

# Uncertainty Quantification

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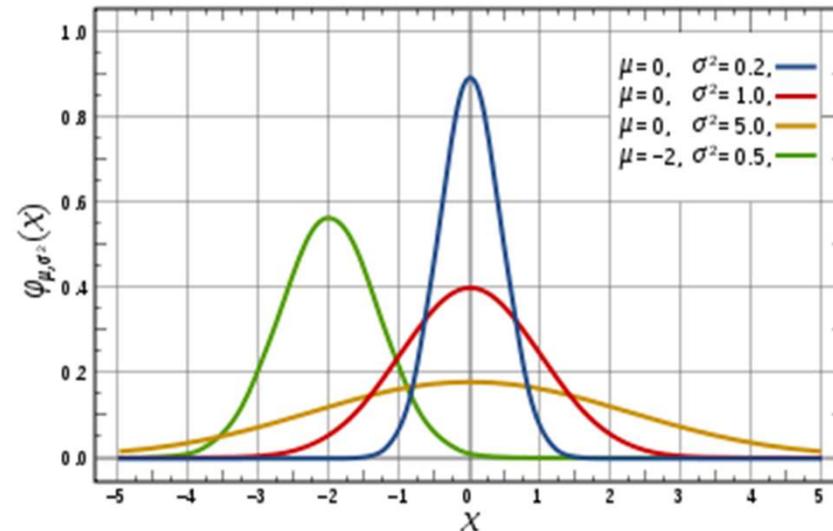
# Gaussian Distribution

- Telescopes and sampling errors
  - The mathematician Gauss (1777-1855) was also a keen astronomer. He acquired a new telescope, and decided to use it to produce a more accurate calculation of the diameter of the moon.
  - To his surprise, he discovered that every time he took a measurement, his answer was slightly different.
  - He plotted the results and found that they formed a bell shaped curve, with most results close to the central average but the occasional one quite inaccurate.
  - Gauss quickly realized that any measurement he took was a ‘sample’ prone to error but which could be used as an estimate of the correct answer. The more readings he took, the closer the average would be to the correct reading.
  - He established that errors in readings belonged to a famous **bell curve** (or **normal distribution** or **Gaussian distribution**).

# Normal Distribution

- The probability density function of the normal distribution with the mean value  $\mu$  and the variance parameter  $\sigma^2$  can be expressed as

$$f(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$
$$= \frac{1}{\sigma} \phi\left(\frac{x-\mu}{\sigma}\right)$$



PDF of the normal distribution

- From the measurements  $Q_i$  ( $i=1, \dots, N$ ), the variance can be estimated by

$$\sigma^2[\bar{Q}] = \frac{1}{N(N-1)} \sum_{i=1}^N (Q_i - \bar{Q})^2; \quad \bar{Q} = \frac{1}{N} \sum_{i=1}^N Q_i$$

# Error vs. Uncertainty

- When we measure a physical quantity with an instrument or obtain a numerical value, we want to **know how close the estimated value is to the true value.**



- The difference between the estimated and true values is the **error.**

$$\text{Error} = Q_{\text{est}} - Q_{\text{true}}$$



**Unfortunately, the true value is unknown and unknowable.**

- We can only **estimate** the error.
- The estimate of the error is called the **uncertainty.**

*Uncertainty can be expressed in either absolute or percentage terms for typically 95% confidence interval, for example,  
5 Volts  $\pm$ 0.5 Volts, 5 Volts  $\pm$ 10%, etc.*

# Types of Errors: Bias & Random Error

- **Random, Stochastic or Precision Error**
  - tend to be random in nature by effects of uncontrolled variables
- **Bias or Systematic Error (Accuracy)**
  - Error that remains with repeated measurements by a faulty equipment or consistent human errors
  - difference between your measurement (mean value) and the truth.

$$\begin{aligned}\sigma^2[\bar{Q}] &= E\left[(\bar{Q} - Q_{\text{true}})^2\right] \\ &= E\left[\left\{(\bar{Q} - E[\bar{Q}]) + (E[\bar{Q}] - Q_{\text{true}})\right\}^2\right] \\ &= E\left[(\bar{Q} - E[\bar{Q}])^2\right] + E\left[(E[\bar{Q}] - Q_{\text{true}})^2\right] + \cancel{2 E\left[(\bar{Q} - E[\bar{Q}])(E[\bar{Q}] - Q_{\text{true}})\right]} \\ &= \sigma_s^2[\bar{Q}] + \text{Bias}^2\end{aligned}$$

# Nuclear Data Uncertainty

- “It is now possible to model and analyze any nuclear system regardless of its complexity, to any degree of accuracy from the computational point of view. *The uncertainties that we do have today in analyzing nuclear systems are due to uncertainties in the nuclear data and not in the computational method.*” [1]  
[1] Yigal Ronen, (Ed.), *CRC Handbook of Nuclear Reactors Calculations*, CRC Press, Inc., Boca Raton, FL (1986).
- The nuclear data uncertainties are inevitable because they are generated from experimental results.
- Most of experimental uncertainties in the current measurements of nuclear data are systematic. Systematic uncertainties are characterized by inducing strong correlations in the nuclear data.
  - As an example, fission cross sections of some actinide nuclides are determined as relative values to those of  $^{235}\text{U}$ , of which uncertainties are known 2-3%.
  - Thus, the uncertainties in the fission cross sections of these nuclides will be larger than and correlated to the uncertainties of  $^{235}\text{U}$ .
  - The  $\nu$  values of actinides are true with respect to  $^{252}\text{Cf}$   $\nu$  which has an uncertainty of  $\sim 0.5\text{-}1\%$ .

# Estimated<sup>a</sup> Capabilities of LWR Parameter Accuracy

Parameter	Accuracy [%]	Parameter	Accuracy [%]
Steady-state power distribution		Fuel burnup	
• Within a fuel pin	± 8	• Peak pellet	± 5
• Fuel pin relative assembly	± 2-4	• Fuel assembly	± 4
• Axial, within an assembly	± 4-8	• Discharge batch	± 3-5
• Radial, between assemblies	± 2-5	Isotopic composition <sup>b</sup> local (pellet)	
• Overall, pellet to average	± 5-9	• <sup>235</sup> U depletion	± 5
Steady-state reactivity		• <sup>239</sup> Pu/U ratio	± 4
• Initial $k_{\text{eff}}$	± 0.3	• Net fissile atoms produced/U	± 4
• Reactivity lifetime	± 2-6	Discharged batch	
		• <sup>235</sup> U depletion	± 5
		• <sup>239</sup> Pu/U ratio	± 5
		• Net fissile atoms produced/U	± 5

a. Estimates are for generic designs, not appropriate for any specific reactor.

b. Assuming that the burnup is known in predictive comparison.

<from C. R. Weisbin et al., Ann. Nucl. Energy, 9, 615 (1982) >

➔ *Theses uncertainties are mainly due to uncertainties in nuclear data dominated by experimental results.*

# Uncertainties in the Design Parameters of Fast Demonstration Reactors

Parameter	Uncertainty <sup>a</sup> (%)		
	FRG (1972)	SNR-300 (1978)	CRBR (1980)
$k_{\text{eff}}$	1.1	0.4	0.7
Peak/average power	2.7	2.5	~4.7 <sup>b</sup>
Control rod worth	6	4-10	5
Doppler coefficient	6-12	15	10 <sup>c</sup>
Sodium void reactivity	12-18	15	20

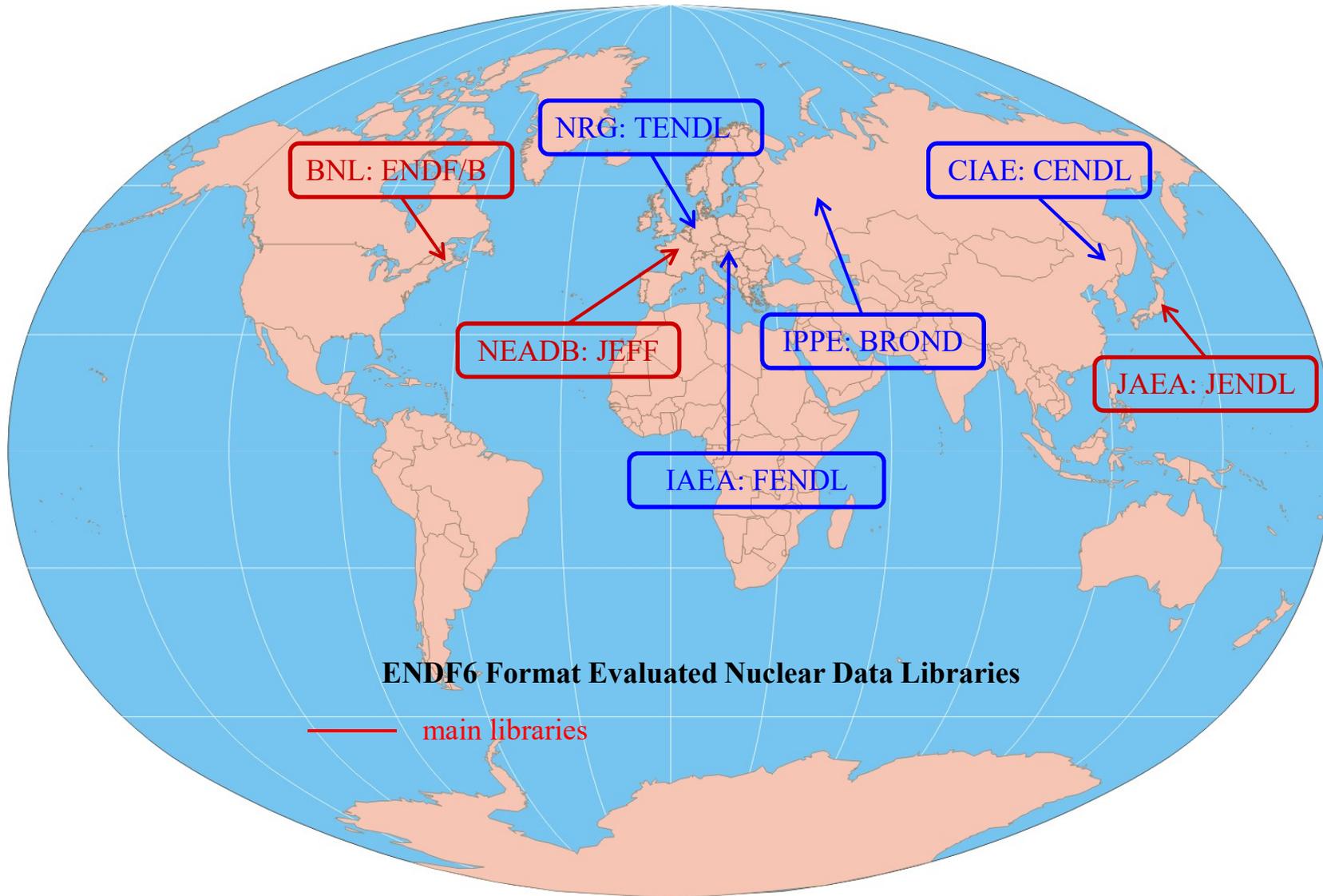
a. 1  $\sigma$  level.

b. Includes many engineering uncertainties; only about 2% comes from ability to calculate power dist.

c. Mainly from SEFOR experiments.

[1] Yigal Ronen, (Ed.), *CRC Handbook of Nuclear Reactors Calculations*, CRC Press, Inc., Boca Raton, FL (1986).

# Evaluated Nuclear Data



# ENDF/B-VII.1 Covariance Data

## Source of covariances for ENDF/B-VII.1

New ORNL, LANL, BNL evaluations

IAEA/IJS evaluations

COMMARA-2.0

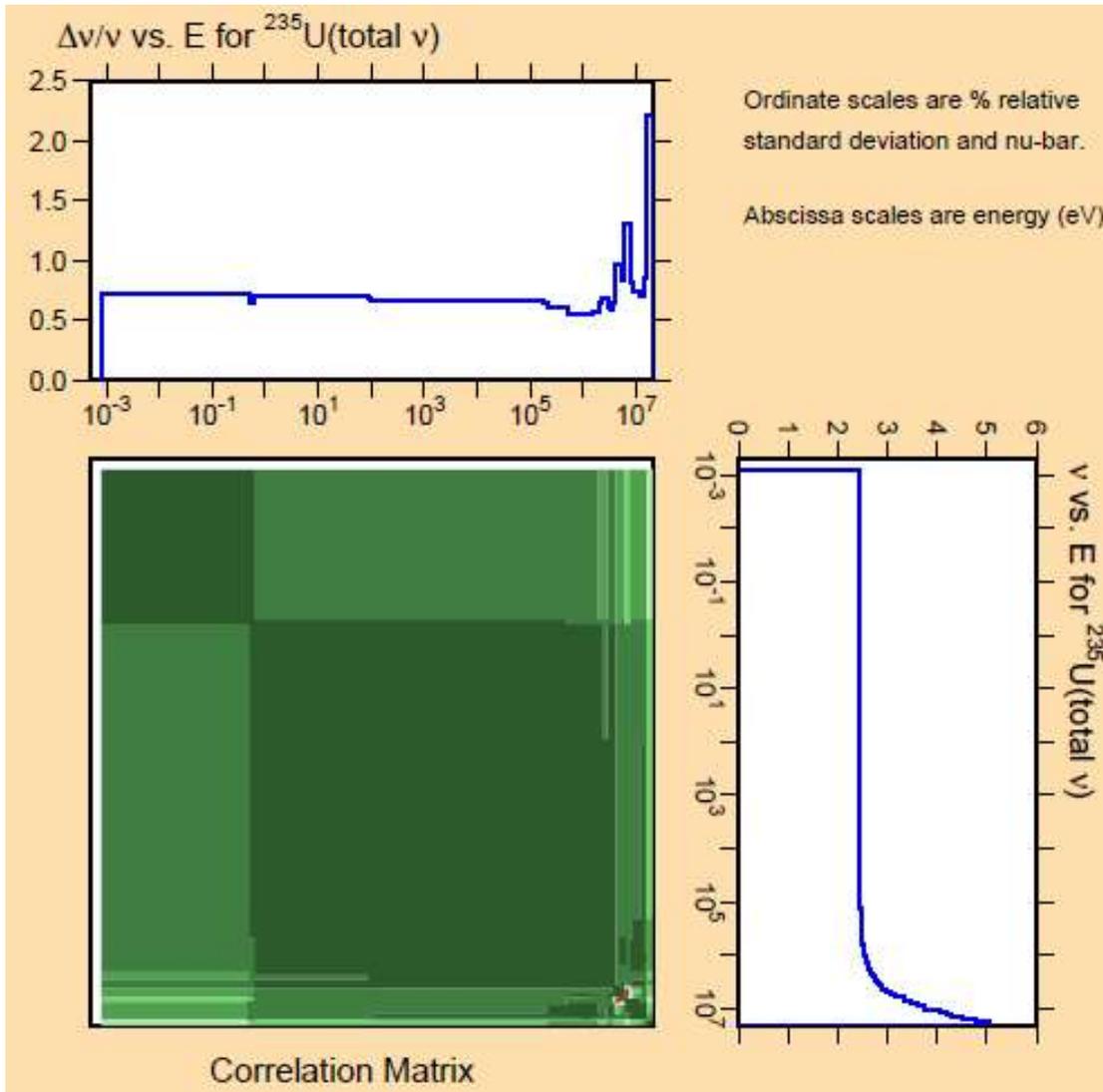
Neutron standards

Type	Number
Light materials	12
Structural & fission products	105
Actinides	20
Minor actinides	53
<b>Total</b>	<b>190</b>

MF	ENDF/B-VII.0	ENDF/B-VII.1
$V_{t,p,d}$ 31	2	73
Resonances 32	10	55
Cross-sections 33	24	183
Angular distr. 34	0	68
Energy distr. 35	0	64
<b>Total</b>	<b>36</b>	<b>443</b>

1,2H, 4He, 6,7Li, 9Be, 10,11B, natC, 15N, 16O, 19F, 23Na, 24,25,26Mg, 27Al, 28,29,30Si, 35,37Cl, 39,41K, 46,47,48,49,50Ti, natV, 50,52,53,54Cr, 55Mn, 54,56,57Fe, 59Co, 58,60Ni, 89Y, 90,91,92,93,94,95,96Zr, 95Nb, 92,94,95,96,97,98,100Mo, 99Tc, 101,102,103,104,106Ru, 103Rh, 105,106,107,108Pd, 109Ag, 127,129I, 131,132,134Xe, 133,135Cs, 139La, 141Ce, 141Pr, 143,145,146,148Nd, 147Pm, 149,151,152Sm, 153,155Eu, 152,153,154,155,156,157,158,160Gd, 166,167,168,170Er, 169,170Tm, 180,182,183,184,186W, 191,193Ir, 197Au, 203,205Tl, 204,206,207,208Pb, 209Bi, 225,226,227Ac, 227,228,229,230,231,232,233,234Th, 229,230,232Pa, 230,231,233,234,235,236,238U, 234,235,236,237,238,239Np, 236,237,238,239,240,241,242Pu, 240,241,242m,243Am, 240,241,242,243,244,245,246,247,248,249,250Cm, 245,246,247,248,249,250Bk, 246,248,249,250,251,252,253,254Cf, 251,252,253,254,254m,255Es, 255Fm

# $\nu$ Uncertainty of $^{235}\text{U}$ in ENDF/B-VII.1



The plots of the ENDF/B-VII.1 covariance matrices (44 & 187 energy groups) for **190** materials can be downloaded from [http://www.nndc.bnl.gov/exfor/endfb7.1\\_covariances.jsp](http://www.nndc.bnl.gov/exfor/endfb7.1_covariances.jsp)

# Mission of Nuclear Data S/U Analysis

$$N^i(\mathbf{r}, t) + \Delta N^i, x_r^i(\mathbf{r}, E, \boldsymbol{\Omega}) + \Delta x_r^i$$



$$\begin{aligned} \frac{1}{v} \frac{\partial \Phi(\mathbf{r}, E, \boldsymbol{\Omega}, t)}{\partial t} &= -\boldsymbol{\Omega} \cdot \nabla \Phi(\mathbf{r}, E, \boldsymbol{\Omega}, t) - \Sigma_t(\mathbf{r}, E, \boldsymbol{\Omega}, t) \Phi(\mathbf{r}, E, \boldsymbol{\Omega}, t) \\ &+ \int_{E'} dE' \int_{4\pi} d\boldsymbol{\Omega}' \Sigma_s(\mathbf{r}, E', \boldsymbol{\Omega}', t) f_s(E' \rightarrow E, \boldsymbol{\Omega}' \rightarrow \boldsymbol{\Omega}, t) \Phi(\mathbf{r}, E', \boldsymbol{\Omega}', t) \\ &+ \int_{4\pi} d\boldsymbol{\Omega}' \int_{E'} dE' \chi(\mathbf{r}, E' \rightarrow E, \boldsymbol{\Omega}' \rightarrow \boldsymbol{\Omega}, t) \nu_f(E) \Sigma_f(\mathbf{r}, E', \boldsymbol{\Omega}', t) \Phi(\mathbf{r}, E', \boldsymbol{\Omega}', t) \\ &+ Q(\mathbf{r}, E, \boldsymbol{\Omega}, t) \end{aligned}$$



$$\begin{aligned} k + \Delta k, \Phi(\mathbf{r}, E, \boldsymbol{\Omega}, t) + \Delta \Phi, \\ \kappa \Sigma_f(\mathbf{r}, E, \boldsymbol{\Omega}, t) \Phi(\mathbf{r}, E, \boldsymbol{\Omega}, t) + \Delta P \end{aligned}$$

# Uncertainty Quantification – Sampling Method

$$\begin{matrix} \bar{x} \pm \sigma_x, \\ \bar{y} \pm \sigma_y \end{matrix} \quad \Rightarrow \quad \boxed{z = f(x, y)} \quad \Rightarrow \quad \bar{z}, \sigma_z ??$$

- Because of the input data uncertainties, there can be an infinitely different set of inputs,  $(x_i, y_i)$  ( $i=1, 2, \dots$ ). This may result in different  $z$ 's as many as the number of input sets.

$$\begin{array}{ccc} \boxed{(x_1, y_1)} & \longrightarrow & z = f(x, y) & \longrightarrow & z_1 \\ \boxed{(x_2, y_2)} & \longrightarrow & z = f(x, y) & \longrightarrow & z_2 \\ \vdots & & & & \vdots \\ \boxed{(x_i, y_i)} & \longrightarrow & \boxed{z_i = f(x_i, y_i)} & \longrightarrow & z_i \\ \vdots & & & & \vdots \end{array} \quad \text{..... (1)}$$

- Then from the results, the variance of  $z$  can be estimated by

$$\sigma_z^2 \equiv \sigma^2[\bar{z}] = \frac{1}{N(N-1)} \sum_i^N (z_i - \bar{z})^2; \quad \bar{z} = \frac{1}{N} \sum_i^N z_i \quad \text{..... (2)}$$

- This methodology is called the **stochastic sampling method** or Brute force method.

# Uncertainty Quantification – S/U Analysis

- Let's assume that  $\bar{z}$  is determined from the best estimates of input variables as

$$\bar{z} = f(\bar{x}, \bar{y}) \quad \text{..... (3)}$$

- The Taylor series expansion of Eq. (1),  $z_i = f(x_i, y_i)$  to the first order of input variations about their mean values,  $(z_i - \bar{z})$  in Eq. (2), the sample variance formulation, leads to

$$z_i - \bar{z} \cong (x_i - \bar{x}) \left( \frac{\partial f}{\partial x} \right) + (y_i - \bar{y}) \left( \frac{\partial f}{\partial y} \right) \quad \text{..... (4)}$$

- The substitution of Eq. (4) into Eq. (2) results in

$$\begin{aligned} \sigma_z^2 &\cong \frac{1}{N(N-1)} \sum_i^N \left( (x_i - \bar{x}) \left( \frac{\partial f}{\partial x} \right) + (y_i - \bar{y}) \left( \frac{\partial f}{\partial y} \right) \right)^2 \\ &= \frac{1}{N(N-1)} \left\{ \sum_i^N (x_i - \bar{x})^2 \left( \frac{\partial f}{\partial x} \right)^2 + \sum_i^N (y_i - \bar{y})^2 \left( \frac{\partial f}{\partial y} \right)^2 + 2 \sum_i^N (x_i - \bar{x})(y_i - \bar{y}) \left( \frac{\partial f}{\partial x} \right) \left( \frac{\partial f}{\partial y} \right) \right\} \\ &= \sigma_x^2 \left( \frac{\partial f}{\partial x} \right)^2 + \sigma_y^2 \left( \frac{\partial f}{\partial y} \right)^2 + 2 \text{cov}[x, y] \left( \frac{\partial f}{\partial x} \right) \left( \frac{\partial f}{\partial y} \right) \quad \text{..... (5)} \end{aligned}$$

# Error Propagation Examples

$$\sigma^2 [f(x, y)] = \sigma_x^2 \left( \frac{\partial f}{\partial x} \right)^2 + \sigma_y^2 \left( \frac{\partial f}{\partial y} \right)^2 + 2 \text{cov}[x, y] \left( \frac{\partial f}{\partial x} \right) \left( \frac{\partial f}{\partial y} \right)$$



Function	Variance
$f = aA$	$\sigma_f^2 = a^2 \sigma_A^2$
$f = aA \pm bB$	$\sigma_f^2 = a^2 \sigma_A^2 + b^2 \sigma_B^2 \pm 2ab \text{cov}_{AB}$
$f = AB$	$\left( \frac{\sigma_f}{f} \right)^2 \approx \left( \frac{\sigma_A}{A} \right)^2 + \left( \frac{\sigma_B}{B} \right)^2 + 2 \frac{\sigma_A \sigma_B}{AB} \rho_{AB}$
$f = \frac{A}{B}$	$\left( \frac{\sigma_f}{f} \right)^2 \approx \left( \frac{\sigma_A}{A} \right)^2 + \left( \frac{\sigma_B}{B} \right)^2 - 2 \frac{\sigma_A \sigma_B}{AB} \rho_{AB}$

# Current Nuclear Data UQ Approaches

## ■ Approach #1 Sensitivity and Uncertainty (S/U) Analysis

- Determination of sensitivity coefficients:
$$S_k = \frac{\Delta k / k}{\Delta \alpha / \alpha}$$
- $k_{\text{eff}}$  uncertainty: 
$$\sigma_k^2 = \sum_{(\alpha\alpha')} S_{k,\alpha}^T C_{\alpha\alpha'} S_{k,\alpha'}$$
- Examples:
  - ✓ McCARD based on Monte Carlo Perturbation Techniques for the sensitivity calculations
  - ✓ TSUNAMI, SUS3D

## ■ Approach #2 Stochastic Sampling (S.S.)

- Probability procedure to sample input parameters (e.g. nuclear data) according to their variances/covariances
- Examples:
  - ✓ GRS: initially Monte Carlo sampling for system codes by SUSA tool  
now also using XSUSA to make nuclear data sampling coupled with SCALE-6
  - ✓ NRG Total MC: sampling and perturbation are done directly to theoretical nuclear model parameters
  - ✓ AREVA: produce sets of randomly perturbed ENDF-formatted data libraries  
The TALYS and NUDUNA codes are available.

# S/U vs. S.S

	Sensitivity / Uncertainty	Stochastic Sampling
<b>Pros</b>	<ul style="list-style-type: none"><li>- reveal individual uncertainty contribution to the total system uncertainty (in <math>k_{\text{eff}}</math>)</li></ul>	<ul style="list-style-type: none"><li>- free of low-order approximations</li><li>- easy to implement, existing statistical tools</li><li>- applicable to any choice of “input <math>\rightarrow</math> output”</li></ul>
<b>Cons</b>	<ul style="list-style-type: none"><li>- inherently “local” because of low-order Taylor expansions</li><li>- implementation complexity increases dramatically if high-order expansion is required to account for non-linear effects</li></ul>	<ul style="list-style-type: none"><li>- high computational cost</li><li>- decomposition of individual uncertainty contribution is not trivial</li></ul>

