

Poisson Regression

Model: $y_i \sim \text{Pois}(\lambda_i)$, $i = 1, \dots, n$

$$\log \lambda_i = \underline{x}_i' \underline{\beta}$$

$$\underline{\beta} \sim N(\underline{\mu}_{\beta}, \underline{\Sigma}_{\beta})$$

Posterior:

$$[\underline{\beta} | \underline{y}] \propto [\underline{y} | \underline{\beta}] [\underline{\beta}]$$

$$\propto \left(\prod_{i=1}^n \frac{(e^{\underline{x}_i' \underline{\beta}})^{y_i} e^{-e^{\underline{x}_i' \underline{\beta}}}}{y_i!} \right) \exp \left\{ -\frac{1}{2} (\underline{\beta} - \underline{\mu}_{\beta})' \underline{\Sigma}_{\beta}^{-1} (\underline{\beta} - \underline{\mu}_{\beta}) \right\}$$

Use M-H w/ block random walk proposals for $\underline{\beta}$.

MCMC Algorithm:

- 1.) Set $\underline{\beta}^{(0)}$, $k=0$
- 2.) $k = k+1$
- 3.) Sample $\underline{\beta}^{(*)} \sim N(\underline{\beta}^{(k-1)}, \sigma_{\text{tune}}^2 \mathbf{I})$
- 4.) Let $\underline{\beta}^{(k)} = \underline{\beta}^{(*)}$ w.p. $\min \left(\frac{[\underline{y} | \underline{\beta}^{(*)}] [\underline{\beta}^{(*)}]}{[\underline{y} | \underline{\beta}^{(k-1)}] [\underline{\beta}^{(k-1)}]}, 1 \right)$
and $\underline{\beta}^{(k)} = \underline{\beta}^{(k-1)}$ otherwise
- 5.) goto 2, until $k=K$.

Model Checking:

We can use posterior prediction to check if model is capable of generating observed data.

Posterior Predictive P-value:

prediction characteristic to check

$$P(f(\tilde{y}) \geq f(y) | y) =$$

posterior pred. distn

$$= \int \mathbb{1}_{\{f(\tilde{y}) \geq f(y)\}} [\tilde{y} | y] d\tilde{y}$$

prod. full-cond. posterior

$$= \int \int \mathbb{1}_{\{f(\tilde{y}) \geq f(y)\}} [\tilde{y} | \theta, y] [\theta | y] d\theta d\tilde{y}$$

note: extreme p-values suggest data are unlikely to arise from model.

With MCMC:

1.) Sample $\theta^{(k)} \sim [\theta | y]$ as usual w/ MCMC

2.) Sample $\tilde{y}^{(k)} \sim [\tilde{y} | \theta^{(k)}, y]$

3.) compute $f(\tilde{y}^{(k)})$

4.) compute $\mathbb{1}_{\{f(\tilde{y}^{(k)}) \geq f(y)\}}$

5.) $P(f(\tilde{y}) \geq f(y) | y) = \frac{\sum_{k=1}^K \mathbb{1}_{\{f(\tilde{y}^{(k)}) \geq f(y)\}}}{K}$

Example: $f(y) = \frac{\sum_{i=1}^n (y_i - E(y_i | \theta))^2}{n}$ (MSE)

Negative Binomial Regression :

$$y_i \sim NB(\mu_i, N) = \frac{\Gamma(y_i + N)}{\Gamma(N) y_i!} \left(\frac{N}{N + \mu_i}\right)^N \left(1 - \frac{N}{N + \mu_i}\right)^{y_i}$$

$$\log(\mu_i) = \underline{x}_i' \beta$$

$$\beta \sim N(\underline{\mu}_\beta, \Sigma_\beta)$$

$$\log(N) \sim N(\mu_N, \sigma_N^2)$$

Posterior :

$$[\beta, \log(N) | y] \propto [y | \beta, \log N] [\beta] [\log N]$$

Full - conditional distns :

$$[\beta | \cdot] \propto \left(\prod_{i=1}^n [y_i | \beta, \log N] \right) [\beta]$$

$$[\log N | \cdot] \propto \left(\prod_{i=1}^n [y_i | \beta, \log N] \right) [\log N]$$

MCMC Algorithm :

1.) Set $\beta^{(0)}, \log N^{(0)}, k=0$

2.) $k = k + 1$

3.) Use M-H to update β w/ $\beta^{(k)} \sim N(\beta^{(k-1)}, \sigma_{\beta}^2 I)$

4.) Use M-H to update $\log N$ w/ $\log N^{(k)} \sim N(\log N^{(k-1)}, \sigma_{\log N}^2)$

5.) Goto 2, until $k=K$.