

### Appendix 3: $R_{adj}^2$ is a special case of $R_{KL,adj}^2$ for Gaussian distribution

For a Gaussian distribution, the scaled deviances of the fitted and intercept-only models are:

$$D^*(\mathbf{y}, \boldsymbol{\mu}) = \frac{\sum (y_i - \mu_i)^2}{\hat{\sigma}^2} = \frac{SS_E}{\hat{\sigma}^2} \quad (1)$$

$$D^*(\mathbf{y}, \boldsymbol{\mu}^0) = \frac{\sum (y_i - \bar{y})^2}{\hat{\sigma}^2} = \frac{SS_T}{\hat{\sigma}^2}$$

Since  $\sigma^2$  is unknown, its unbiased estimate is used in the formula:

$$\hat{\sigma}^2 = \frac{SS_E}{n - k - 1} \quad (2)$$

The adjusted Kullback-Leibler  $R^2$  is:

$$R_{KL,adj}^2 = \frac{\frac{SS_T}{\hat{\sigma}^2} - \frac{SS_E}{\hat{\sigma}^2} - k}{\frac{SS_T}{\hat{\sigma}^2}} = \frac{SS_T - SS_E - \hat{\sigma}^2 k}{SS_T} \quad (3)$$

Substituting (2) into (3), we obtain the commonly used formula for adjusted R-squared:

$$R_{KL,adj}^2 = \frac{SS_T - SS_E - \frac{kSS_E}{n - k - 1}}{SS_T} = 1 - \frac{SS_E}{SS_T} \left( 1 + \frac{k}{n - k - 1} \right) = 1 - (1 - R^2) \frac{n - 1}{n - k - 1} \quad (4)$$