

# STA 601 - Homework 5

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In the first Two Parts of the Assignment, we got the following expressions,

Model for Data:

$$y_i \sim \text{Poisson}(\lambda\gamma^{x_i})$$

Priors:

$$\begin{aligned}\lambda &\sim \text{Gamma}(1, 1) \\ \gamma &\sim \text{Gamma}(1, 1) \\ p(\lambda, \gamma) &= p(\lambda)p(\gamma).\end{aligned}$$

Likelihood:

$$L(\mathbf{y}; \lambda, \gamma) = C(\mathbf{y})\lambda^{\sum_{i=1}^n y_i}\gamma^{\sum_{i=1}^n y_i x_i} \prod_{i=1}^n \exp(-\lambda\gamma^{x_i})$$

Full Conditionals:

$$\begin{aligned}\lambda|\gamma, \mathbf{y} &\sim \text{Gamma}\left(\sum_{i=1}^n y_i + 1, \sum_{i=1}^n \gamma^{x_i} + n\right). \\ \gamma|\lambda, \mathbf{y} &\sim \text{Gamma}\left(\sum_{i=1}^n y_i x_i + 1, \lambda m + 1\right).\end{aligned}$$

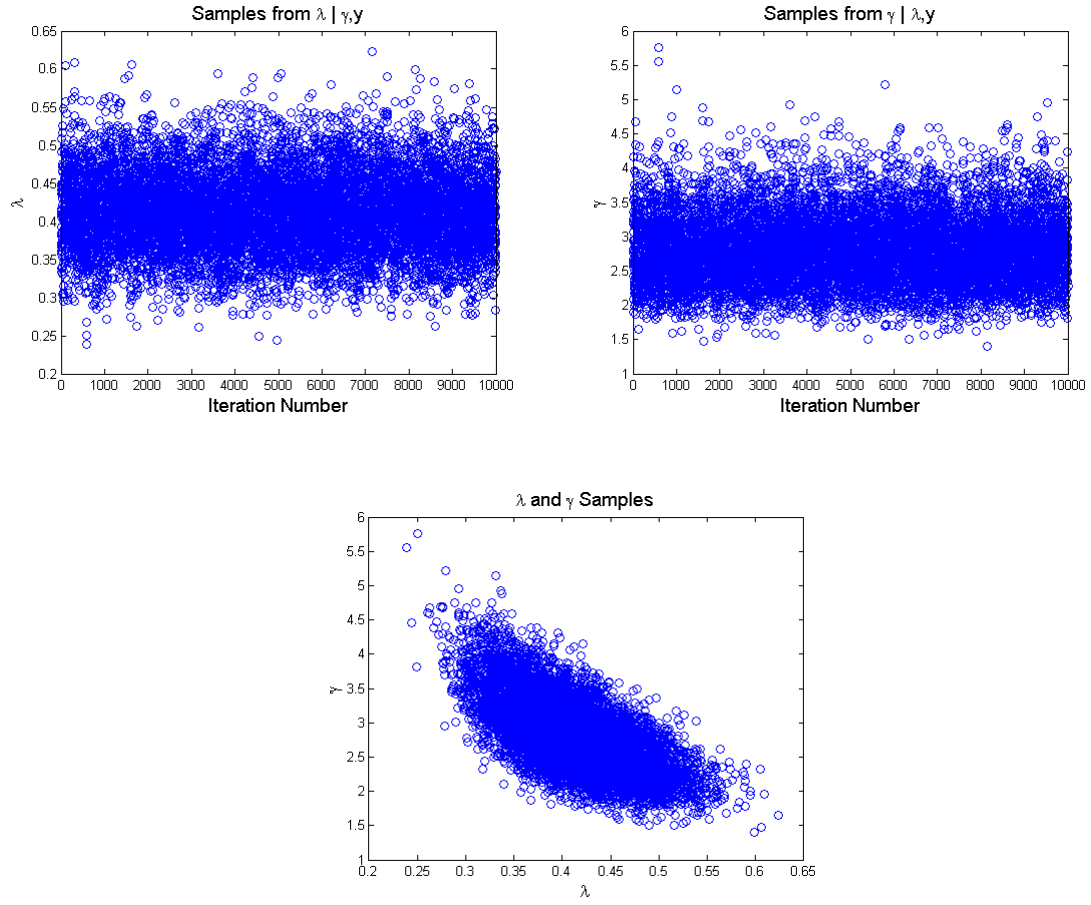
where, m is the number of treated subjects.

To sample from the Joint Posterior we can do Gibbs Sampling:

- Select,  $\gamma^{(0)}$ ,
- Draw,  $\lambda^{(1)} \sim p(\lambda|\gamma^{(0)}, \mathbf{y})$
- Draw,  $\gamma^{(1)} \sim p(\gamma|\lambda^{(1)}, \mathbf{y})$
- Hence, we get  $\{\lambda^{(1)}, \gamma^{(1)}\}$ .
- Repeat.

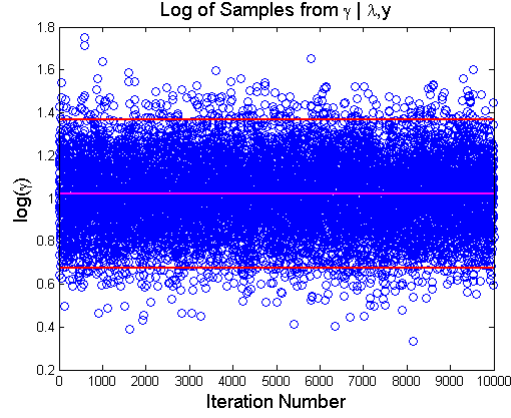
### 3. Simulation:

We can get sample data from  $y_i \sim \text{Poisson}(\lambda\gamma^{x_i})$ , using  $\lambda = \gamma = 1$ . For the both  $x_i = 0$  and  $x_i = 1$ , the Poisson parameter,  $\lambda\gamma^{x_i} = 1$ . The following are trace plots of the samples from the Full Conditional Distributions.



4.(i) Estimation of  $\log(\gamma)$  :

Using the samples of  $\gamma$  from previous step, I get Posterior Mean of  $\log(\gamma) = 1.0198$ . 95% Credible Intervals=[0.6758 1.3684]. The mean is indicated in magenta in the following figure, and the credible intervals in red.



4.(ii) Posterior Predictive Distribution  $p(\tilde{y}|\mathbf{y})$ :

This can be written as,

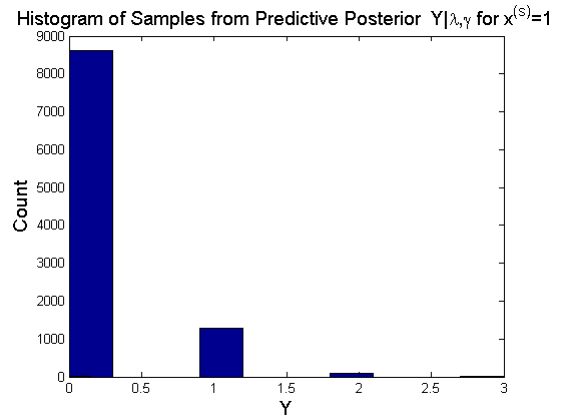
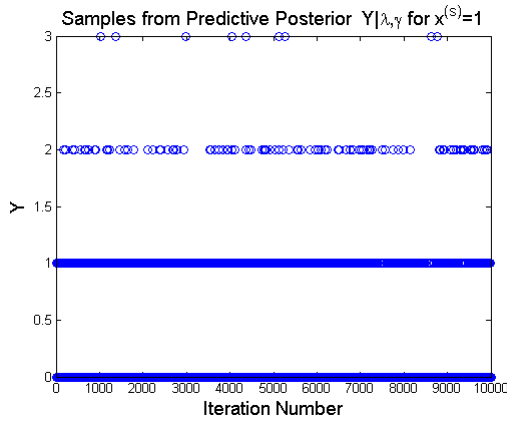
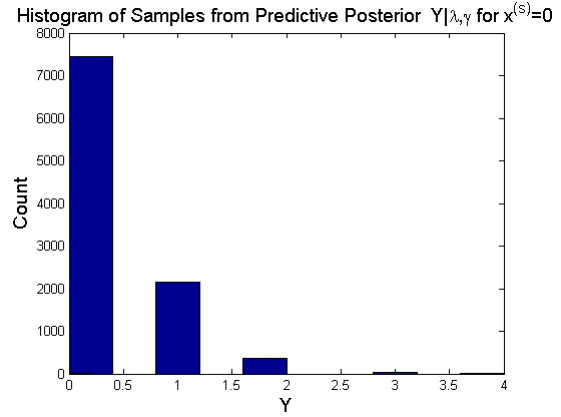
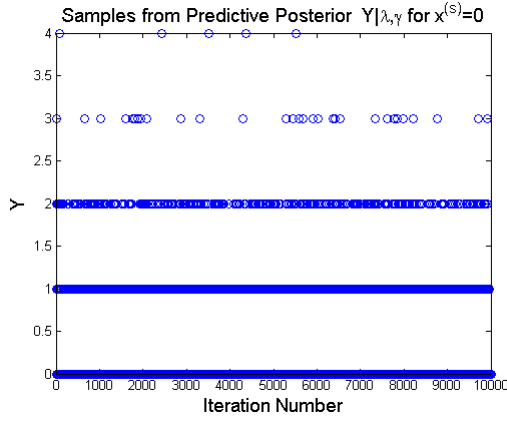
$$\begin{aligned} p(\tilde{y}|\mathbf{y}) &= \int \int p(\tilde{y}|\lambda, \gamma, \mathbf{y}) p(\lambda|\gamma, \mathbf{y}) p(\gamma|\lambda, \mathbf{y}) d\lambda d\gamma \\ &= \int \int p(\tilde{y}|\lambda, \gamma) p(\lambda|\gamma, \mathbf{y}) p(\gamma|\lambda, \mathbf{y}) d\lambda d\gamma \end{aligned}$$

We can estimate the predictive posterior, as follows:

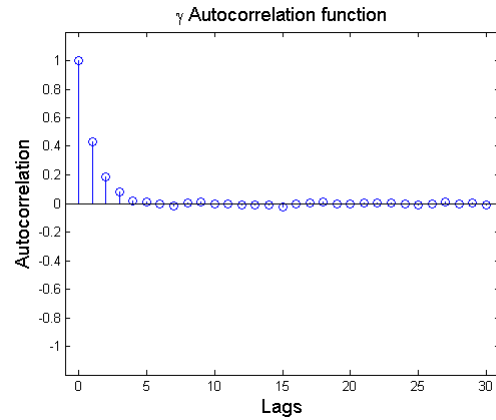
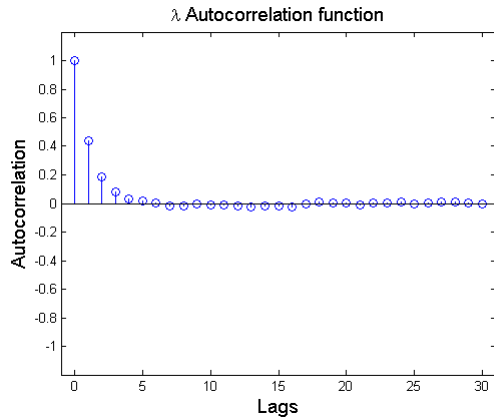
- Select,  $\gamma^{(0)}$ ,
- Draw,  $\lambda^{(1)} \sim p(\lambda|\gamma^{(0)}, \mathbf{y})$
- Draw,  $\gamma^{(1)} \sim p(\gamma|\lambda^{(1)}, \mathbf{y})$
- Using,  $\{\lambda^{(1)}, \gamma^{(1)}\}$ , draw  $\tilde{y}^{(1)} \sim \text{Poisson}(\lambda\gamma^{x_i})$
- Repeat.

Depending on the value of  $x^{(s)}$ , we have different Posterior Predictors,  
 $x^{(s)} = 0, \tilde{y}^{(s)} \sim \text{Poisson}(\lambda)$ .  
 $x^{(s)} = 1, \tilde{y}^{(s)} \sim \text{Poisson}(\lambda\gamma)$ .

The following are trace plots and histograms, with sampling.



5. Convergence Diagnostics: Given below are Autocorrelation function plots for  $\lambda$  and  $\gamma$  samples. We can see that it drops as number of lags increase. This does indicate that we have good mixing in the chain. Also, the mixing in  $\lambda$  and  $\gamma$  is quite similar.



Sample Size:

The effective sample size can be computed by using the formula,  $S_{eff} = Var[\phi]/Var_{MCMC}[\tilde{\phi}]$ .