

Standard Deviation of F({f})

Assume that there is a set $\{f_1, \dots, f_N\}_1$ of values and a set of rules for using this set of values to produce a value $F(\{f\}_I)$. If F can be differentiated with respect to f_i , the difference between F for the $\{f\}_I$ and that for the $\{f\}_J$ is given by

$$F(\{f\}_I) - F(\{f\}_J) = \sum_{i=1}^N \frac{\partial F}{\partial f_i} (f_{i,I} - f_{i,J}) \quad (1.1)$$

The difference squared is

$$(F_I - F_J)^2 = \sum_{i=1, j=1}^N \left(\frac{\partial F}{\partial f_i} \right)_{\delta_i=0} \left(\frac{\partial F}{\partial f_j} \right)_{\delta_j=0} ((f_{i,I} - f_{i,J})(f_{j,I} - f_{j,J})) \quad (1.2)$$

The standard deviation in F is the limit that M_I and $M_J \rightarrow$ infinity in

$$\sigma_{F, M_I, M_J}^2 = \frac{1}{2} \sum_{i=1}^N \frac{1}{M_I (M_J - 1)} \sum_{\substack{I=1 \\ J=1 \\ J \neq I}}^{M_I, M_J} \frac{\partial F}{\partial f_i} \frac{\partial F}{\partial f_j} ((f_{i,I} - f_{i,J})(f_{j,I} - f_{j,J})) \quad (1.3)$$

If f_i and f_j are statistically independent, the terms with $i \neq j$ average to zero so that

$$\sigma_{F, M_I, M_J}^2 = \sum_{i=1}^N \left(\frac{\partial F}{\partial f_i} \right)^2 \left(\frac{1}{2M_I (M_J - 1)} \sum_{\substack{I=1 \\ J=1 \\ J \neq I}}^{M_I, M_J} (f_{i,I} - f_{i,J})^2 \right) \quad (1.4)$$

The term in parenthesis in the limit that M_I and M_J become infinite is the standard deviation of the values of f_i

$$\delta_i^2 = \frac{1}{2M_I (M_J - 1)} \sum_{\substack{I=1 \\ J=1 \\ J \neq I}}^{M_I, M_J} (f_{i,I} - f_{i,J})^2 \quad (1.5)$$

Finally the standard deviation in F is

$$\sigma_F^2 = \sum_{i=1}^N \left(\frac{\partial F}{\partial f_i} \right)^2 \delta_i^2 \quad (1.6)$$

The relationship of σ to the standard deviation in f_i for a Gaussian distribution is derived in [Deviations.docx](#). In the case of Poisson data with more than just a few counts $\delta_i^2 = f_i$. The critical step is the assumption in going from (1.3) to (1.4) that the terms for $i \neq j$ sum to zero.