P8160 - Hurricane Project

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Given Information

The following Bayesian model was suggested.

$$Y_i(t+6) = \beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,i}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t) + \epsilon_i(t)$$

where $Y_i(t)$ the wind speed at time t (i.e. 6 hours earlier), $\Delta_{i,1}(t)$, $\Delta_{i,2}(t)$ and $\Delta_{i,3}(t)$ are the changes of latitude, longitude and wind speed between t and $t+6$, and $\epsilon_{i,t}$ follows a normal distributions with mean zero and variance σ^2, independent across t.

In the model, $\boldsymbol{\beta}_i = (\beta_{0,i}, \beta_{1,i}, ..., \beta_{7,i})$ are the random coefficients associated the ith hurricane, we assume that

$$\boldsymbol{\beta}_i \sim N(\boldsymbol{\beta}, \boldsymbol{\Sigma})$$

follows a multivariate normal distributions with mean $\boldsymbol{\beta}$ and covariance matrix Σ.

We assume the following non-informative or weak prior distributions for σ^2, $\boldsymbol{\beta}$ and Σ.

$$P(\sigma^2) \propto \frac{1}{\sigma^2}; \quad P(\boldsymbol{\beta}) \propto 1; \quad P(\Sigma^{-1}) \propto |\Sigma|^{-(d+1)} \exp(-\frac{1}{2}\Sigma^{-1})$$

d is dimension of β.

Task 1:

Let $\mathbf{B} = (\boldsymbol{\beta}_1^\top, ..., \boldsymbol{\beta}_n^\top)^\top$, derive the posterior distribution of the parameters $\Theta = (\mathbf{B}^\top, \boldsymbol{\beta}^\top, \sigma^2, \Sigma)$.

Note from given Bayesian model:

$$\epsilon_i(t) = Y_i(t+6) - \Big(\beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,i}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t)\Big) \overset{i.i.d}{\sim} N(0, \sigma^2)$$

or

$$Y_i(t+6) \overset{i.i.d}{\sim} N(\mu_i, \sigma^2)$$

where $\mu_i = \beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,1}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t)$. Therefore,

$$f_{Y_i(t+6)}(Y_i \mid \boldsymbol{\beta}_i, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp\Big\{-\frac{1}{2\sigma^2}\Big[Y_i(t+6) - \Big(\beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,i}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t)\Big)\Big]^2\Big\}$$

We can find the posterior distribution for Θ by

$$\pi(\mathbf{B}, \boldsymbol{\beta}, \sigma^2, \Sigma \mid Y_i) \propto f_{Y_i(t+6)}(Y_i \mid \boldsymbol{\beta}, \sigma^2) \times \pi(\mathbf{B}) \times \pi(\boldsymbol{\beta}) \times \pi(\sigma^2) \times \pi(\Sigma),$$

where $\pi(\mathbf{B})$ is the joint multivariate normal density of β,

$$\pi(\mathbf{B}) = \prod_{i=1}^{n} \det(2\pi\Sigma)^{-\frac{1}{2}} \exp(-\frac{1}{2}(\boldsymbol{\beta}_i - \boldsymbol{\beta})^\top \Sigma^{-1}(\boldsymbol{\beta}_i - \boldsymbol{\beta})).$$

So we have the following posterior distribution, from which we can derive conditional posteriors to perform Gibbs sampling.

$$\pi(\mathbf{B}, \boldsymbol{\beta}, \sigma^2, \Sigma \mid Y_i) \propto \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi}\sigma} \exp\Big\{ -\frac{1}{2\sigma^2}\Big(Y_i(t+6) - \mu_i\Big)^2\Big\}$$

$$\times \prod_{i=1}^{n} \det(2\pi\Sigma)^{-\frac{1}{2}} \exp\Big(-\frac{1}{2}(\boldsymbol{\beta}_i - \boldsymbol{\beta})^\top \Sigma^{-1}(\boldsymbol{\beta}_i - \boldsymbol{\beta})\Big) \times \frac{1}{\sigma^2} \times |\Sigma|^{-(d+1)} \exp(-\frac{1}{2}\Sigma^{-1})$$

To find the conditional posterior distributions for Gibbs sampling, we can consider:

$$\pi(\boldsymbol{\beta} \mid \mathbf{B}, \sigma^2, \Sigma, Y_i) = \frac{\pi(\beta, \mathbf{B}, \sigma^2, \Sigma \mid Y_i)}{\pi(\mathbf{B}, \sigma^2, \Sigma)}.$$

In the equation above, $\pi(\mathbf{B}, \sigma^2, \Sigma)$ only depends on $\mathbf{B}, \sigma^2, \Sigma$, so we can focus only on the part of the joint posterior that depends on all four variables β, $\mathbf{B}$, σ^2, and Σ.

$$\pi(\boldsymbol{\beta} \mid \mathbf{B}, \sigma^2, \Sigma, Y_i) \propto ...$$

Old work (I think incorrect, above is better approach)

$$\pi(\boldsymbol{\beta} \mid Y_i) \propto f_{Y_i(t+6)}(Y_i \mid \boldsymbol{\beta}, \sigma^2) \times \pi(\boldsymbol{\beta}) \times \pi(\sigma^2)$$

$$\Rightarrow \pi(\boldsymbol{\beta} \mid Y_i) \propto \frac{1}{\sqrt{2\pi}\sigma^3} \exp\Big\{ -\frac{1}{2\sigma^2}(Y_i(t+6) - \Big(\beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,1}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t)\Big)\Big\}$$

with joint likelihood

$$\pi(\boldsymbol{\beta} \mid Y_i) \propto \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi}\sigma^3} \exp\Big\{ -\frac{1}{2\sigma^2}(Y_i(t+6) - \Big(\beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,1}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t)\Big)\Big\}$$

$$\log \pi(\boldsymbol{\beta} \mid Y_i) \propto \sum_{i=1}^{n} -\frac{1}{2}\log(2\pi) - 3\log\sigma - -\frac{1}{2\sigma^2}(Y_i(t+6) - (\beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,1}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t))$$

Please, feel free to make edits or add work to this.

For $\mathbf{B}$, maybe we try something like this:

$$\pi(\mathbf{B} \mid \boldsymbol{\beta}_i) \propto f_{\mathbf{B}}(\mathbf{B} \mid \boldsymbol{\beta}_i, \Sigma^{-1}) \times \pi(\boldsymbol{\beta}_i) \times \pi(\Sigma^{-1})$$

Since, $\beta_i \sim N(\boldsymbol{\beta}, \Sigma)$,

$$f_{\mathbf{B}}(\mathbf{B} \mid \boldsymbol{\beta}_i, \Sigma^{-1}) = \prod_{i=1}^{n} \det(2\pi\Sigma)^{-\frac{1}{2}} \exp(-\frac{1}{2}(\boldsymbol{\beta}_i - \boldsymbol{\beta})^\top \Sigma^{-1}(\boldsymbol{\beta}_i - \boldsymbol{\beta}))$$

The above is the pdf for a multivariate normal distribution, but I am not sure if we use this here. My thinking is that $\mathbf{B}$ is joint multivariate normal for all independent (could be incorrect assumption) β_i. But this might actually be the distribution for $\pi(\boldsymbol{\beta}_i)$.