

## Chapter 2 Foundations of Probability

- **2.1** Since g is  $\mathcal{G}/\mathcal{H}$ -measurable, therefore  $\forall C \in \mathcal{H}$ ,  $\exists B = g^{-1}(C) \in \mathcal{G}$ . Similarly, since f is  $\mathcal{F}/\mathcal{G}$ -measurable,  $\forall B \in \mathcal{G}$ ,  $\exists A = f^{-1}(B) \in \mathcal{F}$ . Thus  $\forall C \in \mathcal{H}$ ,  $\exists A = f^{-1}(g^{-1}(C)) = (g \circ f)^{-1}(C) \in \mathcal{F}$  and the proof is complete.
- **2.2** We claim that  $X = (X_1, X_2, ..., X_n)$  is  $\mathcal{F}/\mathcal{B}(\mathbb{R}^n)$  measurable. Define  $a = (a_1, a_2, ..., a_n)$   $b = (b_1, b_2, ..., b_n)$  with  $a, b \in \mathbb{R}^n$  where a < b. Since  $X_1, X_2, ..., X_n$  is  $\mathcal{F}/\mathcal{B}(\mathbb{R})$  measurable, therefore  $\exists A_1 = X_1^{-1}((a_1, b_1)), A_2 = X_2^{-1}((a_2, b_2)), ..., A_n = X_n^{-1}((a_n, b_n)) \in \mathcal{F}$ . Let  $A = A_1 \cap A_2 \cap ... \cap A_n = \bigcap_{i=1}^n A_i$ . It follows that  $X^{-1}((a, b)) = \bigcap_{i=1}^n ((a, b)) = A \in \mathcal{F}$ . Therefore X is  $\mathcal{F}/\mathcal{B}(\mathbb{R}^n)$  measurable and X is random vector.

2.3

- (i) We need to show that  $\Sigma_X$  is closed under countable union. Let  $U_i = X^{-1}(A_i), A_i \in \Sigma, i \in \mathbb{N}$ . It follows that  $\bigcup_{i=1}^{\infty} U_i = \bigcup_{i=1}^{\infty} X^{-1}(A_i) = X^{-1}(\bigcup_{i=1}^{\infty} A_i)$ . Since  $\bigcup_{i=1}^{\infty} A_i \in \Sigma(\Sigma)$  is sigma algebra),  $\bigcup_{i=1}^{\infty} U_i \in \Sigma_X$ .
- (ii) We need to show that  $\Sigma_X$  is closed under set subtraction -.  $\forall U_1, U_2 \in \Sigma_X, U_1 U_2 = X^{-1}(A_1) X^{-1}(A_2) = X^{-1}(A_1 A_2)$ . Since  $A_1 A_2 \in \Sigma(Sigma \text{ is sigma algebra}), U_1 U_2 \in \Sigma_X$ .
- (iii) We need to show that  $\Sigma_X$  is closed to  $\mathcal{U}$  itself. Since  $\mathcal{U} = X^{-1}(\mathcal{V})$  and  $\mathcal{V} \in \Sigma$ , it follows that  $\mathcal{U} \in \Sigma_X$ .

## 2.4

- (a) (i) We need to show that  $\mathcal{F}|_A$  is closed under countable union. Let  $X_1 = A \cap B_1, X_2 = A \cap B_2, ...$  and  $X' = \bigcup_{i=1}^{\infty} X_i$  and  $B' = \bigcup_{i=1}^{\infty}$  where  $B_1, B_2, ... \in \mathcal{F}$ . Since  $\mathcal{F}$  is sigma algebra,  $B' \in \mathcal{F}$ . Furthermore, since  $X' = \bigcup_{i=1}^{\infty} X_i = \bigcup_{i=1}^{\infty} A \cap B_i = A \cap \left(\bigcup_{i=1}^{\infty} A \cap B_i\right) = A \cap B'$ , we can see that  $X' \in \mathcal{F}|_A$ .
  - (ii) We need to show that  $\mathcal{F}|_A$  is closed under set subtraction -.  $\forall X_1, X_2 \in \mathcal{F}|_A$ ,  $X_1 X_2 = (A \cap B_1) (A \cap B_2) = A \cap (B_1 B_2)$ . Since  $B_1 B_2 \in \mathcal{F}(F)$  is sigma algebra, it follows that  $X_1 X_2 \in \mathcal{F}|_A$ .
  - (iii) We need to show that  $\Sigma_X$  is closed to A itself. Since  $\emptyset \in \mathcal{F}$ , we have  $\emptyset = A \cap \emptyset \in \mathcal{F}|_A$  and  $A = \emptyset^C \in \mathcal{F}|_A$ .
- (b) Let  $P = \{A \cap B : B \in \mathcal{F}\}, Q = \{B : B \subset A, B \in \mathcal{F}\}.$ 
  - (i) We claim that  $P \subset Q$ . Let  $X = A \cap B$ ,  $B \in \mathcal{F}$ . Since  $A \in \mathcal{F}$ ,  $X = A \cap B \in \mathcal{F}$ . Furthermore,  $X \in Q = \{B : B \subset A, B \in \mathcal{F}\}.$
  - (ii) We claim that  $Q \subset P$ .  $\forall X \in Q$ , we have  $X \subset A$  and  $X \in \mathcal{F}$ , which means that  $X = X \cap A$  and  $X \in \mathcal{F}$ . It follows that  $X \in P$ .
  - (iii) Take both (i)(ii) into consideration, we can see that P = Q.

(a) Clearly  $\sigma(\mathcal{G})$  should be the intersection of all  $\sigma$ -algebras that contain  $\mathcal{G}$ . Formally speaking, let  $\mathcal{K} = \{\mathcal{F} | \mathcal{F} \text{ is a } \sigma\text{-algebra and contains } \mathcal{G}\}$ . Then  $\bigcap_{\mathcal{F} \in \mathcal{K}} \mathcal{F}$  contains exactly those sets that are in every  $\sigma$ -algebra that contains  $\mathcal{G}$ . Given its existence, we only need to prove that  $\bigcap_{\mathcal{F} \in \mathcal{K}} \mathcal{F}$  is the smallest  $\sigma$ -algebra that contains  $\mathcal{G}$ .

First we show  $\bigcap_{\mathcal{F} \in \mathcal{K}} \mathcal{F}$  is a  $\sigma$ -algebra. Since  $\mathcal{F}$  is a  $\sigma$ -algebra and therefore  $\Omega \in \mathcal{F}$  for all  $\mathcal{F} \in \mathcal{K}$ , it follows that  $\Omega \in \bigcap_{\mathcal{F} \in \mathcal{K}} \mathcal{F}$ . Next, for any  $A \in \bigcap_{\mathcal{F} \in \mathcal{K}} \mathcal{F}$ ,  $A^c \in \mathcal{F}$  for all  $\mathcal{F} \in \mathcal{K}$ . Since they are all  $\sigma$ -algebras,  $A^c \in \mathcal{F}$  for all  $\mathcal{F} \in \mathcal{K}$ . Hence  $A^c \in \bigcap_{\mathcal{F} \in \mathcal{K}} \mathcal{F}$ . Finally, for any  $\{A_i\}_i \subset \bigcap_{\mathcal{F} \in \mathcal{K}} \mathcal{F}$ ,  $\{A_i\}_i \subset \mathcal{F}$  for all  $\mathcal{F} \in \mathcal{K}$ . Since they are all  $\sigma$ -algebras,  $\bigcup_i A_i \in \mathcal{F}$  for all  $\mathcal{F} \in \mathcal{K}$ . Hence  $\bigcup_i A_i \in \bigcap_{\mathcal{F} \in \mathcal{K}} \mathcal{F}$ .

It is quite obvious that  $\bigcap_{\mathcal{F} \in \mathcal{K}} \mathcal{F}$  is the smallest one as  $\bigcap_{\mathcal{F} \in \mathcal{K}} \mathcal{F} \subseteq \mathcal{F}'$  for all  $\mathcal{F}' \in \mathcal{K}$ .

(b) We first introduce a useful lemma: the map X is  $\mathcal{F}/\mathcal{G}$ -measurable if and only  $\sigma(X) \subseteq \mathcal{F}$ , where  $\sigma(X) = \{X^{-1}(A) : A \in \mathcal{G}\}$  is the  $\sigma$ -algebra generated by X. With this lemma, the main idea to prove X is  $\mathcal{F}/\sigma(\mathcal{G})$ -measurable is to show that  $\sigma(X) = \{X^{-1}(A) : A \in \sigma(\mathcal{G})\} \subseteq \mathcal{F}$ .

Let  $X^{-1}(\mathcal{G}) = \{X^{-1}(A) : A \in \mathcal{G}\}$ . Clearly we have  $X^{-1}(\mathcal{G}) \subseteq \mathcal{F}$ .  $\sigma(X^{-1}(\mathcal{G}))$  is the smallest  $\sigma$ -algebra that contains  $X^{-1}(\mathcal{G})$ . And we know  $\mathcal{F}$  is a  $\sigma$ -algebra that contains  $X^{-1}(\mathcal{G})$ . According to the result of the previous question,  $\sigma(X^{-1}(\mathcal{G})) \subseteq \mathcal{F}$ . Furthermore,  $\sigma(X^{-1}(\mathcal{G})) = X^{-1}(\sigma(\mathcal{G})) = \{X^{-1}(A) : A \in \sigma(\mathcal{G})\} = \sigma(X)$ . Hence  $\sigma(X) \subseteq \mathcal{F}$ .

Readers can further refer to the penultimate paragraph in Page 16, where the author provides a general idea to check whether a map is measurable.

- (c) The idea is to show  $\forall B \in \mathfrak{B}(\mathbb{R}), \ \mathbb{I}\{A\}^{-1}(B) \in \mathcal{F}.$ If  $\{0,1\} \in B, \ \mathbb{I}\{A\}^{-1}(B) = \Omega \in \mathcal{F}.$  If  $\{0\} \in B, \ \mathbb{I}\{A\}^{-1}(B) = A^c \in \mathcal{F}.$  If  $\{1\} \in B, \ \mathbb{I}\{A\}^{-1}(B) = A \in \mathcal{F}.$  If  $\{0,1\} \cap B = \emptyset, \ \mathbb{I}\{A\}^{-1}(B) = \emptyset \in \mathcal{F}.$
- **2.6** As the hint suggests, Y is not  $\sigma(X)$ -measurable under such conditions since  $Y^{-1}((0,1)) = (0,1) \notin \sigma(X)$ , where  $\sigma(X) = \{X^{-1}(A) : A \in \mathcal{G}\} = \{\emptyset, \mathbb{R}\}.$
- **2.7** First we have  $\mathbb{P}(\Omega \mid B) = \frac{\mathbb{P}(\Omega \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}(B)}{\mathbb{P}(B)} = 1$ . Then, for all  $A \in \mathcal{F}$ ,  $\mathbb{P}(A \mid B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} \geq 0$ . Next, for all  $A \in \mathcal{F}$ ,  $\mathbb{P}(A^c \mid B) = \frac{\mathbb{P}(A^c \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}((\Omega A) \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}(B) \mathbb{P}(A \cap B)}{\mathbb{P}(B)} = 1 \mathbb{P}(A \mid B)$ . Finally, for all countable collections of disjoint sets  $\{A_i\}_i$  with  $A_i \in \mathcal{F}$  for all i, we have  $\mathbb{P}(\bigcup_i A_i \mid B) = \frac{\mathbb{P}((\bigcup_i A_i) \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}(\bigcup_i (A_i \cap B))}{\mathbb{P}(B)} = \sum_i \mathbb{P}(A_i \mid B)$ .
- **2.8** With the definition of conditional probability, we have  $\mathbb{P}(A \mid B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}(B \mid A)\mathbb{P}(A)}{\mathbb{P}(B)}$ .

2.9

(a) There are 36 possible events:

$$1.X_1 < 2, X_2 = \text{even}$$
:

$$X_1 = 1, X_2 = 2$$

$$X_1 = 1, X_2 = 4$$

$$X_1 = 1, X_2 = 6$$

So,P(
$$X_1 < 2, X_2 = \text{even}$$
)=  $\frac{3}{36} = \frac{1}{12}$ 

and 
$$P(X_1 < 2) = \frac{1}{1}(6), P(X_2 = \text{even}) = \frac{1}{2}$$

So, $P(X_1 < 2, X_2 = \text{even}) = P(X_1 < 2) * P(X_2 = \text{even})$ . According to the definition of independent event, two events are independent.

(b) Prove $P(A \cap B) = P(A)P(B)$ 

(a) Empty sets and complete sets are independent of any event:

$$P(A \cap \Omega) = P(A) = 1 * P(A) = P(\Omega) * P(A)$$
$$P(A \cap \phi) = P(\phi) = 0 = P(\phi) * P(A)$$

(b) Prove when P(A)=0 or 1, A is independent of any event: for any  $B\in\Omega$   $P(A)\in\{0,1\}$ 

When 
$$P(A) = 1$$
,  $P(A^c \cap B) \le P(A^c) = 1 - P(A) = 0$ ,  
we have  $P(A \cap B) = P(A \cap B) + P(A^c \cap B) = P(B) = P(A)P(B)$   
When  $P(A) = 0$ , we have  $P(A \cap B) \le P(A) = 0 = P(A)P(B)$ 

- (c)  $P(A^c \cap A) = P(A)P(A^c)$ we have  $0 = P(A)(1 - P(A)) \Rightarrow P(A) \in \{0, 1\}$
- (d)  $P(A \cap A) = P(A)P(A), P(A) = 0, 1$
- (e)  $\Omega = (1,1), (1,0), (0,1), (0,0)$

Just verify that each case is independent :  $P(A = 1, B = 1) = \frac{1}{4} = \frac{1}{2} * \frac{1}{2} = P(A)P(B)$ 

$$P(A = 1, B = 0) = \frac{1}{4} = \frac{1}{2} * \frac{1}{2} = P(A)P(B)$$

$$P(A = 0, B = 1) = \frac{1}{4} = \frac{1}{2} * \frac{1}{2} = P(A)P(B)$$

$$P(A = 0, B = 0) = \frac{1}{4} = \frac{1}{2} * \frac{1}{2} = P(A)P(B)$$

- (f)  $P(X_1 \le 2) = 2/3$   $P(X_1 = X_2) = 3/9 = 1/3$   $P(X_1 \le 2, X_1 = X_2) = P(X_1 = X_2 = 1) + P(X_1 = X_2 = 2) = 1/9 + 1/9 = 2/9$ So,  $P(X_1 \le 2, X_1 = X_2) = P(X_1 = X_2)P(X_1 \le 2)$
- (g) Necessity :  $\frac{|A \cap B|}{n} = P(A \cap B) = P(A)P(B) = \frac{|A|}{n} \frac{|B|}{n}$   $\Rightarrow |A \cap B| * n = |A||B|$ Sufficiency :  $|A \cap B| * n = |A||B| \Rightarrow \frac{|A|}{n} \frac{|B|}{n} = \frac{|A \cap B|}{n}$  $\Rightarrow P(A \cap B) = P(A)P(B)$
- (h)  $|A \cap B| * n = |A||B|, \Rightarrow n \le |A| \le n \Rightarrow A \ne \phi or \Omega$
- (j) Let's take a counter example: roll a die and set the A event to  $\{1,2,3\}$ , B event is set to  $\{1,2,4\}$ , C event is set to  $\{1,4,5,6\}$

$$P(X_1X_2X_3) = \frac{1}{6}$$

$$P(X_1)P(X_2)P(X_3) = (1/2)*(1/2)*(2/3) = 1/6$$
while  $P(X_1 \cap X_2) = 1/3 \neq \frac{1}{2}*\frac{1}{2}$ 

## 2.11

(a)  $X:\Omega \to x$ 

Because X, Y are independent equivalent  $to\sigma(X), \sigma(Y)$  are independent; For any  $A \in \sigma(Y)$ ,

$$P(\phi \cap A) = P(\phi) = 0 = P(\phi)P(A)$$

$$P(\Omega \bigcap A) = P(A) = P(\Omega)P(A)$$

(b) We know that P(X = x) = 1

$$P(X = x|Y) = \frac{P((X = x) \cap Y)}{P(Y)} = 1 = P(X = x)$$

$$P(X \neq x|Y) = 1 - P(X = x|Y) = 0 = P(X \neq x)$$

(c) Notice the relation:P(A) = P(X(A) = 1)

$$P(B) = P(X(B) = 1)$$

$$P(A \cap B) = P(X(A \cap B) = 1)$$

The first two formulas follow the definition. Let's prove the third equation:

$$P(X(A \cap B) = P(X(A) + X(B) - X(A \cup B) = 1)$$

Let's discuss $X(A), X(B), X(A \mid JB)$ :

X(A)	X(B)	X(AUB)	$X(A) + X(B) - X(A \cup B)$
1	1	1	1
1	0	1	0
0	1	1	0
0	0	0	0

We can see that,  $P(X(A \cap B) = P(X(A) + X(B) - X(A \cup B) = 1)$ , this is only one case of the first row of the table.

that is 
$$P(X(A \cap B) = 1) = P(X(A) = 1, X(B) = 1) = P(A \cap B)$$

that is 
$$P(X(A \cap B) = 1) = P(A \cap B)$$

So,
$$P(A \cap B) = P(A)P(B)$$
 is equivalent to  $P(X(A \cap B) = 1) = P(X(A) = 1)P(X(B) = 1)$ 

(d)  $A_i$  pairwise i  $\Leftrightarrow I\{A_i\}$  pairwise i

mutual i 
$$\Leftrightarrow P(\bigcap_i A_i) = \prod_i P(A_i)$$

$$\Leftrightarrow P(\bigcap_{i \in K^I} A_i \cap \bigcap_{i \in K^I} A_i^c)$$

$$= \prod_{i \in K^I} P(A_i) \prod_{i \in K^I} P(A_i^c)$$

$$\Leftrightarrow \{\phi, \Omega, A_i, A_i^c\}$$
 mutual independent

$$\Leftrightarrow \sigma(I\{w \in A_i\})$$
mutual i

$$\Leftrightarrow I\{w \in A_i\}$$
 mutual i

## **2.12** X integrable |X| integrable

- (a) For any  $A \in B(R) \Rightarrow A$  is open, so,  $f^{-1}(A)$  is open, so  $f^{-1}(A) \in B(R)$
- (b) X is known to be a random variable f(x) = |x| continuous.

r.v. X is 
$$\mathbf{F}/\mathbf{B}(R)$$
-measurable

$$\Rightarrow |X|$$
 is  $\mathbf{B}(R)/\mathbf{B}(R)$ -measurable

$$\Rightarrow |X|$$
 is  $\mathbf{F}/\mathbf{B}(R)$ -measurable

$$\Rightarrow |X|$$
 is r.v.

From (a)(b),X integrable  $\Leftrightarrow |X|$  integrable.

(a) Assume  $\forall i, X_i$  is simple function.

$$\begin{split} \mathbb{E}[X] &= \mathbb{E}\left[\sum_{i=1}^n X_i\right] \\ &= \mathbb{E}\left[\sum_{i=1}^n \sum_{j=1}^m \alpha_{i,j} \mathbb{I}_{A_{i,j}} \{\omega\}\right] \\ &= \int_{\Omega} \sum_{i=1}^n \sum_{j=1}^m \alpha_{i,j} \mathbb{I}_{A_{i,j}} \{\omega\} d\mathbb{P}(\omega) \\ &= \sum_{i=1}^n \sum_{j=1}^m \alpha_{i,j} \int_{\Omega} \mathbb{I}_{A_{i,j}} \{\omega\} d\mathbb{P}(\omega) \\ &= \sum_{i=1}^n \sum_{j=1}^m \alpha_{i,j} \mathbb{P}(A_{i,j}) \\ &= \sum_{i=1}^n \mathbb{E}[X_i] \end{split}$$

(b) Assume  $\forall i, X_i$  is non-negative random variable.

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^{n} X_i\right]$$

$$= \sup\left\{\int_{\Omega} h d\mathbb{P} : h \text{ is simple and } 0 \le h \le X = \sum_{i=1}^{n} X_i\right\}$$

$$= \sum_{i=1}^{n} \sup\left\{\int_{\Omega} h_i d\mathbb{P} : h_i \text{ is simple and } 0 \le h_i \le X_i\right\}$$

$$= \sum_{i=1}^{n} \mathbb{E}[X_i]$$

(c) Assume  $\forall i, X_i$  is arbitrary random variable.

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^{n} X_{i}\right]$$

$$= \mathbb{E}\left[\sum_{i=1}^{n} (X_{i}^{+} - X_{i}^{-})\right]$$

$$= \mathbb{E}\left[\sum_{i=1}^{n} X_{i}^{+}\right] - \mathbb{E}\left[\sum_{i=1}^{n} X_{i}^{-}\right]$$

$$= \sum_{i=1}^{n} \mathbb{E}\left[X_{i}^{+}\right] - \sum_{i=1}^{n} \mathbb{E}\left[X_{i}^{-}\right]$$

$$= \sum_{i=1}^{n} (\mathbb{E}[X_{i}^{+}] - \mathbb{E}[X_{i}^{-}])$$

$$= \sum_{i=1}^{n} \mathbb{E}[X_{i}]$$

(a) Assume X is simple function.

$$\begin{split} \mathbb{E}[cX] &= \mathbb{E}\left[c\sum_{i=1}^{n}\alpha_{i}\mathbb{I}_{A_{i}}\{\omega\}\right] \\ &= \int_{\Omega}c\sum_{i=1}^{n}\alpha_{i}\mathbb{I}_{A_{i}}\{\omega\}d\mathbb{P}(\omega) \\ &= c\int_{\Omega}\sum_{i=1}^{n}\alpha_{i}\mathbb{I}_{A_{i}}\{\omega\}d\mathbb{P}(\omega) \\ &= c\mathbb{E}[X] \end{split}$$

(b) Assume X is non-negative random variable.

$$\begin{split} \mathbb{E}[cX] &= \sup \left\{ \int_{\Omega} h d\mathbb{P} : h \text{ is simple and } 0 \leq h \leq cX \right\} \\ &= c \sup \left\{ \int_{\Omega} h' d\mathbb{P} : h' \text{ is simple and } 0 \leq h' \leq X \right\} \\ &= c \mathbb{E}[X] \end{split}$$

(c) Assume X is arbitrary random variable.

(i) 
$$c \ge 0$$

$$\mathbb{E}[cX] = \mathbb{E}[(cX)^+] - \mathbb{E}[(cX)^-]$$
$$= \mathbb{E}[c(X)^+] - \mathbb{E}[c(X)^-]$$
$$= c\mathbb{E}[(X)^+] - c\mathbb{E}[(X)^-]$$
$$= c\mathbb{E}[X]$$

(ii) c < 0

By definition, we have

$$(cX)^+ = cX\mathbb{I}\{cX > 0\}$$
  
=  $cX\mathbb{I}\{x < 0\}$  (since c<0)  
=  $(-c)(-X)\mathbb{I}\{X < 0\}$   
=  $(-c)(X)^-$ 

Along the similar line, we have

$$(cX)^{-} = -cX\mathbb{I}\{cX < 0\}$$
$$= -cX\mathbb{I}\{X > 0\}$$
$$= -c(X)^{+}$$

Now we can see that

$$\mathbb{E}[cX] = \mathbb{E}[(cX)^+] - \mathbb{E}[(cX)^-]$$

$$= \mathbb{E}[(-c)(X)^-] - \mathbb{E}[-c(X)^+]$$

$$= -c\mathbb{E}[(X)^-] + c\mathbb{E}[(X)^+]$$

$$= c\mathbb{E}[X]$$

(a) Assume  $X = \sum_{i=1}^{n} \alpha_i \mathbb{I}_{A_i} \{\omega\}, Y = \sum_{j=1}^{m} \beta_j \mathbb{I}_{B_j} \{\omega\}$  are simple functions.

$$\mathbb{E}[XY] = \mathbb{E}\left[\sum_{i=1}^{n} \sum_{j=1}^{m} \alpha_{i}\beta_{j}\mathbb{I}_{A_{i}}\{\omega\}\mathbb{I}_{B_{j}}\{\omega\}\right]$$

$$= \int_{\Omega} \sum_{i=1}^{n} \sum_{j=1}^{m} \alpha_{i}\beta_{j}\mathbb{I}_{A_{i}}\{\omega\}\mathbb{I}_{B_{j}}\{\omega\}d\mathbb{P}(\omega)$$

$$= \sum_{i=1}^{n} \sum_{j=1}^{m} \alpha_{i}\beta_{j}\mathbb{P}(A_{i} \cap B_{j})$$

$$= \sum_{i=1}^{n} \sum_{j=1}^{m} \alpha_{i}\beta_{j}\mathbb{P}(A_{i})\mathbb{P}(B_{j}) \text{ (by the definition of independence)}$$

$$= \left(\sum_{i=1}^{n} \alpha_{i}\mathbb{P}(A_{i})\right) \left(\sum_{j=1}^{m} \beta_{j}\mathbb{P}(B_{i})\right)$$

$$= \mathbb{E}[X]\mathbb{E}[Y]$$

(b) Assume X, Y are non-negative random variables.

$$\begin{split} \mathbb{E}[XY] &= \sup \left\{ \mathbb{E}[h] : h \text{ h is simple and } 0 \leq h \leq XY \right\} \\ &= \sup \left\{ \mathbb{E}[h_1 h_2] : h_1, h_2 \text{ are simple and } 0 \leq h_1 \leq X, 0 \leq h_2 \leq Y \right\} \\ &= \sup \left\{ \mathbb{E}[h_1] \mathbb{E}[h_2] : h_1, h_2 \text{ are simple and } 0 \leq h_1 \leq X, 0 \leq h_2 \leq Y \right\} \\ &= \sup \left\{ \mathbb{E}[h_1] : h_1 \text{ is simple and } 0 \leq h_1 \leq X \right\} \cdot \sup \left\{ \mathbb{E}[h_2] : h_2 \text{ is simple and } 0 \leq h_2 \leq Y \right\} \\ &= \mathbb{E}[X] \mathbb{E}[Y] \end{split}$$

(c) Assume X, Y are arbitrary random variables.

$$\begin{split} \mathbb{E}[XY] &= \mathbb{E}[(X^{+} - X^{-})(Y^{+} - Y^{-})] \\ &= \mathbb{E}[X^{+}Y^{+} - X^{+}Y^{-} - X^{-}Y^{+} + X^{-}Y^{-}] \\ &= \mathbb{E}[X^{+}]\mathbb{E}[Y^{+}] - \mathbb{E}[X^{+}]\mathbb{E}[Y^{-}] - \mathbb{E}[X^{-}]\mathbb{E}[Y^{+}] + \mathbb{E}[X^{-}]\mathbb{E}[Y^{-}] \\ &= (\mathbb{E}[X^{+}] - \mathbb{E}[X^{-}])(\mathbb{E}[Y^{+}] - \mathbb{E}[Y^{-}]) \\ &= \mathbb{E}[X]\mathbb{E}[Y] \end{split}$$

**2.17** Before proving Ex.2.17, we need to make minor changes to the definition of conditional expectation and give a small lemma.

**Definition 1.** Assume  $(\Omega, \mathcal{F}, \mathbb{P})$  is a probability space.  $\mathcal{G} \subset \mathcal{F}$  is a sub- $\sigma$ -algebra of  $\mathcal{F}$ .  $X : \Omega \to \mathbb{R}$  is a random variable. The conditional expectation of X given  $\mathcal{G}$  is denoted by any random variable Y which satisfies the following 2 properties:

- Y is G-measurable
- $\forall A \in \mathcal{G}$ ,

$$\int_{A} Y d\mathbb{P} = \int_{A} X d\mathbb{P}$$

Formally, we denoted Y by notation  $\mathbb{E}[X|\mathcal{G}]$ .

**Lemma 1.** If X is  $\mathcal{G}$ -measurable, then  $\mathbb{E}[X|\mathcal{G}] = X$  holds a.s.

*Proof.* Since X is  $\mathcal{G}$ -measurable, property 1 holds. And property 2 holds trivially.

We can now handily prove Ex.2.17. Since  $\mathbb{E}[X|\mathcal{G}_1]$  is  $\mathcal{G}_1$ -measurable and  $\mathcal{G}_1 \subset \mathcal{G}_2$ , we can see that  $\mathbb{E}[X|\mathcal{G}_1]$  is  $\mathcal{G}_2$ -measurable. By Lemma 1,  $\mathbb{E}[\mathbb{E}[X|\mathcal{G}_1]|\mathcal{G}_2] = \mathbb{E}[X|\mathcal{G}_1]$  holds almost surely.