

WUN2K FOR LECTURE 4

These are notes summarizing the main concepts you need to understand and be able to apply.

- The dimensionless “correlation coefficient” for variables u and v is defined as $\rho \equiv \frac{\sigma_{uv}^2}{\sigma_u \sigma_v}$. It can take values $-1 \leq \rho \leq 1$; if the variables are completely uncorrelated, $\rho = 0$; $\rho = \pm 1$ corresponds to complete (linear) correlation (or anti-correlation).
- The “error matrix” is a compact way of specifying uncertainties and correlations for multiple variables (u_1, u_2, \dots); the elements of the error matrix are $M_{ij} \equiv \langle (u_i - \bar{u}_i)(u_j - \bar{u}_j) \rangle$. We have for (u, v, w, \dots) , $M =$

$$\begin{bmatrix} \sigma_u^2 & \sigma_{uv}^2 & \sigma_{uw}^2 & \dots \\ \sigma_{uv}^2 & \sigma_v^2 & \sigma_{vw}^2 & \dots \\ \sigma_{uw}^2 & \sigma_{vw}^2 & \sigma_w^2 & \dots \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}.$$

The error matrix is symmetric, and for uncorrelated variables, it's diagonal.

- A “binormal” joint probability for two random variables u, v (with zero mean) can be written $P(u, v) = \frac{1}{2\pi\sigma_u\sigma_v} \frac{1}{\sqrt{1-\rho^2}} e^{-\frac{1}{2} \left[\frac{1}{1-\rho^2} \left(\frac{u^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2} - 2\frac{\rho uv}{\sigma_u\sigma_v} \right) \right]}$. More generally for k variables with non-zero means, this can be written $P(u_1, u_2, \dots) = \frac{1}{(2\pi)^{k/2}} \frac{1}{|M|^{1/2}} e^{-\frac{1}{2}(\mathbf{u}-\boldsymbol{\mu})^T \mathbf{M}^{-1}(\mathbf{u}-\boldsymbol{\mu})}$, where \mathbf{M} is the error matrix, \mathbf{u} is a column vector of variables, and $\boldsymbol{\mu}$ is a column vector of their means.
- The “error ellipse” corresponding to two random variables u and v with binormal joint probability $P(u, v)$ is a contour in u - v space for which the joint probability $P(u, v)$ is $1/\sqrt{e}$ of its maximum. This ellipse will be tilted for non-zero ρ .

- Uses of error matrices (which in general make calculations by computer easy):

- For usual error propagation, to find the uncertainty on a function of some variables $x = f(u, v, \dots)$, we can write $\sigma_x^2 = \mathbf{D}^T \mathbf{M} \mathbf{D}$, where \mathbf{D}^T is a row vector of derivatives, $\mathbf{D}^T = [\frac{\partial x}{\partial u}, \frac{\partial x}{\partial v}, \dots]$, and \mathbf{M} is the error matrix.

- For a change of variables, $u' = f_1(u, v, \dots)$, $v' = f_2(u, v, \dots)$, the error matrix for the transformed variables is given by

$$\mathbf{M}' = \mathbf{A}^T \mathbf{M} \mathbf{A}, \text{ where } \mathbf{A} = \begin{bmatrix} \frac{\partial u'}{\partial u} & \frac{\partial v'}{\partial u} & \cdots \\ \frac{\partial u'}{\partial v} & \frac{\partial v'}{\partial v} & \cdots \\ \vdots & \vdots & \vdots \end{bmatrix}.$$

- For a function of changed variables,

$z = g(u', v', \dots)$, we can find the uncertainty on z according to

$$\sigma_z^2 = \mathbf{D}^T \mathbf{A}^T \mathbf{M} \mathbf{A} \mathbf{D}, \text{ where in this case } \mathbf{D} = \begin{pmatrix} \frac{\partial z}{\partial u'} \\ \frac{\partial z}{\partial v'} \\ \vdots \end{pmatrix}.$$