

## § 1.4 Conditional Probability

Let  $(\Omega, P)$  be the probability space,  $A, B$  any subsets of  $\Omega$ . The **(conditional) probability** of  $B$  given  $A$  is defined as

$$P(A \cap B) / P(A).$$

It is denoted by  $P(B|A)$  or  $P_A(B)$ . When  $P(A) = 0$ , though  $P_A(B)$  is meaningless, it is convenient to write

$$P_A(B) = \begin{cases} 1, & \omega_0 \in B, \\ 0, & \omega_0 \notin B. \end{cases}$$

Here,  $\omega_0$  is any arbitrary fixed point in  $\Omega$ .

**Theorem 1.12** (i)  $P(A \cap B) = P(A) P_A(B)$

(ii) When  $P_A(B)$  is viewed as a function of  $B$  with  $A$  fixed, it is a probability measure on  $\Omega$ . (In this sense, the set function  $P_A$  is the **(conditional) probability law** given  $A$ .)

**Proof** (i) When  $P(A) > 0$ , it is straightforward from the definition. Even when  $P(A) = 0$ , it is understandable from the above constraint that the theorem holds. ■

To repeat the above theorem's (i),

$$P(A_1 \cap A_2 \cap A_3) = P(A_1) P_{A_1}(A_2) P_{A_1 \cap A_2}(A_3),$$

and more generally,

$$P(A_1 \cap A_2 \cap \cdots \cap A_n) = P(A_1) P_{A_1}(A_2) \cdots P_{A_1 \cap A_2 \cap \cdots \cap A_{n-1}}(A_n)$$

is obtained.

Let  $P_A(B)$ ,  $A = X^{-1}\{x\}$  ( $x \in \Omega^X$ ), and define  $P_{X^{-1}\{x\}}(B)$ . Since  $X^{-1}\{x\} = \{\omega | X(\omega) = x\}$ ,  $P_{X^{-1}\{x\}}(B)$  is written as

$$P_{X=x}(B) \quad \text{or} \quad P(B|X = x).$$

This is called "the conditional probability of  $B$  given the condition of  $X = X$ ."  $P_{X=x}(B)$  is a function of  $x \in \Omega^X$  and  $B \subset \Omega$ . Next, when  $x$  is fixed,  $P_{X=x}(B)$  is a probability measure on  $\Omega$  as a function of  $B$ . When  $x$  is rewritten as  $X(\omega)$ , that is, when

$$P_{X=x}(B)|_{x=X(\omega)}$$

is expressed as  $P_X(B)$  or  $P(B|X)$ , it is called the "conditional probability of  $B$  given that the value of  $X(\omega)$  is known." When  $B$  is fixed,  $P_X(B)$  is a function of  $X(\omega)$  hence a function of  $\omega$ , and can be considered as the probability variable on  $(\Omega, P)$ .

**Theorem 1.13**

$$P(X^{-1}(F) \cap B) = \sum_{x \in F} P\{X = x\} P_{X=x}(B) = E^X(P_{X=x}(B), F) = E(P_X(B), X^{-1}(F)).$$

**Proof** From  $X^{-1}(F) = \sum_{x \in F} X^{-1}\{x\}$ , the first equality is evident. With  $P\{X = x\} = P^X\{x\}$ , the second equality emerges. To show the third equality, denote  $P_{X=x}(B)$  by  $\varphi_B(x)$ ,

$$\begin{aligned} E^X(P_{X=x}(B), F) &= E^X(\varphi_B, F) = E^X(\varphi_B 1_F), \\ E(P_X(B), X^{-1}(F)) &= E(\varphi_B(X(\omega)), X^{-1}(F)) = E(\varphi_B(X(\omega)) 1_F(X(\omega))), \end{aligned}$$

is obtained. From Theorem 1.9, it is easy to understand that these two equations are equal. **■**

Since  $P_A$  is a probability law on  $\Omega$ , with respect to a function  $Y(\omega)$  on  $\Omega$ , the average value  $E_A Y$  of  $Y(\omega)$  with respect to  $P_A$  can be defined by

$$E_A(Y) = \sum_{\omega \in \Omega} Y(\omega) P_A\{\omega\}.$$

Directly defined by

$$E_A(Y) = \begin{cases} E(Y, A)/P(A), & P(A) > 0, \\ Y(\omega_0), & P(A) = 0 \end{cases}$$

yields the same thing also. Here  $\omega_0$  is that which is fixed when  $P(A) = 0$  in the definition of  $P_A(B)$ . Accordingly,

$$E(Y, A) = P(A) E_A(Y).$$

Same as the definition of  $P_{X=x}(B), P_X(B)$  by  $P_A(B)$ , it is possible to define  $E_{X=x}(Y), E_X(Y)$  with  $E_A(Y)$ . Corresponding to Theorem 1.13, the following theorem is obtained:

**Theorem 1.14**

$$E(Y, X^{-1}(F)) = \sum_{x \in F} P\{X = x\} E_{X=x}(Y) = E^X(E_{X=x}(Y), F) = E(E_X(Y), X^{-1}(F)).$$

**Proof** Same as Theorem 1.13. **■**

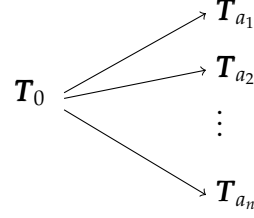
At times,  $E_A(Y), E_{X=x}(Y)$ , and  $E_X(Y)$  are also written as, respectively,

$$E(Y|A), \quad E(Y|X = x), \quad E(Y|X).$$

Let  $B = \{\omega | Y \in F\} = Y^{-1}(F)$  in  $P_A(B)$  and define  $P_A\{Y \in F\}$ . As a function of  $F$ , it is a probability measure. Since this probability measure is the probability law of  $Y(\omega)$  when  $Y(\omega)$  is seen as the proba-

bility variable on  $(\Omega, P_A)$ , it can be written as  $(P_A)^Y$ . By the same token, one can consider  $P_{X=x}\{Y \in F\}$ ,  $P_X\{y \in F\}$ ,  $(P_{X=x})^Y$ , and  $(P_X)^Y$ .

The conditional probability has a close relationship with the tree union discussed in the previous section. Consider the tree union



Let the probability space of  $T_0$  be

$$(\Omega_0 \equiv \{a_1, a_2, \dots, a_n\}, P_0),$$

and that of  $T_a$  be  $(\Omega_a, P_a)$ . The probability space  $(\Omega, P)$  of this tree union is given by

$$\Omega = \{(a, b) | a \in \Omega_0, b \in \Omega_a\},$$

$$P\{(a, b)\} = P_0\{a\} P_a\{b\}.$$

The result of the first trial  $T_0$  of  $T$ , and the result of the next trial (one amongst  $T_{a_1}, T_{a_2}, \dots, T_{a_n}$ ) are the probability variables on  $(\Omega, P)$ . They are denoted by  $X(\omega)$  and  $Y(\omega)$ . That is

$$X(\omega) = \pi_1(\omega), \quad Y(\omega) = \pi_2(\omega) \quad (\pi_i \text{ is image}).$$

Thus,  $Y(\omega)$  is a probability variable that takes value in one of  $\bigcup_{i=1}^n \Omega_{a_i}$ , and

$$P\{(a, b)\} = P\{X = a, Y = b\} = P\{X = a\} P_{X=a}\{Y = b\},$$

$$P\{X = a\} = \sum_{b \in \Omega_a} P\{X = a, Y = b\} = \sum_{b \in \Omega_a} P\{(a, b)\} = \sum_{b \in \Omega_a} P_0\{a\} P_a\{b\} = P_0\{a\}.$$

From these emerge

$$P_{X=a}\{Y = b\} = \frac{P\{(a, b)\}}{P\{X = a\}} = \frac{P_0\{a\} P_a\{b\}}{P_0\{a\}} = P_a\{b\}.$$

Hence, the following theorem is obtained.

**Theorem 1.15**  $P_{X=a}\{Y = b\} = P_a\{b\}.$

Similarly, for tree union with many periods, denote the results of the first, second,  $\dots$  by, respectively,  $X, Y, Z, \dots$ , and

$$P_{X=a}\{Y = b\} = P_a\{b\},$$

$$P_{X=a, Y=b}\{Z = c\} = P_{a,b}\{c\}$$

.....

In the case of direct union,  $P_{X=a}\{Y = b\}$  is unrelated to  $a$ , and  $P_{X=a, Y=b}\{Z = c\}$  is unrelated to  $a, b$ .

**Exercise 1.4** When  $\Omega = A_1 + A_2 + \cdots + A_n$ , prove the following equation

$$P_B(A_i) = \frac{P(A_i) P_{A_i}(B)}{\sum_{k=1}^n P(A_k) P_{A_k}(B)} \quad (\text{Bayes' Theorem})$$