

457.646 Topics in Structural Reliability
In-Class Material: Class 08

III. Structural Reliability (Component)

⊙ **Joint Probability Distribution Models**

② **Joint Lognormal**

X_1, \dots, X_n are jointly lognormal if $\ln X_1, \dots, \ln X_n$ are jointly _____

a) Parameters

$$\lambda_i = E[\ln X_i] = \ln \mu_i - 0.5 \ln(1 + \delta_i^2)$$

$$\xi_i^2 = \text{Var}[\ln X_i] = \ln(1 + \delta_i^2) \quad (\cong \delta_i^2 \text{ for } \delta \ll 1)$$

$$\rho_{\ln X_i, \ln X_j} = \frac{1}{\xi_i \xi_j} \ln(1 + \rho_{ij} \delta_i \delta_j)$$

b) Properties

- Completely defined in terms of (λ_i) & (ξ_i^2)
- All lower order distribution are jointly lognormal
- Conditional distribution are jointly lognormal
- Uncorrelated \nRightarrow S.I.
- Product / Quotient of jointly lognormal r.v.'s follows lognormal

$$\rho_{X_i, X_j} = \frac{1}{\xi_i \xi_j} \delta_j \rho_{ij}$$

③ **General Joint Distribution Forms**

e.g. Johnson & Kotz (1976)

\Rightarrow on multivariate prob. distribution models

④ **Joint Distribution by conditioning** (e.g. Bayesian Networks)

$$f(x_1, \dots, x_n) = f(x_n | x_1, \dots, x_{n-1}) \times$$

⑤ **Joint Distribution model with :** Prescribed marginals: $f_i(x_i), i=1, \dots, n$ and

correlation coefficient matrix :

- **Read CRC Ch.14**
- **See Liu & Kiureghian (1986)** a) Morgenstern
 b) Nataf

※ “Copula”: formula to construct joint PDF with marginal distributions
 (Review by Jongmin Park (SNU): Term Project Report in 2014)

a) Morgenstern distribution

$$F_{\mathbf{X}}(\mathbf{x}) = \prod_{i=1}^n F_{X_i}(x_i) \cdot \left\{ 1 + \sum_{i < j} \alpha_{ij} [1 - F_{X_i}(x_i)] [1 - F_{X_j}(x_j)] \right\}$$

Q) Can we derive $F_{X_i}(x_i)$ from $F_{\mathbf{X}}(\mathbf{x})$?

i.e. $x_2, x_3, \dots, x_n \rightarrow$ then $F_{\mathbf{X}}(\mathbf{x}) =$?

Q) Can we describe dependence using α_{ij} ?

$$F_{X_i X_j}(x_i, x_j) =$$

$$f_{X_i X_j}(x_i, x_j) = \text{_____}$$

$$= f_{X_i}(x_i) \cdot f_{X_j}(x_j) \cdot \left\{ 1 + \alpha_{ij} [1 - 2F_{X_i}(x_i)] [1 - 2F_{X_j}(x_j)] \right\}$$

$$\Rightarrow \quad \leq \alpha_{ij} \leq$$

$$\begin{cases} \alpha_{ij} = 0 \\ \alpha_{ij} \neq 0 \end{cases}$$

Therefore, α_{ij} is a parameter that represents (corr coeff.)

But $\alpha_{ij} \quad \rho_{ij}$

Lin & Der Kiureghian (1986) showed

$$\rho_{ij} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left(\frac{x_i - \mu_i}{\sigma_i} \right) \left(\frac{x_j - \mu_j}{\sigma_j} \right) f_{X_i X_j}(x_i, x_j) dx_i dx_j$$

$$= 4\alpha_{ij} Q_i Q_j \quad \Rightarrow \quad |\rho_{ij}| \leq 0.30$$

$$\text{Where } Q_i = \int_{-\infty}^{\infty} \left[\left(\frac{x_i - \mu_i}{\sigma_i} \right) F_{X_i}(x_i) \right] f_{X_i}(x_i) dx_i \approx 0.28$$

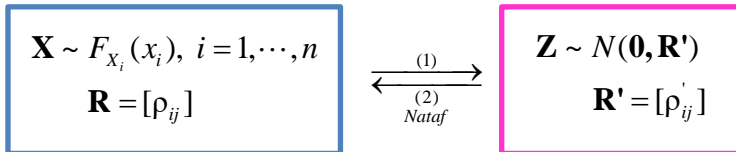
Table 1: selected distribution

Table 2: Q_i

Table 3 : maximum $|\rho_{ij}|$

⇒ In summary, using Morgenstern's model, you cannot describe X_i, X_j
 whose $|\rho_{ij}| > 0.30$

b) Nataf model (Nataf, 1962) (“Gaussian Copula”)



Transformation to \mathbf{Z}

$$Z_i =$$

Why?

$$f_{Z_i}(z_i) = f_{X_i}(x_i) \cdot \left| \frac{dx_i}{dz_i} \right|$$

$$f_{Z_i}(z_i) \cdot \quad = f_{X_i}(x_i) \cdot$$

$$\Phi(\quad) = F_{X_i}(\quad)$$

