

A short course on

# Probabilities and Random Variables

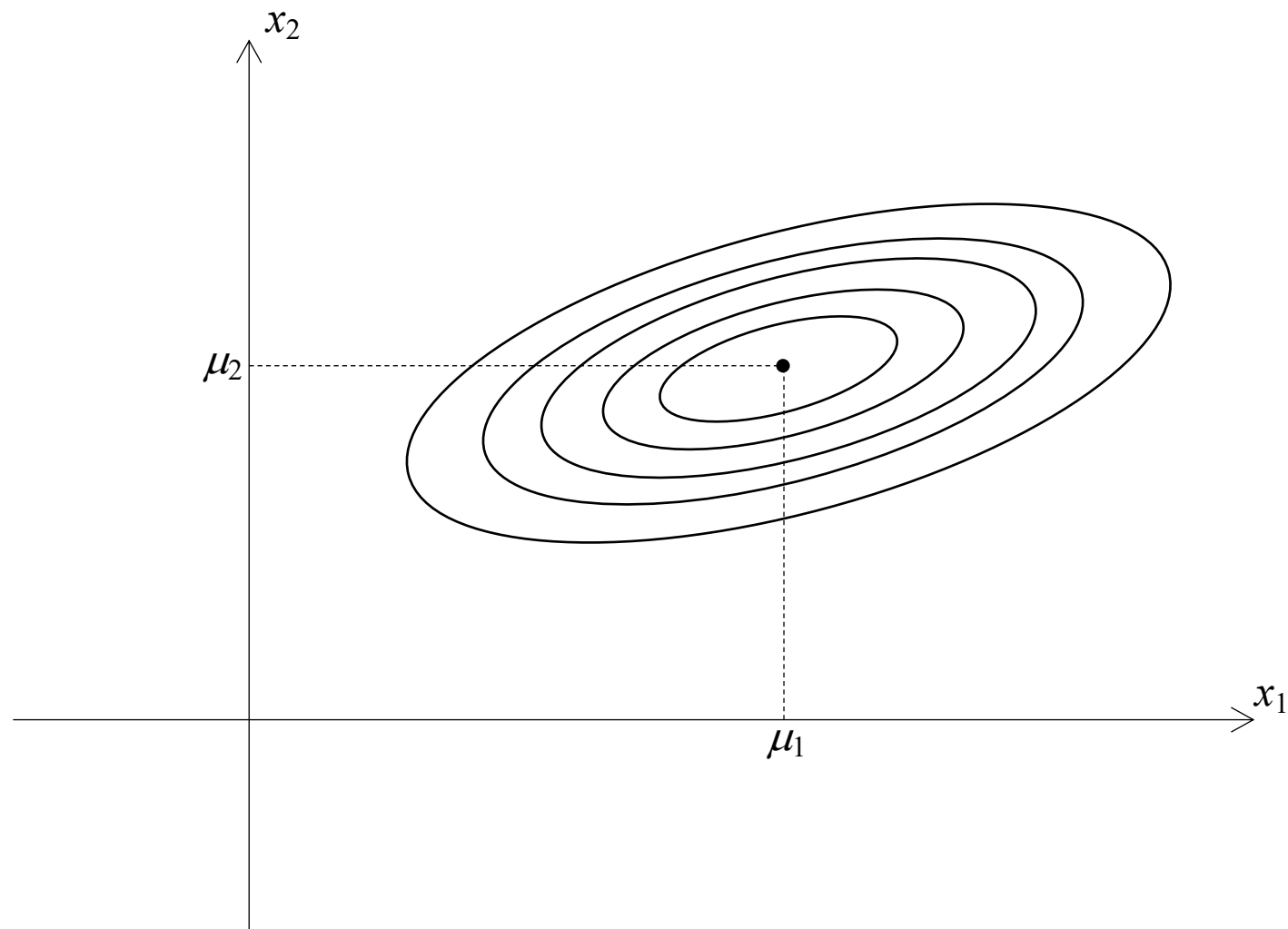
This video:

**Multiple Random Variables: Joint Distributions & Matrix Notation**

Terje's Toolbox is freely available at [terje.civil.ubc.ca](http://terje.civil.ubc.ca)

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# Joint Distribution



# Properties

$$f(x,y) \cdot dx \cdot dy = P(x < X \leq x + dx \cap y < Y \leq y + dy)$$

$$f(x,y) \geq 0$$

$$f(y) = \int_{-\infty}^{\infty} f(x,y) dx$$

$$f(x) = \int_{-\infty}^{\infty} f(x,y) dy$$

} Marginal distributions from joint distribution

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) dx dy = 1$$

$$F(x,y) = P(X \leq x \cap Y \leq y) = \int_{-\infty}^x \int_{-\infty}^y f(x,y) dx dy$$

$$f(x,y) = \frac{\partial^2 F(x,y)}{\partial x \partial y}$$

# Moments

Mean product:

$$E[XY] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x \cdot y \cdot f(x, y) dx dy$$

Covariance:

$$\text{Cov}[X, Y] = E[(X - \mu_X)(Y - \mu_Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X) \cdot (y - \mu_Y) \cdot f(x, y) dx dy$$

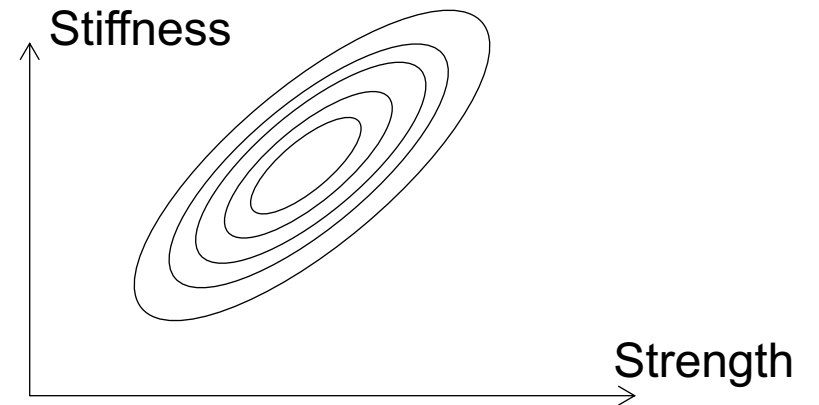
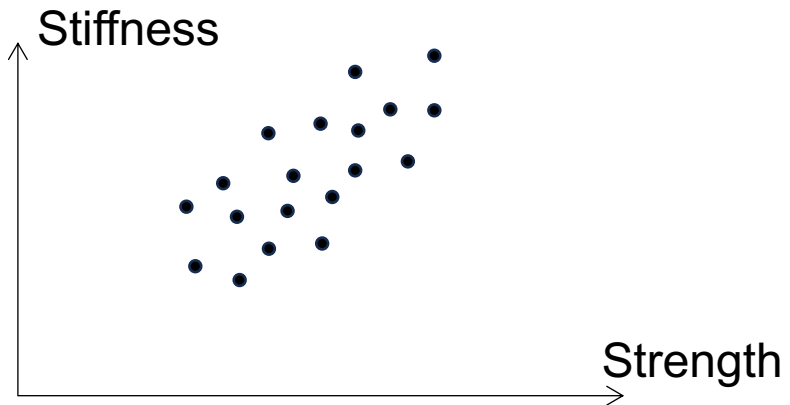
# Poem

Covariance is mean product minus the product of the means

$$\begin{aligned}\text{Cov}[X, Y] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X) \cdot (y - \mu_Y) \cdot f(x, y) dx dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x \cdot y + \mu_X \cdot \mu_Y - x \cdot \mu_Y - y \cdot \mu_X) \cdot f(x, y) dx dy \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x \cdot y \cdot f(x, y) dx dy + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mu_X \cdot \mu_Y \cdot f(x, y) dx dy - \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x \cdot \mu_Y \cdot f(x, y) dx dy - \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y \cdot \mu_X \cdot f(x, y) dx dy \\ &= E[XY] + \mu_X \cdot \mu_Y \cdot \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy - \mu_Y \cdot \int_{-\infty}^{\infty} x \cdot \int_{-\infty}^{\infty} f(x, y) dx dy - \mu_X \cdot \int_{-\infty}^{\infty} y \cdot \int_{-\infty}^{\infty} f(x, y) dx dy \\ &= E[XY] + \mu_X \cdot \mu_Y \cdot 1 - \mu_Y \cdot \int_{-\infty}^{\infty} x \cdot f(x) dx - \mu_X \cdot \int_{-\infty}^{\infty} y \cdot f(y) dy \\ &= E[XY] + \mu_X \cdot \mu_Y \cdot 1 - \mu_Y \cdot \mu_X - \mu_X \cdot \mu_Y = E[XY] - \mu_X \cdot \mu_Y\end{aligned}$$

# Correlation Coefficient

$$\rho_{XY} = \frac{\text{Cov}[X,Y]}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} = E\left[\frac{X - \mu_X}{\sigma_X} \cdot \frac{Y - \mu_Y}{\sigma_Y}\right]$$



# Vector-Matrix Notation

$$\mathbf{M}_x = \begin{Bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{Bmatrix}$$

$$\Sigma_{xx} = \begin{bmatrix} \sigma_1^2 & \rho_{12} \cdot \sigma_1 \cdot \sigma_2 & \rho_{13} \cdot \sigma_1 \cdot \sigma_3 \\ \rho_{12} \cdot \sigma_1 \cdot \sigma_2 & \sigma_2^2 & \rho_{23} \cdot \sigma_2 \cdot \sigma_3 \\ \rho_{13} \cdot \sigma_1 \cdot \sigma_3 & \rho_{23} \cdot \sigma_2 \cdot \sigma_3 & \sigma_3^2 \end{bmatrix}$$

Later:  $f(\mathbf{x}), h(\mathbf{x}), g(\mathbf{x}), \nabla g(\mathbf{x})$

$\Sigma_{xx} = \mathbf{D}_{xx} \mathbf{R}_{xx} \mathbf{D}_{xx}$ , where  $\mathbf{D}$  is diagonal matrix with standard deviations

$$\mathbf{R}_{xx} = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix}$$

# Joint Normal

General: 
$$f(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^n} \cdot \sqrt{\det(\boldsymbol{\Sigma}_{XX})}} \cdot \exp\left(-\frac{1}{2}(\mathbf{x} - \mathbf{M}_X)^T \boldsymbol{\Sigma}_{XX}^{-1} (\mathbf{x} - \mathbf{M}_X)\right)$$

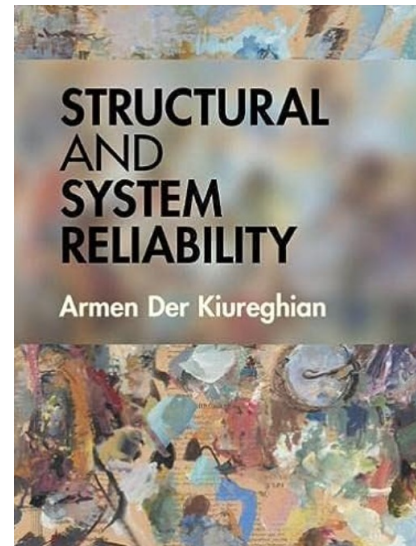
Bi-variate: 
$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \cdot \exp\left(-\frac{z}{2(1-\rho^2)}\right) \quad z = \left(\frac{x_1 - \mu_1}{\sigma_1}\right)^2 + \left(\frac{x_2 - \mu_2}{\sigma_2}\right)^2 - \frac{2\rho(x_1 - \mu_1)(x_2 - \mu_2)}{\sigma_1\sigma_2}$$

Joint standard normal: 
$$\varphi(\mathbf{y}) = \frac{1}{\sqrt{(2\pi)^n}} \cdot \exp\left(-\frac{1}{2}\mathbf{y}^T \mathbf{y}\right)$$



# Joint Lognormal

## Section 3.3



# Joint from Conditional

$$f(x|y) \cdot dx = \frac{f(x,y) \cdot dx \cdot dy}{f(y) \cdot dy} \Rightarrow f(x|y) = \frac{f(x,y)}{f(y)}$$

$$f(x,y) = f(x|y) \cdot f(y) = f(y|x) \cdot f(x)$$

What is statistical independence for random variables?

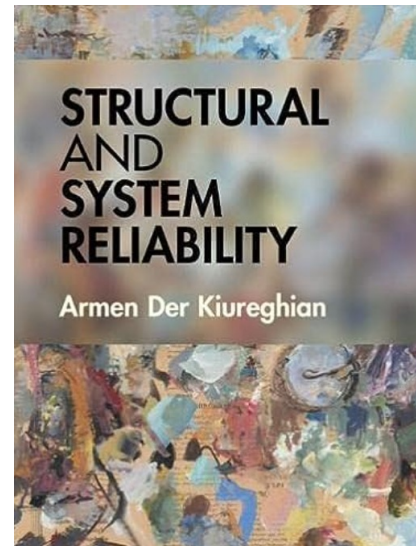
Consequence of statistical independence:  $f(x,y) = f(x)f(y)$

What is the difference between correlation and statistical dependence?

# Joint from Marginals + Correlation

Morgenstern

Nataf



More in the short course on Structural Reliability

More lectures:

Terje's Toolbox:

[terje.civil.ubc.ca](http://terje.civil.ubc.ca)