

STAT 450: Statistical Theory

Independence, conditional distributions

Def'n: A density $f_{X,Y}$ is said to be independent if $f_{X,Y}(x,y) = f_X(x)f_Y(y)$. Often modelling leads to a specification in terms of marginal and conditional distributions.

$$P(AB) = P(A)P(B).$$

Def'n: $A_i, i = 1, \dots, p$ are **independent** if

(Notation: AB is the event that both A and B happen, also written $A \cap B$.)

$$P(A_{i_1} \cdots A_{i_r}) = \prod_{j=1}^r P(A_{i_j})$$

Example: $p = 3$

for any $1 \leq i_1 < \cdots < i_r \leq p$.

$$P(A_1 A_2 A_3) = P(A_1)P(A_2)P(A_3)$$

$$P(A_1 A_2) = P(A_1)P(A_2)$$

$$P(A_1 A_3) = P(A_1)P(A_3)$$

$$P(A_2 A_3) = P(A_2)P(A_3)$$

All these equations needed for independence!

Example: Toss a coin twice.

$$A_1 = \{\text{first toss is a Head}\}$$

$$A_2 = \{\text{second toss is a Head}\}$$

$$A_3 = \{\text{first toss and second toss different}\}$$

Then $P(A_i) = 1/2$ for each i and for $i \neq j$

$$P(A_i \cap A_j) = \frac{1}{4}$$

but

$$P(A_1 \cap A_2 \cap A_3) = 0 \neq P(A_1)P(A_2)P(A_3).$$

Def'n: X and Y are **independent** if

$$P(X \in A; Y \in B) = P(X \in A)P(Y \in B)$$

for all A and B .

Def'n: Rvs X_1, \dots, X_p **independent**:

$$P(X_1 \in A_1, \dots, X_p \in A_p) = \prod P(X_i \in A_i)$$

for any A_1, \dots, A_p . If A_1 and A_2 are independent then for all x, y

Theorem:

1. If X and Y are independent with joint density $f_{X,Y}(x,y) = f_X(x)f_Y(y)$ then X and Y have densities f_X and f_Y , and $f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy$ and $f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx$.
2. If X and Y are independent with joint density $f_{X,Y}(x,y) = f_X(x)f_Y(y)$ then X and Y have densities f_X and f_Y , and $f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy$ and $f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx$.
3. If X and Y independent with marginal densities $f_X(x)$ and $f_Y(y)$ then (X, Y) has joint density $f_{X,Y}(x,y) = f_X(x)f_Y(y)$.
4. If (X, Y) has density $f(x, y)$ and there exist $g(x)$ and $h(y)$ st $f(x, y) = g(x)h(y)$ for (almost) **all** (x, y) then X and Y are independent with densities given by $f_X(x) = \int_{-\infty}^{\infty} f(x, y) dy$ and $f_Y(y) = \int_{-\infty}^{\infty} f(x, y) dx$.

$$f_X(x) = g(x) / \int_{-\infty}^{\infty} g(u) du$$

$$f_Y(y) = h(y) / \int_{-\infty}^{\infty} h(u) du.$$

Proof: See STAT 802

Theorem: If X_1, \dots, X_p are independent and $Y_i = g_i(X_i)$ then Y_1, \dots, Y_p are independent. Moreover, (X_1, \dots, X_q) and (X_{q+1}, \dots, X_p) are independent.

Conditional probability

Def'n: $P(A|B) = P(AB)/P(B)$ if $P(B) \neq 0$.

Def'n: For discrete X and Y the conditional probability mass function of Y given X is

$$\begin{aligned} f_{Y|X}(y|x) &= P(Y = y|X = x) \\ &= f_{X,Y}(x, y)/f_X(x) \\ &= f_{X,Y}(x, y) / \sum_t f_{X,Y}(x, t) \end{aligned}$$

For absolutely continuous X $P(X = x) = 0$ for all x . What is $P(A|X = x)$ or $f_{Y|X}(y|x)$? Solution: use limit

$$P(A|X = x) = \lim_{\delta x \rightarrow 0} P(A|x \leq X \leq x + \delta x)$$

If, e.g., X, Y have joint density $f_{X,Y}$ then with $A = \{Y \leq y\}$ we have

$$\begin{aligned} P(A|x \leq X \leq x + \delta x) &= \frac{P(A \cap \{x \leq X \leq x + \delta x\})}{P(x \leq X \leq x + \delta x)} \\ &= \frac{\int_{-\infty}^y \int_x^{x+\delta x} f_{X,Y}(u, v) du dv}{\int_x^{x+\delta x} f_X(u) du} \end{aligned}$$

Divide top, bottom by δx ; let $\delta x \rightarrow 0$. Denom converges to $f_X(x)$; numerator converges to

$$\int_{-\infty}^y f_{X,Y}(x, v) dv$$

Define conditional cdf of Y given $X = x$:

$$P(Y \leq y|X = x) = \frac{\int_{-\infty}^y f_{X,Y}(x, v) dv}{f_X(x)}$$

Differentiate wrt y to get def'n of conditional density of Y given $X = x$:

$$f_{Y|X}(y|x) = f_{X,Y}(x, y)/f_X(x);$$

in words "conditional = joint/marginal".