

1. Background parameterization

Link two parameterization of gamma distribution

$$\begin{aligned} \text{gamma}(x) = g_1(c, s) &= \frac{1}{\Gamma(c)s^c} x^{c-1} e^{-\frac{x}{s}} = \frac{\left(\frac{x}{s}\right)^{c-1} e^{-\frac{x}{s}}}{s\Gamma(c)} \\ &= g_2(\mu, \sigma) = \frac{1}{(\sigma^2\mu)^{1/\sigma^2}} \frac{y^{(1/\sigma^2-1)} \exp\left(-\frac{x}{\sigma^2\mu}\right)}{\Gamma\left(1/\sigma^2\right)} \end{aligned} \quad (0.1)$$

to link the two function, we have

$$\begin{cases} c = 1/\sigma^2 \\ s = \sigma^2\mu \end{cases} \Leftrightarrow \begin{cases} \sigma^2 = 1/c \\ \mu = sc \end{cases} \quad (0.2)$$

Then we have in general the function:

$$g_1(c, s) = g_2(\mu, \sigma) = g_1\left(\frac{1}{\sigma^2}, \sigma^2\mu\right) = g_2\left(sc, \sqrt{1/c}\right) \quad (0.3)$$

Some properties of gamma distribution: convolutions:

$$f_{X_1}(x) = g_1(c_1, s), f_{X_2}(x) = g_1(c_2, s) \Leftrightarrow f_{X_1+X_2}(x) = g_1(c_1 + c_2, s) \quad (0.4)$$

$$f_{X_k}(x) = g_1(c_k, s) \Leftrightarrow f_{\sum X_k}(x) = g_1\left(\sum c_k, s\right) \quad (0.5)$$

Equations (0.4) and (0.5) are well known but not directly interpretable. Let set them into mean and variance format as

$$f_{X_k}(x) = g_1(c_k, s) = g_2\left(sc_k, \sqrt{1/c_k}\right) \Leftrightarrow f_{\sum X_k}(x) = g_1\left(\sum c_k, s\right) = g_2\left(s\sum c_k, \sqrt{\frac{1}{\sum c_k}}\right) \quad (0.6)$$

2. using Poisson-gamma Mixture to sample the mutation rate heterogeneity among samples

Suppose $y_i^{d,s}$ and $\lambda_i^{d,s}$ denote the mutation count and mutation rate for bin i , disease d and sample s . S_d represents the number of sample in disease d . We assume that the conditional distribution of $y_i^{d,s}$ follows a Poisson distribution with PMF.

$$P\{y_i^{d,s} | \lambda_i^{d,s}\} = \frac{(\lambda_i^{d,s})^{y_i^{d,s}} \exp\{-\lambda_i^{d,s}\}}{(y_i^{d,s})!} \quad (1)$$

When these samples are independent, we pool the samples from the same disease by

$$y_i^d = \sum_{s=1}^{S_d} y_i^{d,s} \quad (2)$$

When $\lambda_i^{d,s}$ is fixed (nonrandom but still can be different, and no conditional needed), the PMF of y_i^d can be written into

$$P\{y_i^d\} = \frac{\left(\sum_{s=1}^{S_d} \lambda_i^{d,s}\right)^{y_i^d} \exp\left\{-\left(\sum_{s=1}^{S_d} \lambda_i^{d,s}\right)\right\}}{(y_i^d)!} \quad (3).$$

Specifically, in a constant rate assumption, $\lambda_i^{d,s} \triangleq \lambda$, the equation (3) can be written as

$$P\{y_i^d\} = \frac{(S_d \lambda)^{y_i^d} \exp(-S_d \lambda)}{(y_i^d)!} \quad (4).$$

Now in our model, we assume that **When $\lambda_i^{d,s}$ i.i.d gamma random variables**, and its distribution is

$$p(\lambda_i^{d,s} = x) = \left(\frac{x}{s}\right)^{c-1} \frac{\exp\left(-\frac{x}{s}\right)}{\{s\Gamma(c)\}} = g_1(s, c) \quad (5).$$

Then we have the distribution of pooled mutation rate as

$$p(\lambda_i^d = x) = p\left(\sum_{s=1}^{S_d} \lambda_i^{d,s} = x\right) \sim \left(\left(\frac{x}{s}\right)^{nc-1} \frac{\exp\left(-\frac{x}{s}\right)}{\{s\Gamma(nc)\}}\right) = g_1(nc, s) \quad (6).$$

We may rewrite (3) with the λ_i^d (**random variable**) as

$$P\{y_i^d | \lambda_i^d\} = \frac{(\lambda_i^d)^{y_i^d} \exp(-\lambda_i^d)}{(\lambda_i^d)!} \quad (7).$$

Putting (6) & (7) together we have

$$P(y_i^d = y) = \left(\frac{1}{1+s}\right)^{nc} \frac{\Gamma(nc+y)}{\Gamma(nc)y!} \left(\frac{s}{1+s}\right)^y \quad (8).$$

Then the mean and variance can be expressed by $E(y) = nsc$ and $\text{var}(y) = nsc(1+s) = (1+s)E(y)$.

Let

$$\begin{cases} 1/\sigma' = nc \\ s = \sigma'\mu' \end{cases} \Leftrightarrow \begin{cases} c = 1/(n\sigma') \\ s = \sigma'\mu' \end{cases} \Leftrightarrow \begin{cases} \sigma' = 1/(nc) \\ \mu' = nsc \end{cases} \quad (9)$$

Put (9) into (8), we can re-parameterize our NBI distribution using $\hat{\mu}$ and $\hat{\sigma}$ notations as

$$p(y_i^d = y | \mu', \sigma') = \frac{\Gamma(y+1/\sigma')}{\Gamma(1/\sigma')y!} \left(\frac{\sigma'\mu'}{1+\sigma'\mu'}\right)^y \left(\frac{1}{1+\sigma'\mu'}\right)^{(1/\sigma')} \quad (10).$$

It can be regarded as a Poisson-gamma mixture distribution with

$$P(Y|\mu\gamma), \gamma \sim g_2(1, \sqrt{\sigma})$$

$$P(Y|\lambda), \lambda \sim g_2(\mu, \sqrt{\sigma}) = g_2(nsc, \sqrt{1/(nc)}) = g_1(nc, s) \quad (11).$$

It means that the gamma distribution goes $g_1(c, s) \Rightarrow g_1(nc, s)$, or $g_2(sc, \sqrt{1/c}) \Rightarrow g_2(nsc, \sqrt{1/(nc)})$ before and after integral across samples.