

Remark: From $F_{\underline{x}}$ we can obtain F_{x_1} by the formula

$$F_{x_1}(x_1) = \lim_{y \rightarrow \infty} P(X_1 \leq x_1, X_2 \leq y, X_3 \leq y, \dots, X_N \leq y)$$

↑ marginal cdf

And similarly in the continuous case

$$f_{x_1}(x_1) = \int_{\mathbb{R}} \dots \int_{\mathbb{R}} f_{\underline{x}}(x_1, x_2, \dots, x_n) dx_2 \dots dx_n$$

↑ marginal pdf
N-1 integrals

As before $g: \mathbb{R}^N \rightarrow \mathbb{R}$ continuous

$$E(g(\underline{X})) = \iiint_{\mathbb{R}^N} g(\underline{x}) f_{\underline{x}}(\underline{x}) d\underline{x}$$

↑ dx_1, dx_2, \dots, dx_n
N-k random v.

Def. **Conditional pdf or pmf** for X_{k+1}, \dots, X_N knowing X_1, \dots, X_k is given by

$$f(x_{k+1}, \dots, x_N | x_1, \dots, x_k) = \frac{f_{\underline{x}}(x_1, \dots, x_N)}{f_{x_1, \dots, x_k}(x_1, \dots, x_k)}$$

if the denominator is not 0.

(Example 4.2.2 + 4.2.4 for motivation)

I.5 Covariance and correlation

Consider X and Y random variables on S ,

with $E(X) = \mu_X$, $E(Y) = \mu_Y$, $\text{Var}(X) = \sigma_X^2$, $\text{Var}(Y) = \sigma_Y^2$ We assume they exist.

Def. The **covariance** of X and Y is defined by

$$\text{Cov}(X, Y) = E((X - \mu_X)(Y - \mu_Y)) = E(XY) - \sigma_X \sigma_Y$$

The **correlation** of X and Y is defined by

$$\rho_{XY} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} \in [-1, 1]$$

Lemma: If X and Y are independent then $\text{Cov}(X, Y) = \rho_{XY} = 0$ easy exercise

⚠ The converse is not true.

The covariance measures a linear relationship:

$$|\rho_{XY}| = 1 \text{ iff } P(Y = aX + b) = 1 \exists a, b \in \mathbb{R}$$

The pages 3,4 in Appendix 3 are helpful and easy.