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... solutions for robust engineering

Probability theory basics

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'HPC and Uncertainty Treatment – Examples with Open TURNS and Uranie'

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Motivation

- Uncertainty includes variability, randomness and lack-of-knowledge.
 - Aleatory uncertainty
 - Lack of control over environmental variability and test settings, errors made during testing.
 - Can be better characterized but cannot be reduced with more measurements or simulations.
 - **Epistemic** uncertainty
 - Lack-of-knowledge and assumptions made during testing and modeling.
 - Can be reduced by collecting more information and evidence.

These sources of uncertainty can be modeled thanks to probability theory

Note: Other theories have been developed to represent epistemic uncertainty such as Imprecise Theory (IP), Possibility theory, Fuzzy sets and fuzzy logic.



Outline

General definitions

Random variables

- Definitions
- Cumulative distribution function and probability density function
- Moments
- Confidence intervals (CI)

Random vectors

- Definitions
- Moments
- Copulas



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Random experiment

Repeatable procedure leading to possible outcomes.

Sample space Ω

Set of all possible outcomes of the experiment.

Event

Set of outcomes of an experiment (a subset of Ω).



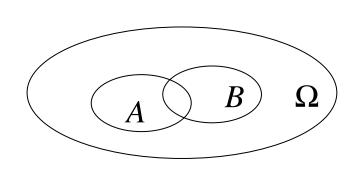
Probability

- Measure between 0 and 1 applied to events: $\mathbb{P}[A] \in [0,1]$
- Satisfies Kolmogorov axioms

Throwing 2 dice			
Event A _i	$\mathbb{P}[A_{\boldsymbol{i}}]$		
Do an even number	$\frac{1}{2}$		
Do more than 2	35		
	36		

Common properties:

- $\mathbb{P}[\emptyset] = 0$, $\mathbb{P}[\Omega] = 1$
- $\mathbb{P}[\overline{A}] = 1 \mathbb{P}[A]$
- $\mathbb{P}[A \setminus B] = \mathbb{P}[A] \mathbb{P}[A \cap B]$
- $\mathbb{P}[A \cup B] = \mathbb{P}[A] + \mathbb{P}[B] \mathbb{P}[A \cap B]$
- $A \subseteq B \Rightarrow \mathbb{P}[A] \leq \mathbb{P}[B]$



Conditional probability

probability of A given B

$$\mathbb{P}[A|B] = \frac{\mathbb{P}[A \cap B]}{\mathbb{P}[B]}$$

Independence

B does not affect the probability of A, and vice versa:

$$\mathbb{P}[A|B] = \mathbb{P}[A] \Longrightarrow \mathbb{P}[A \cap B] = \mathbb{P}[A]\mathbb{P}[B]$$

Bayes' theorem

Shows the probability of *A* <u>updated</u> by the knowledge of B

contained in B

Defined from the conditional probability definition

$$\mathbb{P}[A|B] = \frac{\mathbb{P}[B|A]}{\mathbb{P}[B]} \mathbb{P}[A]$$
Initial probability of A



HPC & UQ - Basics

Probability theory

Frequentist interpretation of probabilities

Probabilities can be estimated by N observations

$$\mathbb{P}[A] = \lim_{N \to \infty} \frac{N_A}{N}$$



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- Random vectors $\overline{\Phi}$
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HPC & UQ - Basics

Probability theory

Definition

A random variable (r.v.) X is a measurable function

$$X: \Omega \longrightarrow \mathcal{D}_X$$
$$\omega \longmapsto x = X(\omega)$$

Can be discrete $(\mathcal{D}_X \subseteq \mathbb{Z})$ or continuous $(\mathcal{D}_X \subseteq \mathbb{R})$

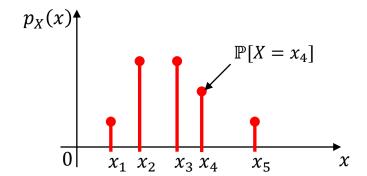
Probability Density Function (PDF)

Discrete: probability mass function

$$p_X(x_i) = \mathbb{P}[X = x_i]$$

$$\forall x_i, 0 \leq p_X(x_i) \leq 1$$

$$\sum_{x_i} p_X(x_i) = 1$$

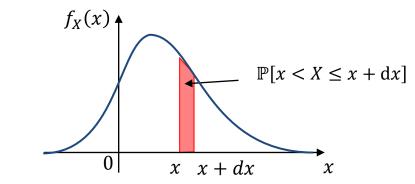


Continuous: probability density function

$$f_X(x) dx = \mathbb{P}[x < X + dx]$$

$$\forall x, f_X(x) \geq 0$$

$$\int_{x \in \mathbb{X}} f_X(x) \, \mathrm{d}x = 1$$



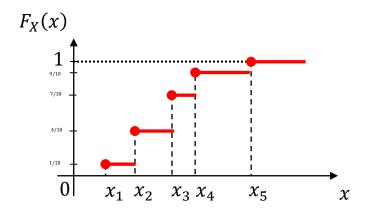
Cumulative Distribution Function (CDF)

Discrete

$$F_X(x) = \mathbb{P}[X \le x] = \sum_{x \le x_i} p_X(x_i)$$

$$\lim_{x \to \sup \mathcal{D}_X} F_X(x) = 1$$

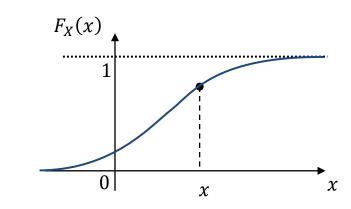
$$\lim_{x \to \inf \mathcal{D}_X} F_X(x) = 0$$



Continuous

$$F_X(x) = \mathbb{P}[X \le x] = \int_{-\infty}^x f_X(x) dx$$
$$dF_Y(x)$$

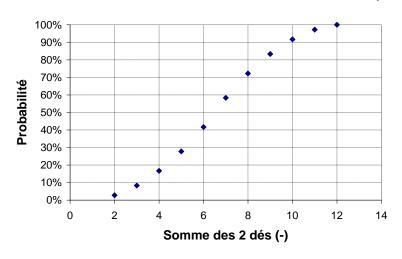
$$f_X(x) = \frac{\mathrm{d}F_X(x)}{\mathrm{d}x}$$



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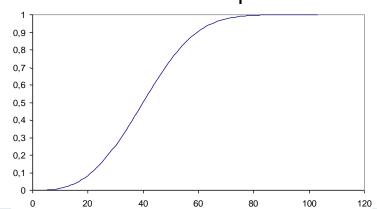
© Cumulative Distribution Function (CDF)

• Discrete: Sum of 2 dice: $\Omega \rightarrow \{2,...,12\}$





• Continuous: Wind speed: $\Omega \to \mathbb{R}^+$





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Random variables

Link between several r.v.

Let S the sum of two independent continuous r.v. X and Y:

$$S = X + Y$$

➤ The distribution of S can be deduced by convolution or characteristics functions

Composition

$$Y = \varphi(X)$$

➤ In some cases, the distribution of Y can be computed analytically. Otherwise, we must generate a sample.





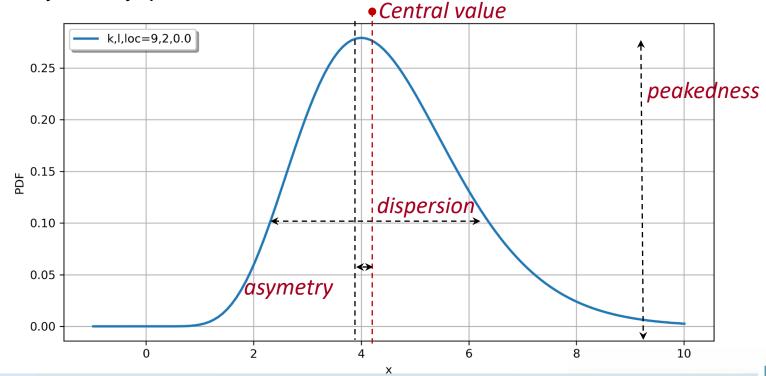
Measure = true value + error

Characterization of a random variable

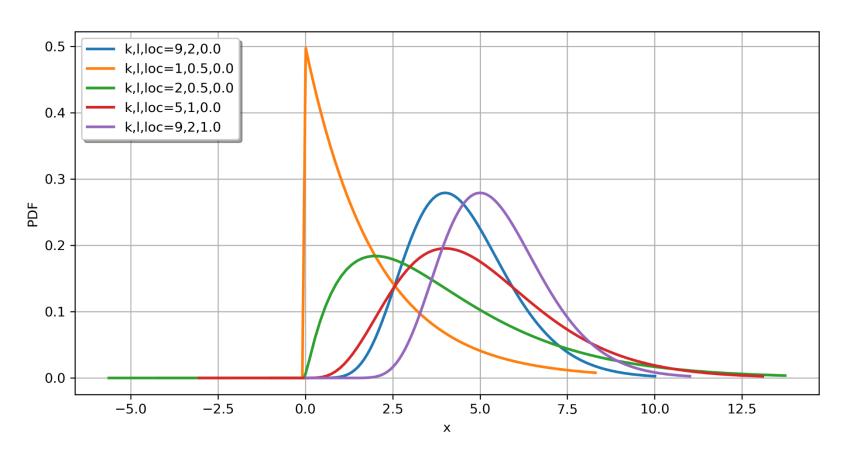
A distribution is characterized by its **moments**:

- central value
- dispersion

asymmetry, peakedness Gamma(k,l,loc)



Gamma(k,l,loc)



\square Moments of order r(>0)

$$\mu_{X \ centered, standardized}^{r} = \mathbb{E}\left[\frac{(X - \mu_{X})^{r}}{\sigma_{X}^{r}}\right]$$

r = 1	r = 2	r = 3	r = 4
Mean	Variance	skewness	kurtosis
central value	Dispersion	asymmetry	flattening
μ_X	σ_X^2	δ_X	κ_X



Coefficient of variation

c.o.v.
$$=\frac{\sigma_X}{|\mu_X|}$$
, $\mu_X \neq 0$

Expected value (Mean value)

Given X and Y, two r.v. and a and b two reals.

- For discrete r.v : $\mathbb{E}[X] = \sum_{x_i} x_i p_X(x_i)$
- For continuous r.v. : $\mathbb{E}[X] = \int_{x \in \mathbb{X}} x f_X(x) dx$
- $\mathbb{E}[aX + bY] = a\mathbb{E}[X] + b\mathbb{E}[Y]$ Linearity:
- only if X and Y are independent: $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$

Variance (dispersion around the mean)

$$\sigma_X^2 = \operatorname{Var}[X] = \mathbb{E}[(X - \mu_X)^2]$$
 (if it exists, cf Cauchy distribution)

- König-Huyghens formula: $Var[X] = \mathbb{E}[X^2] \mathbb{E}[X]^2 = \mathbb{E}[X^2] \mu_X^2$
- $Var[aX + b] = a^2 Var[X]$

•
$$Var[X + Y] = var[X] + Var[Y] + 2\mathbb{E}[(X - \mu_X)(Y - \mu_Y)]$$

$$Cov[X, Y]$$

If X and Y are independent:

$$Var[XY] = Var[X] Var[Y] + Var[X] \mathbb{E}[Y]^2 + Var[Y] \mathbb{E}[X]^2$$

Quantiles

The quantile \mathbf{x}_{α} at probability level α , is

$$F_X(x_{\alpha}) = \alpha \quad \Rightarrow \quad x_{\alpha} = F_X^{-1}(\alpha), \quad 0 \le \alpha \le 1$$

First quartile	<i>α</i> = 25 %
median	<i>α</i> = 50 %
Third quartile	<i>α</i> = 75 %

Confidence intervals



Estimated moments are also random variables

To sum up the variability of a r.v. bounded by two quantiles centered on the median.

Confidence interval at the probability level of $1 - \alpha$:

$$[x_{\alpha/2}; x_{1-\alpha/2}] = [F_X^{-1}(\alpha/2); F_X^{-1}(1-\alpha/2)], \quad 0 \le \alpha \le 1$$

Outline

- General definitions
- Random variables
 - Definitions
 - Cumulative distribution function (CDF) and probability density function (PDF)
 - Discrete / continuous random variables
 - Statistical moments
 - Confidence intervals (CI)

Random vectors

- Definitions
- Moments
- Copulas



Definition

A random vector is a measurable function

$$\mathbf{X} : \Omega \to \mathbb{X} \subseteq \mathbb{R}^n$$

$$\omega \mapsto \mathbf{x} = \mathbf{X}(\omega) = (X_1(\omega), \dots, X_n(\omega))^t$$

- Defined by:
 - Its joint cumulative distribution function

$$F_{\mathbf{X}}(\mathbf{x}) = \mathbb{P}\left[\bigcap_{i=1}^{n} X_i \le x_i\right]$$

Its joint probability density function

$$f_{\mathbf{X}}(\mathbf{x}) = \frac{\mathbb{P}\left[\bigcap_{i=1}^{n} x_{i} \le X_{i} \le x_{i} + dx_{i}\right]}{\prod_{i=1}^{n} dx_{i}} = \frac{\partial F_{\mathbf{X}}(\mathbf{x})}{\partial x_{1} \dots \partial x_{-}n}$$

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Random vectors

Complements

marginal PDF: If $X = (X_1, X_2)^t$, the marginal density of X_1 (in X) is given by:

$$f_{\mathbf{X}_1}(\mathbf{x}_1) = \int_{\mathbf{x}_2 \in \mathbb{X}_2} f_{\mathbf{X}}(\mathbf{x}_1, \mathbf{x}_2) d\mathbf{x}_2$$

conditional PDF: If $X = (X_1, X_2)^t$ the conditional PDF of X_1 given $x_2 = b$ is:

$$f_{\mathbf{X}_1|\mathbf{X}_2}(\mathbf{x}_1|\mathbf{x}_2=b) = \frac{f_{\mathbf{X}}(\mathbf{x}_1,b)}{\int_{\mathbf{x}_1\in\mathbb{X}_1}f_{\mathbf{X}}(\mathbf{x}_1,b)d\mathbf{x}_1} = \frac{f_{\mathbf{X}}(\mathbf{x}_1,b)}{f_{\mathbf{X}_2}(b)}$$

- Copula: a stochastic dependence structure, in case of r.v. are correlated.
 - Sklar Theorem : $F_{\mathbf{X}}(\mathbf{x}) = C(F_{X_1}(x_1), F_{X_2}(x_2))$

Moments

Expected value: vector of expected values of random variables

$$\mathbb{E}[\mathbf{X}] = (\mathbb{E}[X_i], i = 1, ..., n)^t$$

Covariance matrix:

$$\sigma_{ij} = \text{Cov}[X_i, X_j] = \mathbb{E}\left[(X_i - \mu_{X_i})(X_j - \mu_{X_j})\right], \quad i, j = 1, ..., n$$

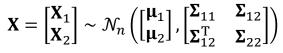
	X_1	X_2
X_1	$\sigma_1^{\ 2}$	$Cov[X_1, X_2]$
X_2	$Cov[X_2, X_1]$	$\sigma_2^{\ 2}$

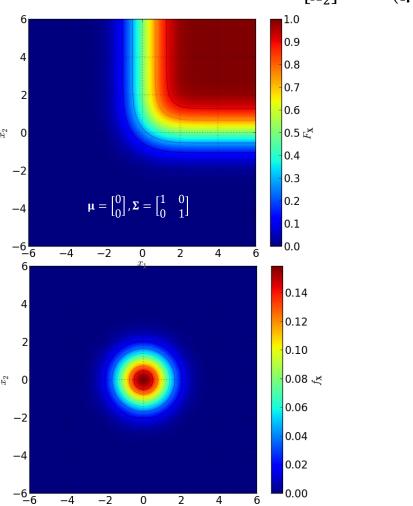


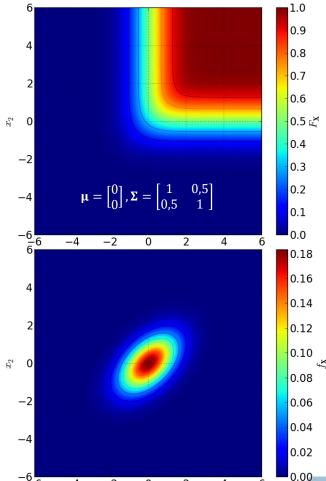
Correlation matrix:
$$\rho_{ij} = \frac{\text{Cov}[x_i, x_j]}{\sqrt{\text{Var}[x_i]\text{Var}[x_j]}} = \frac{\sigma_{ij}}{\sigma_i \sigma_j}, \quad i, j = 1, ..., n$$



Multivariate normal distribution

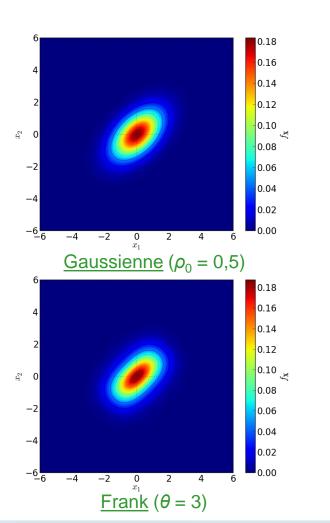


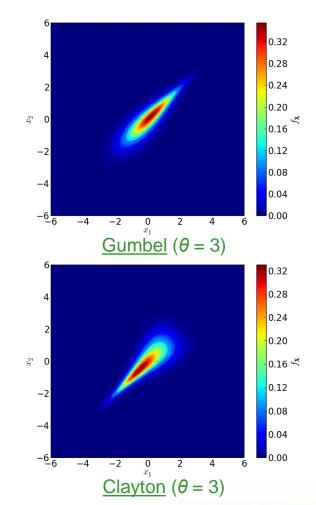




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Multivariate normal distribution with copulas





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Synthesis

- Defined by a joint distribution ...
- ... or a collection of marginal distributions, and a copula if required.
- Used for multi-dimensional problems.

Some references

- Probability, Random Variables and Stochastic Processes, 4th Edition International Edition, Athanasios Papoulis, S. Unnikrishna Pillai, Mc Graw Hill (2002) (<u>www.mhhe.com/engcs/electrical/Papoulis</u>)
- Nelsen, Roger B. An introduction to copulas. Springer Science & Business Media, 2007.