MCMC Algorithm Derivation

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Given XZ, k, the log likelihood and the composite likelihood are

$$\begin{split} \ell\left(\tau_{k}^{XZ^{2}},\mu_{k}^{XZ}\right) &= -\frac{1}{2}\sum_{i \in N_{XZ}^{k}} \left[\log\left(s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}\right) + \frac{\left(y_{k,i}^{XZ} - \mu_{k}^{XZ}\right)^{2}}{s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}}\right] \\ &= \sum_{i \in N_{XZ}^{k}} \left[\log\frac{1}{\sqrt{s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}}} - \frac{\left(y_{k,i}^{XZ} - \mu_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}\right)}\right] \\ L\left(\tau_{k}^{XZ^{2}},\mu_{k}^{XZ}\right) &= \left[\prod_{i \in N_{XZ}^{k}} \left(\frac{1}{\sqrt{s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}}}\right)\right] \cdot \exp\left(\sum_{i \in N_{k_{2}}^{k}} - \frac{\left(y_{k,i}^{XZ} - \mu_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}\right)}\right) \\ &= \left[\prod_{i \in N_{XZ}^{k}} \left(\frac{1}{\sqrt{s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}}}\right)\right] \cdot \exp\left(\sum_{i \in N_{X_{2}}^{k}} - \frac{\left(y_{k,i}^{XZ} - \mu_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}\right)}\right) - \sum_{i \in N_{k_{2}}^{k}} \frac{\left(\bar{y}_{k}^{XZ} - \mu_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}\right)}\right) \\ &= \left[\prod_{i \in N_{XZ}^{k}} \left(\frac{1}{\sqrt{s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}}}\right)\right] \cdot \exp\left(-\sum_{i \in N_{XZ}} \frac{\left(y_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}\right)}\right) \exp\left(-\sum_{i \in N_{XZ}} \frac{\left(\bar{y}_{k}^{XZ} - \mu_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}\right)}\right) \\ &= \left[\prod_{i \in N_{XZ}^{k}} \frac{1}{\sqrt{s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}}}\right] \cdot \exp\left[\sum_{i \in N_{k_{2}}} - \frac{\left(y_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{XZ} + \tau_{k}^{XZ}\right)}\right] \cdot \exp\left[\left(\bar{y}_{k}^{XZ} - \mu_{k}^{XZ}\right)^{2} \sum_{i \in N_{XZ}} \frac{1}{2\left(s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}\right)}\right] \right] \cdot \exp\left[\sum_{i \in N_{k_{2}}} - \frac{\left(y_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{XZ} + \tau_{k}^{XZ}\right)}\right] \cdot \exp\left[\left(\bar{y}_{k}^{XZ} - \mu_{k}^{XZ}\right)^{2} + \frac{1}{2\left(s_{k,i}^{XZ} + \tau_{k}^{XZ}\right)}\right] \cdot \exp\left[\sum_{i \in N_{k_{2}}} - \frac{\left(y_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{XZ} + \tau_{k}^{XZ}\right)}\right] \cdot \exp\left[\left(\bar{y}_{k}^{XZ} - \mu_{k}^{XZ}\right)^{2} + \frac{1}{2\left(s_{k,i}^{XZ} + \tau_{k}^{XZ}\right)}\right] \cdot \exp\left[\left(\bar{y}_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)^{2} + \frac{1}{2\left(s_{k,i}^{XZ} + \tau_{k}^{XZ}\right)}\right] \cdot \exp\left[\left(\bar{y}_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)^{2} + \frac{1}{2\left(s_{k,i}^{XZ} + \tau_{k}^{XZ}\right)}\right] \cdot \exp\left[\left(\bar{y}_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)^{2} + \frac{1}{2\left(s_{k,i}^{XZ} + \tau_{k}^{XZ}\right)}\right] \cdot \exp\left[\left(\bar{y}_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)\right]$$

where

$$\begin{split} n_k^{xz} &= \sum_{i \in N_{XZ}^k} \mathbb{1}_{i \in N_{XZ}^k} \\ \bar{y}_k^{xz} &= \frac{1}{n_{xz}^k} \sum_{i \in N_{XZ}^k} y_{k,i}^{xz} \end{split}$$

Let

$$\sum_{i \in N_{XZ}^k} \frac{1}{\left(s_{k,i}^{XZ} + \tau_k^{XZ^2}\right)} = \frac{n_{xz}^k}{\sigma_k^{XZ^2}}$$

Then the composite likelihood and marginal likelihood can also

$$\begin{split} L\left(\tau_{k}^{XZ^{2}},\mu^{XZ}\right) &= \left[\prod_{i \in N_{XZ}^{k}} \frac{1}{\sqrt{s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}}}\right] \exp\left[\sum_{i \in N_{Nk}^{k}} -\frac{\left(y_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{xz^{2}} + \tau_{k}^{XZ^{2}}\right)}\right] \exp\left[-\frac{n_{xz}^{k}}{2\sigma_{k}^{xz^{2}}}\left(\bar{y}_{xz}^{k} - \mu_{k}^{xz}\right)^{2}\right] \\ L\left(\tau_{k}^{XZ^{2}}\right) &= \int_{-\infty}^{\infty} L\left(\tau_{k}^{XZ^{z}},\mu_{k}^{XZ}\right) d\mu_{k}^{XZ} \\ &= \left[\prod_{i \in N_{XZ}^{k}} \frac{1}{\sqrt{s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}}}\right] \exp\left[\sum_{i \in N_{Nk}^{k}} -\frac{\left(y_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{xz^{2}} + \tau_{k}^{XZ^{2}}\right)}\right] \sqrt{\frac{2\pi\sigma_{k}^{xz^{2}}}{n_{xz}^{k}}} \int_{-\infty}^{\infty} \sqrt{\frac{n_{xz}^{k}}{2\pi\sigma_{k}^{xz^{2}}}} \exp\left[-\frac{n_{xz}^{k}}{2\sigma_{k}^{xz^{2}}}\left(\mu_{k}^{xz} - \bar{y}_{k}^{xz}\right)^{2}\right] \\ &= \left[\prod_{i \in N_{XZ}^{k}} \frac{1}{\sqrt{s_{k,i}^{XZ^{2}} + \tau_{k}^{XZ^{2}}}}\right] \exp\left[\sum_{i \in N_{Nk}^{k}} -\frac{\left(y_{k,i}^{XZ} - \bar{y}_{k}^{XZ}\right)^{2}}{2\left(s_{k,i}^{xz^{2}} + \tau_{k}^{XZ^{2}}\right)}\right] \sqrt{\frac{2\pi\sigma_{k}^{xz^{2}}}{n_{xz}^{k}}} \end{split}$$

Conditioning on $\tau_k^{XZ^2}$ and y, the posterior distribution of μ_k^{XZ} follows

$$\begin{split} p(\mu_k^{XZ} | \tau_k^{XZ^2}, y) &= \frac{P\left(\mu_k^{XZ}, \tau_k^{XZ^2}, y\right)}{P\left(\tau_k^{XZ^2}, y\right)} \\ &= \frac{p\left(y \mid \tau_k^{XZ^2}, \mu_k^{XZ}\right) \cdot P\left(\tau_k^{XZ^2}, \mu_k^{XZ}\right)}{p\left(\tau_k^{XZ^2}, y\right)} \\ &= \frac{P\left(y \mid \tau_k^{XZ^2}, \mu_k^{XZ}\right) P\left(\tau_k^{XZ^2}, \mu_k^{XZ}\right)}{P\left(y \mid \tau_k^{XZ^2}\right) P\left(\tau_k^{XZ^2}, \mu_k^{XZ}\right)} \\ &\propto \frac{L\left(\tau_k^{XZ^2}, \mu_k^{XZ}\right)}{L\left(\tau_k^{XZ^2}\right)} \\ &= \sqrt{\frac{n_{XZ}^k}{2\pi\sigma_k^{XZ^2}}} \exp\left[-\frac{n_{xz}^k}{2\sigma_k^{XZ^2}} \left(\bar{y}_{XZ}^k - \mu_k^{XZ}\right)^2\right] \end{split}$$

Conditioning on μ_k^{XZ} and y, the postier distribution of τ_k^{XZ} follows

$$\begin{split} p(\tau_k^{XZ^2} | \mu_k^{XZ}, y) &\propto P(y | \tau_k^{XZ^2}, \mu_k^{XZ}) P(\tau_k^{XZ^2}, \mu_k^{XZ}) \\ &\propto L\left(\tau_k^{XZ^2}, \mu_k^{XZ}\right) \left(\tau_k^{XZ}\right)^{-2} \\ &\propto \left[\prod_{i \in N_{XZ}^k} \left(\frac{1}{\sqrt{s_{k,i}^{XZ^2} + \tau_k^{XZ^2}}}\right)\right] \cdot \exp\left(\sum_{i \in N_{x_2}^k} -\frac{\left(y_{k,i}^{XZ} - \mu_k^{XZ}\right)^2}{2\left(s_{k,i}^{xz^2} + \tau_k^{XZ^2}\right)}\right) \left(\tau_k^{XZ}\right)^{-2} \end{split}$$

where

$$P\left(\tau_k^{XZ^2}, \mu_k^{XZ}\right) \propto \left(\tau_k^{XZ^2}\right)^{-1}$$

$$\frac{P\left(\tau_k^{XZ^2}, \mu_k^{XZ}\right)}{P\left(\tau_k^{XZ^2}\right)} \propto 1$$

We use Gibbs Sampler to sample μ_k^{XZ} and $\tau_k^{XZ^2}$ from the posterior distribution

Input: data y

Output: A realization of length N from a Markov Chain for $(\tau_k^{XZ}, \mu_k^{XZ})$

$$\begin{array}{ll} \text{for } k \in \{1,2\} \\ \text{for } XZ \in \{AB,AC,BC\} \\ \text{for } t = 1 \cdots N; \\ \text{sample } \mu_k^{XZ(p)} & \sim & N\left(\bar{y}_{XZ}^k, \frac{\left(\sigma_k^{XZ}\right)^2}{n_{xz}^k}\right) \text{ where } \frac{\left(\sigma_k^{XZ}\right)^2}{n_{xz}^k} = \frac{1}{\sum_{i \in N_{XZ}^k} \frac{1}{\left(s_{k,i}^{XZ} + \tau_k^{XZ^2}\right)}} \text{ and } \bar{y}_{xz}^k = \frac{1}{n_{xz}^k} \sum_{i \in N_{XZ}^k} y_{k,i}^{xz} \\ \text{sample } \tau_k^{XZ(p)} & \sim p\left(\tau_k^{XZ^2} | y, \mu_k^{XZ(p)}\right) \\ \tau_k^{XZ^2(t)} & = \tau_k^{XZ(p)} \\ \mu_k^{XZ(t)} & = \mu_k^{XZ(p)} \end{array}$$

We use Metropolis-Hasting algorithm to sample τ_k^{XZ} from $p(\tau_k^{XZ^2}|y,\mu_k^{XZ}).$

Input: data y

Output: A realization of length N from a Markov Chain for τ_k^{XZ} from $p(\tau_k^{XZ^2}|y)$

Propose
$$q\left(\tau_{k,t}^{XZ^2} | \tau_{k,t-1}^{XZ^2}\right) = N(\tau_{k,t-1}^{XZ^2}, 0.1)$$

 $\tau^{XZ^2} = 0.3$

$$\begin{split} \tau_{k,0}^{XZ^2} &= 0.3 \\ \text{for } t \text{ from 1 to } N : \\ \text{sample } \tau_{k,*}^{XZ^2} &\sim N(\tau_{k,t-1}^{XZ^2}, 0.1) \\ a &= \frac{P(\tau_{k,*}^{XZ^2}|y,\mu_k^{XZ})/q(\tau_{k,*}^{XZ^2}|\tau_{k,t-1}^{XZ^2})}{P(\tau_{k,t-1}^{XZ^2}|y,\mu_k^{XZ})/q(\tau_{k,t-1}^{XZ^2}|\tau_{k,*}^{XZ^2},)} \\ \text{if } runif(1) &< min(a,1) : \\ \tau_{k,t}^{XZ^2} &= \tau_{k,*}^{XZ^2} \\ \text{else:} \\ \tau_{k,t}^{XZ^2} &= \tau_{k,t-1}^{XZ^2} \end{split}$$