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HW 11
Stat 360

- 2) In Gibbs sampler, the proposal distribution for U is the full conditional distribution of U given $V=v$. Thus in Metropolis-Hastings sampler,

$$J_u(u^* | u^{(s)}, v^{(s)}) = p_0(u^* | v^{(s)})$$

where J_u is proposal distribution and p_0 is the full conditional.

The Metropolis-Hastings acceptance ratio for U ,

$$r = \frac{p_0(u^*, v^{(s)})}{p_0(u^{(s)}, v^{(s)})} \times \frac{J_u(u^{(s)} | u^*, v^{(s)})}{J_u(u^* | u^{(s)}, v^{(s)})}$$

$$= \frac{p_0(u^*, v^{(s)})}{p_0(u^{(s)}, v^{(s)})} \times \frac{p_0(u^{(s)} | v^{(s)})}{p_0(u^* | v^{(s)})}$$

$$= \frac{\cancel{p_0(u^* | v^{(s)})} \cancel{p_0(v^{(s)})} p_0(u^{(s)} | v^{(s)})}{\cancel{p_0(u^{(s)} | v^{(s)})} \cancel{p_0(v^{(s)})} \cancel{p_0(u^* | v^{(s)})}}$$

$$= 1$$

If we propose a value from the full conditional, the acceptance probability is 1, which is equivalent to Gibbs sampler.

3) Let u and v be 2 possible states

$$a) \quad T = \begin{matrix} & \begin{matrix} u & v \end{matrix} \\ \begin{matrix} u \\ v \end{matrix} & \begin{pmatrix} 0.5 & 0.5 \\ 0 & 1 \end{pmatrix} \end{matrix}$$

T is not irreducible because $\forall t$,

$$P(X_t = u | X_0 = v) = 0$$

$$b) \quad T = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = I$$

The identity matrix has that given any row vector π , $\pi I = \pi$,
i.e., there are infinitely many possibilities for π .

$$c) \quad T = \begin{matrix} & \begin{matrix} u & v & w \end{matrix} \\ \begin{matrix} u \\ v \\ w \end{matrix} & \begin{pmatrix} 0.7 & 0.2 & 0.1 \\ 0.1 & 0.7 & 0.2 \\ 0.2 & 0.1 & 0.7 \end{pmatrix} \end{matrix}$$

$$\pi = \left(\frac{1}{3} \quad \frac{1}{3} \quad \frac{1}{3} \right)$$

$\pi T = \pi$, so π is stationary distribution of T , but does not have detailed balance, e.g.,

$$\pi(u) T(uv) = \frac{1}{3} \cdot 0.2 = \frac{1}{15}$$

$$\pi(v) T(vu) = \frac{1}{3} \cdot 0.1 = \frac{1}{30}$$

Since they don't equal, π and T do not have detailed balance.

$\forall u, v$ finite

d) Suppose transition matrix T is irreducible. Thus, there is a t such that $P(X_t = u | X_0 = v) > 0$. In addition by hypothesis that there is a state "b" such that $T_{bb} > 0$, at least one diagonal entry is positive. Therefore, for all states besides "b" (say "a"), $t_a \geq 1$ such that

$$P(X_{t_a} = a | X_0 = a) > 0$$

and for state "b", $t_b = 1$ such that $P(X_{t_b} = b | X_0 = b) > 0$

Clearly, $\text{GCD}\{t_a, t_b\} = 1$ for all "a". Thus the MC is aperiodic.

$$\begin{aligned} 4) \quad \pi^{(1)} &= \pi^{(0)} T = (0.7 \quad 0.2 \quad 0.1) \\ \pi^{(2)} &= \pi^{(1)} T = (0.53 \quad 0.29 \quad 0.18) \\ \pi^{(3)} &= \pi^{(2)} T = (0.436 \quad 0.327 \quad 0.237) \\ \pi^{(4)} &= \pi^{(3)} T = (0.3853 \quad 0.3398 \quad 0.2749) \\ \pi^{(5)} &= \pi^{(4)} T = (0.35867 \quad 0.34241 \quad 0.29892) \\ \pi^{(6)} &= \pi^{(5)} T = (0.34509 \quad 0.34131 \quad 0.31359) \\ \pi^{(7)} &= \pi^{(6)} T = (0.33842 \quad 0.3393 \quad 0.32229) \\ \pi^{(8)} &= \pi^{(7)} T = (0.33528 \quad 0.33742 \quad 0.3273) \end{aligned}$$

$$\pi = (\frac{1}{3} \quad \frac{1}{3} \quad \frac{1}{3}) \quad ?$$

$$\pi T = (\frac{1}{3} \quad \frac{1}{3} \quad \frac{1}{3}) \begin{pmatrix} \frac{7}{10} & \frac{2}{10} & \frac{1}{10} \\ \frac{1}{10} & \frac{7}{10} & \frac{2}{10} \\ \frac{2}{10} & \frac{1}{10} & \frac{7}{10} \end{pmatrix} = (\frac{1}{3} \quad \frac{1}{3} \quad \frac{1}{3})$$

$$\text{So } \pi = (\frac{1}{3} \quad \frac{1}{3} \quad \frac{1}{3})$$

5) First, we need to find proposal distribution:

$$a^* = a_i e^{x_i} \Rightarrow x_i = \log(a^*) - \log(a_i)$$

Given $x_i \sim N(0, \sigma^2)$, we know

$$p_{x_i}(x_i) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{x_i^2}{2\sigma^2}\right\}$$

Using transformation formula, we have

$$p_{a^*}(a^* | a_i) = p_{x_i}(\log(a^*) - \log(a_i)) \left| \frac{\partial}{\partial a^*} (\log(a^*) - \log(a_i)) \right|$$

$$= \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(\log a^* - \log a_i)^2}{2\sigma^2}\right\} \cdot \left|\frac{1}{a^*}\right|$$

$$= \text{LN}(a^* | \log a_i, \sigma^2)$$

The acceptance ratio is

$$r = \frac{p(y, a^*, b_i)}{p(y, a_i, b_i)} \times \frac{p_{a^*}(a^* | a_i)}{p_{a^*}(a_i | a^*)}$$

$$= \frac{p(y | a^*, b_i)}{p(y | a_i, b_i)} \frac{p(a^*) p(b_i)}{p(a_i) p(b_i)} \times \frac{p_{a^*}(a^* | a_i)}{p_{a^*}(a_i | a^*)}$$

$$= \frac{\prod_{j=1}^n \text{Gamma}(y_j | a^*, b_i)}{\prod_{j=1}^n \text{Gamma}(y_j | a_i, b_i)} \times \frac{\text{Gamma}(a^* | r, s)}{\text{Gamma}(a_i | r, s)} \times \frac{\text{LN}(a^* | \log a_i, \sigma^2)}{\text{LN}(a_i | \log a^*, \sigma^2)}$$

$$= \frac{\left(\prod_{j=1}^n \frac{b_i^{a^*}}{\Gamma(a^*)} y_j^{a^*-1} e^{-b_i y_j}\right)}{\left(\prod_{j=1}^n \frac{b_i^{a_i}}{\Gamma(a_i)} y_j^{a_i-1} e^{-b_i y_j}\right)} \times \frac{\frac{s^r}{\Gamma(r)} a^{r-1} e^{-sa^*}}{\frac{s^r}{\Gamma(r)} a_i^{r-1} e^{-sa_i}} \times \frac{\frac{1}{a^* \sqrt{2\pi}\sigma} \exp\left\{-\frac{(\log a^* - \log a_i)^2}{2\sigma^2}\right\}}{\frac{1}{a_i \sqrt{2\pi}\sigma} \exp\left\{-\frac{(\log a_i - \log a^*)^2}{2\sigma^2}\right\}}$$

$$= \frac{\frac{b_i^{na^*}}{\Gamma^{na^*}(a^*)} \left(\prod_{j=1}^n y_j\right)^{a^*-1}}{\frac{b_i^{na_i}}{\Gamma^{na_i}(a_i)} \left(\prod_{j=1}^n y_j\right)^{a_i-1}} \cdot \left(\frac{a^*}{a_i}\right)^{r-1} e^{-s(a^*-a_i)} \cdot \frac{a_i}{a^*}$$

$$= \frac{b_i^{n(a^*-a_i)}}{\frac{\Gamma^n(a^*)}{\Gamma^n(a_i)}} \left(\prod_{j=1}^n y_j \right)^{a^*-a_i} \left(\frac{a^*}{a_i} \right)^{r-2} e^{-s(a^*-a_i)}$$

• also, we need $p(b|y, a) = p(b|y)$.

$$\begin{aligned} p(b|y) &\propto p(y|b) p(b) = \left[\prod_{j=1}^n \text{Gamma}(y_j | a, b) \right] \text{Gamma}(u, v) \\ &= \left(\prod_{j=1}^n \frac{b^a}{\Gamma(a)} y_j^{a-1} e^{-by_j} \right) \left(\frac{v^n}{\Gamma(u)} b^{u-1} e^{-vb} \right) \\ &\propto \left(b^{na} e^{-b \sum y_j} \right) b^{u-1} e^{-vb} = b^{(u+na)-1} e^{-b(v + \sum y_j)} \\ &\propto \text{Gamma}(b | u+na, v + \sum_{j=1}^n y_j) \end{aligned}$$

The MH-within-Gibbs sampler is as follows:

1) Set initial starting point

• sample $a_1 \sim \text{Gamma}(r, s)$

2) Update b_i

• sample $b_i \sim \text{Gamma}(u+na_i, v + \sum_{j=1}^n y_j)$

3) Update a_i

• sample $a^* \sim \text{LN}(\log a_{i-1}, \sigma^2)$

• compute acceptance ratio r as derived above

• set $a_i = a^*$ with probability $\min(1, r)$ or
set $a_i = a_{i-1}$ with probability $\max(0, 1-r)$.

4) Repeat (2), (3) until sampler converges.