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Cumulative Distribution Functions

Suppose X and Y are two random variables

- $F_{XY}(x, y) = P(X \leq x \text{ and } Y \leq y)$ is the cumulative distribution function for X and Y
- When X and Y are independent then

$$P(X \leq x \text{ and } Y \leq y) = P(X \leq x)P(Y \leq y)$$

i.e.

$$F_{XY}(x, y) = F_X(x)F_Y(y)$$

When X and Y are discrete random variable taking values $\{x_1, \dots, x_n\}$ and $\{y_1, \dots, y_m\}$

- $F_{XY}(x, y) = \sum_{i: x_i \leq x} \sum_{j: y_j \leq y} P(X = x_i \text{ and } Y = y_j)$

When X and Y are jointly continuous-valued random variables there exists a probability density function (PDF) $f_{XY}(x, y) \geq 0$ such that

$$F_{XY}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{XY}(u, v) du dv$$

Can think of $P(u \leq X \leq u + du \text{ and } v \leq Y \leq v + dv) \approx f_{XY}(u, v) du dv$ when du, dv are infinitesimally small.

Conditional Probability Density Function

Suppose X and Y are two continuous random variables with joint PDF $f_{XY}(x, y)$. Define conditional PDF:

$$f_{X|Y}(x | y) = \frac{f_{XY}(x, y)}{f_Y(y)}$$

Compare with conditional probability for discrete RVs:

$$P(X = x | Y = y) = \frac{P(X = x \text{ and } Y = y)}{P(Y = y)}$$

Chain Rule for PDFs

Since

$$f_{X|Y}(x | y) = \frac{f_{XY}(x, y)}{f_Y(y)}$$

the chain rule also holds for PDFs:

$$f_{XY}(x, y) = f_{X|Y}(x | y)f_Y(y) = f_{Y|X}(y | x)f_X(x)$$

Also

- $\int_{-\infty}^{\infty} f_{X|Y}(x | y)dx = \frac{\int_{-\infty}^{\infty} f_{XY}(x, y)dx}{f_Y(y)} = \frac{f_Y(y)}{f_Y(y)} = 1$
- We can marginalise PDFs:

$$\int_{-\infty}^{\infty} f_{XY}(x, y)dy = \int_{-\infty}^{\infty} f_{Y|X}(y | x)f_X(x)dy = f_X(x) \int_{-\infty}^{\infty} f_{Y|X}(y | x)dy = f_X(x)$$

Bayes Rule for PDFs

Since

$$f_{X|Y}(x | y) = \frac{f_{XY}(x, y)}{f_Y(y)}$$

then

$$f_{X|Y}(x | y)f_Y(y) = f_{XY}(x, y) = f_{Y|X}(y | x)f_X(x)$$

and so we have Bayes Rule for PDFs:

$$f_{Y|X}(Y | X) = \frac{f_{X|Y}(x | y)f_Y(y)}{f_X(x)}$$

Independence

Suppose X and Y are two continuous random variables with joint PDF $f_{XY}(x, y)$. Then X and Y are independent when

$$f_{XY}(x, y) = f_X(x)f_Y(y)$$

Why?

$$P(X \leq x \text{ and } Y \leq y) = \int_{-\infty}^x \int_{-\infty}^y f_{XY}(u, v) du dv = \int_{-\infty}^x f_X(u) du \int_{-\infty}^y f_Y(v) dv = P(X \leq x)P(Y \leq y)$$