The model:

• First level:  $X_{ij} \sim Poisson(\lambda_{ij} * E_{ij})$ 

where  $E_{ij}$  is the expected count of drug i and adverse event j and  $N_{ij}$  is the observed count. For simplicity in this demonstration, let's assume  $E_{ij} = 1$ , so

$$X_{ij} \sim Poisson(\lambda_{ij})$$

• Second level:  $\lambda_{ij} \sim Mixture \ of \ 2 \ gamma \ distributions$  with pdf:

$$\pi(\lambda; \alpha_1, \beta_1, \alpha_2, \beta_2, p) = pg(\lambda; \alpha_1, \beta_1) + (1 - p)g(\lambda; \alpha_2, \beta_2), \ \alpha_1, \beta_1, \alpha_2, \beta_2 > 0, 0 \le p \le 1$$

where  $g(\lambda; \alpha_1, \beta_1)$  and  $g(\lambda; \alpha_2, \beta_2)$  are the probability density functions of the Gamma Distribution with shape parameters  $\alpha_1, \alpha_2$  and scale parameters  $\beta_1, \beta_2$ , and p is the weight of the first distribution.  $\alpha_1, \beta_1, \alpha_2, \beta_2, p$  are estimated from the data (Empirical Bayes).

We already know that the marginal distribution of X follows a mixture of 2 negative binomial distributions. We also know that  $\lambda | X \sim \pi(\lambda; \alpha_1 + X, \beta_1 + 1, \alpha_2 + X, \beta_2 + 1, p)$ . But let's ignore these truths and use Gibbs Sampling and MH algorithm to simulate X and  $\lambda$  and compare with the true distributions.

- 1. Gibbs Sampling steps:
- Choose arbitrary  $X_1$  and  $\lambda_1$
- For each t = 2, 3, 4, etc.:
  - o Draw  $X_t$  from  $Poisson(\lambda_{t-1})$
  - Draw  $\lambda$  from posterior distribution of  $\lambda$  given  $X_t$ :

$$\lambda | X_{t-1} \sim \frac{\pi(\lambda; \alpha_1, \beta_1, \alpha_2, \beta_2, p) * \frac{e^{-\lambda} \lambda^X}{X!}}{\sum_{\lambda=1}^{\infty} \pi(\lambda; \alpha_1, \beta_1, \alpha_2, \beta_2, p) * \frac{e^{-\lambda} \lambda^X}{X!}}$$

We numerically estimate the Cumulative Distribution function and then use inversion method to draw  $\lambda$ 

This was done for 4 sequences with 4 initial points  $(X, \lambda) = (1,1), (1,10), (10,1), (10,1)$  and we use Potential Scale Reduction to determine convergence.

2. Metropolis – Hastings algorithm steps:

I tried different proposal functions such as Binomial, Geometric, discrete Uniform for X and Gamma, continuous Uniform for  $\lambda$ . It turned out discrete Uniform for X and continuous Uniform for  $\lambda$  works the best.

Steps:

- Choose arbitrary  $X_1$  and  $\lambda_1$
- For each t = 2, 3, 4, etc.:
  - O Draw  $\lambda^*$  from Continuous Uniform(0,30), draw  $X^*$  from Discrete Uniform(0,30)
  - o Calculate the density ratio:

$$\alpha = \frac{\pi(\lambda^*;\alpha_1,\beta_1,\alpha_2,\beta_2,p) * \frac{e^{-\lambda^*}\lambda^{X^*}}{X^*!}}{\pi(\lambda_{t-1};\alpha_1,\beta_1,\alpha_2,\beta_2,p) * \frac{e^{-\lambda_{t-1}\lambda^{X_{t-1}}}}{X_{t-1}!}}$$

- Accept/Reject proposal: set  $X_t = X^*$  and  $\lambda_t = \lambda^*$  with probability min( $\alpha$ , 1), otherwise  $X_t = X_{t-1}$  and  $\lambda_t = \lambda_{t-1}$
- This was done for 4 sequences with 4 initial points  $(X, \lambda) = (1,1), (1,10), (10,1), (10,1)$  and we use Potential Scale Reduction to determine convergence.