

October 12, 2023

R-code

```
> source( "http://educ.jmu.edu/~garrenst/math325.dir/Rfunctions" )
```

Selected formulas

$$\sigma^2 = V(Y) = E(Y - \mu)^2 = \sum_y (y - \mu)^2 p(y) = \sum_y y^2 p(y) - \mu^2$$

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y})^2 = \left[\sum_{i=1}^n Y_i^2 - \left(\sum_{i=1}^n Y_i \right)^2 / n \right] / (n-1)$$

$$V(\bar{Y}) = \frac{\sigma^2}{n} \left(\frac{N-n}{N-1} \right)$$

$$\hat{V}(\bar{Y}) = \frac{s^2}{n} \left(1 - \frac{n}{N} \right)$$

$D = B^2/4$ when estimating μ , and $D = B^2/(4N^2)$ when estimating τ

$$n = \frac{N\sigma^2}{(N-1)D + \sigma^2}$$

$$\hat{V}(\bar{Y}_1 - \bar{Y}_2) = \frac{s_1^2}{n_1} \left(1 - \frac{n_1}{N_1} \right) + \frac{s_2^2}{n_2} \left(1 - \frac{n_2}{N_2} \right)$$

$$\hat{V}(\hat{p}_1 - \hat{p}_2) = \hat{p}_1(1 - \hat{p}_1)/n + \hat{p}_2(1 - \hat{p}_2)/n + 2\hat{p}_1\hat{p}_2/n$$

$$\hat{V}(\hat{p}_1 - \hat{p}_2) = \hat{p}_1(1 - \hat{p}_1)/n_1 + \hat{p}_2(1 - \hat{p}_2)/n_2$$

$$\hat{V}(\bar{Y}_{st}) = \frac{1}{N^2} \sum_{i=1}^L N_i^2 \left(1 - \frac{n_i}{N_i} \right) \frac{s_i^2}{n_i}$$

$$n = \frac{\sum_{i=1}^L N_i^2 \sigma_i^2 / a_i}{N^2 D + \sum_{i=1}^L N_i \sigma_i^2}$$

$$n_i = n \left(\frac{N_i \sigma_i / \sqrt{c_i}}{\sum_{k=1}^L N_k \sigma_k / \sqrt{c_k}} \right)$$

$$n = \frac{\left(\sum_{k=1}^L N_k \sigma_k / \sqrt{c_k} \right) \left(\sum_{i=1}^L N_i \sigma_i \sqrt{c_i} \right)}{N^2 D + \sum_{i=1}^L N_i \sigma_i^2}$$

$$\hat{V}_p(\bar{Y}_{st}) = \frac{1}{n} \left(1 - \frac{n}{N} \right) \sum_{i=1}^L A_i s_i^2 + \frac{1}{n^2} \sum_{i=1}^L (1 - A_i) s_i^2$$

$$\hat{V}(\bar{Y}'_{st}) = \frac{n'}{n'-1} \sum_{i=1}^L \left[\left(a_i'^2 - \frac{a_i'}{n'} \right) \frac{s_i^2}{n_i} + \frac{a_i'(\bar{Y}_i - \bar{Y}'_{st})^2}{n'} \right]$$

$$\hat{V}(r) = \left(1 - \frac{n}{N}\right) \frac{1}{\mu_x^2} \frac{s_r^2}{n}$$

$$s_r^2 = \frac{\sum_{i=1}^n (Y_i - rX_i)^2}{n-1}$$

$$n = \frac{N\sigma^2}{ND + \sigma^2}, \text{ where } D = \begin{cases} B^2\mu_x^2/4, & \text{when estimating } R = \mu_y/\mu_x, \\ B^2/4, & \text{when estimating } \mu_y, \\ B^2/(4N^2), & \text{when estimating } \tau_y \end{cases}$$

$$\hat{\mu}_{yL} = \bar{Y} + b(\mu_X - \bar{X})$$

$$\hat{V}(\hat{\mu}_{yL}) = \left(1 - \frac{n}{N}\right) \left(\frac{1}{n}\right) \left[\frac{\sum_{i=1}^n [y_i - (a + bx_i)]^2}{n-2}\right] = \left(1 - \frac{n}{N}\right) \left(\frac{\text{MSE}}{n}\right)$$

$$\hat{V}(\hat{\mu}_{yD}) = \left(1 - \frac{n}{N}\right) \left(\frac{1}{n}\right) \frac{\sum_{i=1}^n (d_i - \bar{d})^2}{n-1}$$

$$\hat{V}(\hat{\mu}) = \left(1 - \frac{n}{N}\right) \frac{s_r^2}{n (M/N)^2}$$

s_r^2 is sample variance of $(Y_i - \hat{\mu} m_i)$

$$n = \frac{N\sigma_r^2}{ND + \sigma_r^2} \text{ where } D = B^2M^2/(4N^2) \text{ for estimating } \mu$$

$$n = \frac{N\sigma_r^2}{ND + \sigma_r^2} \text{ with } D = B^2/(4N^2) \text{ for estimating } \tau$$

$$n = \frac{N\sigma_t^2}{ND + \sigma_t^2} \text{ with } D = B^2/(4N^2) \text{ for estimating } \tau$$

s_t^2 is sample variance of Y_i

$$\hat{V}(\hat{N}) = \frac{t^2 n (n-s)}{s^3},$$

where t = number captured and s = number recaptured with tags

$$\hat{p} = \frac{1}{(2\theta - 1)} \left(\frac{n_1}{n}\right) - \left(\frac{1-\theta}{2\theta - 1}\right), \text{ for } \theta \neq \frac{1}{2}$$

$$\hat{V}(\hat{p}) = \frac{1}{(2\theta - 1)^2} \frac{1}{n} \left(\frac{n_1}{n}\right) \left(1 - \frac{n_1}{n}\right)$$