

## Negative Binomial Models

The negative binomial distribution can be expressed with two parameters  $r$  and  $b$  with mean  $rb$  and variance  $rb(1+b)$ . The log of the probability of  $k$  events is:

$$\log(p_k) = \sum_{i=0}^{k-1} \log(r+i) + k \log(b) - \log(k!) - (r+k) \log(1+b)$$

When the mean is expressed as a function of the parameters of a model,  $r$  can be replaced by  $m/b$ , or  $b$  can be replaced by  $m/r$ . These give two somewhat different effects. In the first case, with parameters  $m$  and  $b$ , the mean is  $m$  and the variance is  $m(1+b)$ , and so is proportional to the mean. In the second case, with parameters  $m$  and  $r$ , the mean is still  $m$ , but now the variance is  $m(1+m/r)$ , which is quadratic in the mean. The latter form is a member of the exponential family, and is used in GLM. The former is more like a Poisson with over-dispersion, with the variance a multiple of the mean.

For MLE, the derivative of the log probability with respect to  $m$  is needed. In the  $m,b$  case where  $r$  is replaced by  $m/b$  this is:

$$-\frac{\log(1+b)}{b} + \sum_{i=0}^{k-1} \frac{1}{m+bi}$$

For the  $m,r$  GLM case where  $b$  is replaced by  $m/r$  it is:

$$\frac{k}{m} - \frac{r+k}{r+m}$$

In the mortality study,  $k = D_{w,d}$  is the number of deaths in the  $w,d$  cell and  $m = m_{w,d}E_{w,d}$ . Then in the  $m,b$  case:

$$\frac{\partial L_{w,d}}{\partial m_{w,d}} = -E_{w,d} \frac{\log(1+b)}{b} + \sum_{i=0}^{D_{w,d}-1} \frac{1}{m_{w,d}E_{w,d} + bi}$$

In the  $m,r$  case:

$$\frac{\partial L_{w,d}}{\partial m_{w,d}} = \frac{D_{w,d}}{m} - \frac{r + D_{w,d}}{r/E_{w,d} + m}$$