearly singular, certain elements of β or (linear combinations of β) may have huge variances under the g-prior (or flat prior) as the MLEs are highly unstable!

Ridge regression protects against the explosion of variances and ill-conditioning with the conjugate priors:

$$\beta \mid \phi \sim \mathsf{N}(0, \frac{1}{\phi\lambda} I_p)$$

Ridge Regression

If $X^T X$ is nearly singular, certain elements of β or (linear combinations of β) may have huge variances under the g-prior (or flat prior) as the MLEs are highly unstable!

Ridge regression protects against the explosion of variances and ill-conditioning with the conjugate priors:

$$\beta \mid \phi \sim \mathsf{N}(0, \frac{1}{\phi\lambda} I_p)$$

Posterior for β (conjugate case)

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

Bayes Regression

- Posterior mean (or mode) given λ is biased, but can show that there **always** is a value of λ where the frequentist's expected squared error loss is smaller for the Ridge estimator than MLE!

Bayes Regression

- Posterior mean (or mode) given λ is biased, but can show that there **always** is a value of λ where the frequentist's expected squared error loss is smaller for the Ridge estimator than MLE!

- related to penalized maximum likelihood estimation

Bayes Regression

- Posterior mean (or mode) given λ is biased, but can show that there **always** is a value of λ where the frequentist's expected squared error loss is smaller for the Ridge estimator than MLE!
- related to penalized maximum likelihood estimation
- Choice of λ

Bayes Regression

- Posterior mean (or mode) given λ is biased, but can show that there **always** is a value of λ where the frequentist's expected squared error loss is smaller for the Ridge estimator than MLE!
- related to penalized maximum likelihood estimation
- Choice of λ
- 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!

Bayes Regression

- Posterior mean (or mode) given λ is biased, but can show that there **always** is a value of λ where the frequentist's expected squared error loss is smaller for the Ridge estimator than MLE!
- related to penalized maximum likelihood estimation
- Choice of λ
- 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!

Comments

- Why don't we treat each individual β_j as a separate block?

Comments

- Why don't we treat each individual β_j as a separate block?
- Gibbs always accepts, but can mix slowly if parameters in different blocks are highly correlated!

Comments

- Why don't we treat each individual β_j as a separate block?
- Gibbs always accepts, but can mix slowly if parameters in different blocks are highly correlated!
- Use block sizes in Gibbs that are as big as possible to improve mixing (proven faster convergence)

Comments

- Why don't we treat each individual β_j as a separate block?
- Gibbs always accepts, but can mix slowly if parameters in different blocks are highly correlated!
- Use block sizes in Gibbs that are as big as possible to improve mixing (proven faster convergence)
- Collapse the sampler by integrating out as many parameters as possible (as long as resulting sampler has good mixing)

Comments

- Why don't we treat each individual β_j as a separate block?
- Gibbs always accepts, but can mix slowly if parameters in different blocks are highly correlated!
- Use block sizes in Gibbs that are as big as possible to improve mixing (proven faster convergence)
- Collapse the sampler by integrating out as many parameters as possible (as long as resulting sampler has good mixing)
- can use Gibbs steps and (adaptive) Metropolis Hastings steps together

Comments

- Why don't we treat each individual β_j as a separate block?
- Gibbs always accepts, but can mix slowly if parameters in different blocks are highly correlated!
- Use block sizes in Gibbs that are as big as possible to improve mixing (proven faster convergence)
- Collapse the sampler by integrating out as many parameters as possible (as long as resulting sampler has good mixing)
- can use Gibbs steps and (adaptive) Metropolis Hastings steps together
- Introduce latent variables (data augmentation) to allow Gibbs steps (Next class)