

# Multinomial Distribution

**Table 1.** The multinomial distribution as a statistical model for the vector of observed proportions  $\mathbf{y}$ , given the predicted proportions  $\mathbf{p}$  and the sample size  $n$ .

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$$\mathbf{v} \sim \mathcal{M}(\mathbf{p}, n) \tag{T1.1}$$

$$\mathbf{y} = \frac{\mathbf{v}}{\sum_{j=1}^g v_j} = \frac{\mathbf{v}}{n} \tag{T1.2}$$

$$P(\mathbf{y} | \mathbf{p}, n) = \frac{n!}{(ny_1)!(ny_2)! \dots (ny_g)!} \prod_{i=1}^g p_i^{ny_i} \tag{T1.3}$$

$$\ell(\mathbf{p} | \mathbf{y}, n) = -n \sum_{i=1}^g y_i \log p_i \tag{T1.4}$$

$$E[y_i] = p_i \tag{T1.5}$$

$$\text{Var}[y_i] = \frac{p_i(1-p_i)}{n} \tag{T1.6}$$

$$\text{Cov}[y_i, y_j] = -\frac{p_i p_j}{n} \quad \text{for } i \neq j \tag{T1.7}$$

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## Dirichlet Distribution

**Table 2.** The Dirichlet distribution as a statistical model for the vector of observed proportions  $\mathbf{y}$ , given the predicted proportions  $\mathbf{p}$  and an effective sample size  $n$ . The model applies when  $\mathbf{y}$  comes from the composition (T2.2) of independent variates (T2.1) drawn from gamma distributions with a common scale parameter  $n > 0$ . The approximate modal estimate  $\hat{n}$  in (T2.5) depends on Stirling's approximation to the gamma function.

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$$v_i \sim \mathcal{G}(\text{shape} = np_i, \text{scale} = n) \quad (\text{T2.1})$$

$$y_i = \frac{v_i}{\sum_{j=1}^g v_j} \quad (\text{T2.2})$$

$$P(\mathbf{y} | \mathbf{p}, n) = \frac{\Gamma(n)}{\Gamma(np_1)\Gamma(np_2)\dots\Gamma(np_g)} \prod_{i=1}^g y_i^{np_i-1} \quad (\text{T2.3})$$

$$\ell(\mathbf{p}, n | \mathbf{y}) = \sum_{i=1}^g [\log \Gamma(np_i) - np_i \log y_i] - \log \Gamma(n) \quad (\text{T2.4})$$

$$\hat{n} \approx \frac{g-1}{2} \left( \sum_{i=1}^g p_i \log \frac{p_i}{y_i} \right)^{-1} \quad (\text{T2.5})$$

$$E[y_i] = p_i \quad (\text{T2.6})$$

$$\text{Var}[y_i] = \frac{p_i(1-p_i)}{n+1} \quad (\text{T2.7})$$

$$\text{Cov}[y_i, y_j] = -\frac{p_i p_j}{n+1} \quad \text{for } i \neq j \quad (\text{T2.8})$$

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## Logistic-Normal Distribution

**Table 3.** The logistic-normal distribution as a statistical model for the vector of observed proportions  $\mathbf{y}$ , given the predicted proportions  $\mathbf{p}$  and a standard deviation  $\sigma$ . The model applies when  $\mathbf{y}$  comes from the logistic transformation (T3.2) of independent variates (T3.1) drawn from normal distributions with a common standard deviation  $\sigma$ . Calculations involve the geometric means  $\tilde{y}$  and  $\tilde{p}$  of  $\mathbf{y}$  and  $\mathbf{p}$ , respectively. The modal estimate  $\hat{\sigma}$  in (T3.5) is exact. The approximations (T3.9)–(T3.11) apply when  $\sigma$  is small.

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$$u_i = \log p_i + \sigma \varepsilon_i \quad \text{where } \varepsilon_i \sim \mathcal{N}(0,1) \quad (\text{T3.1})$$

$$y_i = \frac{e^{u_i}}{\sum_{j=1}^g e^{u_j}} \quad (\text{T3.2})$$

$$P(\mathbf{y} | \mathbf{p}, \sigma) = \left( \frac{1}{\sqrt{2\pi} \sigma} \right)^{g-1} \left( \sqrt{g} \prod_{i=1}^g y_i \right)^{-1} \exp \left[ -\frac{1}{2\sigma^2} \sum_{i=1}^g \left( \log \frac{y_i}{\tilde{y}} - \log \frac{p_i}{\tilde{p}} \right)^2 \right] \quad (\text{T3.3})$$

$$\ell(\mathbf{p}, \sigma | \mathbf{y}) = (g-1) \log \sigma + \frac{1}{2\sigma^2} \sum_{i=1}^g \left( \log \frac{y_i}{\tilde{y}} - \log \frac{p_i}{\tilde{p}} \right)^2 \quad (\text{T3.4})$$

$$\hat{\sigma}^2 = \frac{1}{g} \sum_{i=1}^g \left( \log \frac{y_i}{\tilde{y}} - \log \frac{p_i}{\tilde{p}} \right)^2 \quad (\text{T3.5})$$

$$E[\log(y_i/y_j)] = \log(p_i/p_j) \quad (\text{T3.6})$$

$$\text{Var}[\log(y_i/y_j)] = 2\sigma^2 \quad \text{for } i \neq j \quad (\text{T3.7})$$

$$\text{Cov}[\log(y_i/y_k), \log(y_j/y_k)] = \sigma^2 \quad \text{for } i \neq j \neq k \neq i \quad (\text{T3.8})$$

$$E[y_i] \approx p_i \quad (\text{T3.9})$$

$$\text{Var}[y_i] \approx \sigma^2 p_i^2 \left( 1 - 2p_i + \sum_{i=1}^g p_i^2 \right) \quad (\text{T3.10})$$

$$\text{Cov}[y_i, y_j] \approx -\sigma^2 p_i p_j \left( p_i + p_j - \sum_{i=1}^g p_i^2 \right) \quad \text{for } i \neq j \quad (\text{T3.11})$$


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