INTRODUCTION TO PROBABILITY

CARSON JAMES

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3.1. **Distributions.**

Definition 3.1.1. Let Ω be a set and $\mathcal{P} \subset \mathcal{P}(X)$. Then $\mathcal{P}$ is said to be a **π-system** on Ω if for each $A, B \in \mathcal{P}$, $A \cap B \in \mathcal{P}$.

Definition 3.1.2. Let Om be a set and $\mathcal{L} \subset \mathcal{P}(\Omega)$. Then $\mathcal{L}$ is said to be a **λ-system** on Ω if

(1) $\mathcal{L} \neq \varnothing$
(2) for each $A \in \mathcal{L}$, $A^c \in \mathcal{L}$
(3) for each $(A_n)_{n\in\mathbb{N}} \subset \mathcal{L}$, if $(A_n)_{n\in\mathbb{N}}$ is disjoint, then $\bigcup\limits_{n\in\mathbb{N}} A_n \in \mathcal{L}$

Exercise 3.1.3. Let Ω be a set and $\mathcal{L}$ a λ-system on Ω. Then

(1) $\Omega, \varnothing \in \mathcal{L}$

Proof. Straightforward. $\square$

Definition 3.1.4. Let Ω be a set and $\mathcal{C} \subset \mathcal{P}(\Omega)$. Put

$$\mathcal{S} = \{\mathcal{L} \subset \mathcal{P}(\Omega) : \mathcal{L} \text{ is a } \lambda\text{-system on } \Omega \text{ and } \mathcal{C} \subset \mathcal{L}\}$$

We define the **λ-system on Ω generated by** $\mathcal{C}$, $\lambda(\mathcal{C})$, to be

$$\lambda(\mathcal{C}) = \bigcap_{\mathcal{L} \in \mathcal{S}} \mathcal{L}$$

Exercise 3.1.5. Let Ω be a set and $\mathcal{C} \subset \mathcal{P}(\Omega)$. If $\mathcal{C}$ is a λ-system and $\mathcal{C}$ is a π-system, then $\mathcal{C}$ is a σ-algebra.

Proof. Suppose that $\mathcal{C}$ is a λ-system and $\mathcal{C}$ is a π-system. Then we need only verify the third axiom in the definition of a σ-algebra. Let $(A_n)_{n \in \mathbb{N}} \subset \mathcal{C}$. Define $B_1 = A_1$ and for $n \geq 2$, define $B_n = A_n \cap \left(\bigcup\limits_{k=1}^{n-1} A_k \right)^c = A_n \cap \left(\bigcap\limits_{k=1}^{n-1} A_k^c \right) \in \mathcal{C}$. Then $(B_n)_{n \in \mathbb{N}}$ is disjoint and therefore $\bigcup\limits_{n \in \mathbb{N}} A_n = \bigcup\limits_{n \in \mathbb{N}} B_n \in \mathcal{C}$. $\square$

Theorem 3.1.6. (Dynkin's Theorem)
Let Ω be a set.

(1) Let $\mathcal{P}$ be a π-system on Ω and $\mathcal{L}$ a λ-system on Ω. If $\mathcal{P} \subset \mathcal{L}$, then $\sigma(\mathcal{P}) \subset \mathcal{L}$.
(2) Let $\mathcal{P}$ be a π-system on Ω. Then $\sigma(\mathcal{P}) = \lambda(\mathcal{P})$

Exercise 3.1.7. Let $(\Omega, \mathcal{F})$ be a measurable space and μ, ν probability measures on $(\Omega, \mathcal{F})$. Put $\mathcal{L}_{\mu,\nu} = \{A \in \mathcal{F} : \mu(A) = \nu(A)\}$. Then $\mathcal{L}_{\mu,\nu}$ is a λ-system on Ω.

Proof.

(1) $\varnothing \in \mathcal{L}_{\mu,\nu}$.
(2) Let $A \in \mathcal{L}_{\mu,\nu}$. Then $\mu(A) = \nu(A)$. Thus

$$\begin{aligned} \mu(A^c) &= 1 - \mu(A) \\ &= 1 - \nu(A) \\ &= \nu(A^c) \end{aligned}$$

So $A^c \in \mathcal{L}_{\mu,\nu}$.
(3) Let $(A_n)_{n \in \mathbb{N}} \subset \mathcal{L}_{\mu,\nu}$. So for each $n \in \mathbb{N}$, $\mu(A_n) = \nu(A_n)$. Suppose that $(A_n)_{n \in \mathbb{N}}$ is disjoint. Then

$$\begin{aligned} \mu\left(\bigcup_{n \in \mathbb{N}} A_n \right) &= \sum_{n \in \mathbb{N}} \mu(A_n) \\ &= \sum_{n \in \mathbb{N}} \nu(A_n) \\ &= \nu\left(\bigcup_{n \in \mathbb{N}} A_n \right) \end{aligned}$$

Hence $\bigcup_{n \in \mathbb{N}} A_n \in \mathcal{L}_{\mu,\nu}$.

$\square$

Exercise 3.1.8. Let $(\Omega, \mathcal{F})$ be a measurable space, μ, ν probability measures on $(\Omega, \mathcal{F})$ and $\mathcal{P} \subset \mathcal{A}$ a π-system on Ω. Suppose that for each $A \in \mathcal{P}$, $\mu(A) = \nu(A)$. Then for each $A \in \sigma(\mathcal{P})$, $\mu(A) = \nu(A)$.

Proof. Using the previous exercise, we see that $\mathcal{P} \subset \mathcal{L}_{\mu,\nu}$. Dynkin's theorem implies that $\sigma(\mathcal{P}) \subset \mathcal{L}_{\mu,\nu}$. So for each $A \in \sigma(\mathcal{P})$, $\mu(A) = \nu(A)$. □

Definition 3.1.9. Let $F : \mathbb{R} \to \mathbb{R}$. Then F is said to be a **probability distribution function** if

(1) F is right continuous
(2) F is increasing
(3) $F(-\infty) = 0$ and $F(\infty) = 1$

Definition 3.1.10. Let P be a probability measure on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$. We define $F_P : \mathbb{R} \to \mathbb{R}$, by

$$F_P(x) = P((-\infty, x])$$

We call F_P the **probability distribution function of** P.

Exercise 3.1.11. Let $(\Omega, \mathcal{F}, P)$ be a probability measure. Then F_P is a probability distribution function.

Proof. (1) Let $x \in \mathbb{R}$ and $(x_n)_{n\in\mathbb{N}} \subset [x, \infty)$. Suppose that $x_n \to x$. Then $(x, x_n] \to \varnothing$ because $\limsup\limits_{n\to\infty}(x, x_n] = \varnothing$. Thus

$$F(x_n) - F(x) = P((x, x_n]) \to P(\varnothing) = 0$$

This implies that

$$F(x_n) \to F(x)$$

. So F is right continuous.

(2) Clearly F_P is increasing.

(3) Continuity from below tells us that

$$F(-\infty) = \lim_{n\to-\infty} F(n) = \lim_{n\to-\infty} P((-\infty, n]) = 0$$

and continuity from above tell us that

$$F(\infty) = \lim_{n\to\infty} F(n) = \lim_{n\to\infty} P((-\infty, n]) = 1$$

□

Exercise 3.1.12. Let μ, ν be probability measures on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$. Then $F_\mu = F_\nu$ iff $\mu = \nu$.

Proof. Clearly if $\mu = \nu$, then $F_\mu = F_\nu$. Conversely, suppose that $F_\mu = F_\nu$. Then for each $x \in \mathbb{R}$,

$$\begin{aligned}\mu((-\infty, x]) &= F_\mu(x) \\ &= F_\nu(x) \\ &= \nu((-\infty, x])\end{aligned}$$

Put $\mathcal{C} = \{(-\infty, x] : x \in \mathbb{R}\}$. Then $\mathcal{C}$ is a π-system and for each $A \in \mathcal{C}$, $\mu(A) = \nu(A)$. Hence for each $A \in \sigma(C) = \mathcal{B}(\mathbb{R})$, $\mu(A) = \nu(A)$. So $\mu = \nu$. □

Definition 3.1.13. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X : \Omega \to \mathbb{R}^n$. Then X is said to be a **random vector** on $(\Omega, \mathcal{F})$ if X is $\mathcal{F}$-$\mathcal{B}(\mathbb{R}^n)$ measurable. If $n = 1$, then X is said to be a **random variable**. We define

$$L^0_n(\Omega, \mathcal{F}, P) = \{X : \Omega \to \mathbb{R}^n : X \text{ is a random vector}\}$$

and

$$L^p_n(\Omega, \mathcal{F}, P) = \left\{ X \in L^0_n : \int \|X\|^p dP < \infty \right\}$$

Definition 3.1.14. Let $(\Omega, \mathcal{F}, P)$ be a probability space and X a random variable on $(\Omega, \mathcal{F})$. We define the **probability distribution** of X, $P_X : \mathcal{B}(R) \to [0, 1]$, to be the measure

$$P_X = X_* P$$

That is, for each $A \in \mathcal{B}(\mathbb{R})$,

$$P_X(A) = P(X^{-1}(F))$$

We define the **probability distribution function** of X, $F_X : \mathbb{R} \to [0, 1]$, to be

$$F_X = F_{P_X}$$

Definition 3.1.15. Let $(\Omega, \mathcal{F}, P)$ be a probability space and X a random variable on $(\Omega, \mathcal{F})$. If $P_X \ll m$, we define the **probability density** of X, $f_X : \mathbb{R} \to \mathbb{R}$, by

$$f_X = \frac{dP_X}{dm}$$

Exercise 3.1.16. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $(X_n)_{n\in\mathbb{N}}$ be a sequence of random variables on $(\Omega, \mathcal{F})$. Then for each $x \in \mathbb{R}$,

$$\mathbb{P}\left(\liminf_{n\to\infty} X_n > x \right) \le \liminf_{n\to\infty} P(X_n > x)$$

Proof. Let $\omega \in \left\{ \liminf\limits_{n\to\infty} X_n > x \right\}$. Then $x < \liminf\limits_{n\to\infty} X_n(\omega) = \sup\limits_{n\in\mathbb{N}} \left(\inf\limits_{k\ge n} X_k(\omega) \right)$. So there exists $n^* \in \mathbb{N}$ such that $x < \inf\limits_{k\ge n^*} X_k(\omega)$. Then for each $k \in \mathbb{N}$, $k \ge n^*$ implies that $x < X_k(\omega)$. So there exists $n^* \in \mathbb{N}$ such that for each $k \in \mathbb{N}$, $k \ge n^*$ implies that $\mathbf{1}_{\{X_k > x\}}(\omega) = 1$. Hence $\inf\limits_{k\ge n^*} \mathbf{1}_{\{X_k>x\}}(\omega) = 1$. Thus $\liminf\limits_{n\to\infty} \mathbf{1}_{\{X_k>x\}}(\omega) = \sup\limits_{n\in\mathbb{N}} \left(\inf_{k\ge n} \mathbf{1}_{\{X_k>x\}}(\omega) \right) = 1$. Therefore $\omega \in \liminf\limits_{n\to\infty} \{X_k > x\}$ and we have shown that

$$\left\{ \liminf_{n\to\infty} X_n > x \right\} \subset \liminf_{n\to\infty} \{X_k > x\}$$

Then

$$\begin{aligned} P\left(\liminf_{n\to\infty} X_n > x \right) &\le P\left(\liminf_{n\to\infty} \{X_k > x\} \right) \\ &\le \liminf_{n\to\infty} P(\{X_k > x\}) \end{aligned}$$

□

Definition 3.1.17. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X \in L^+(\Omega) \cup L^1$. Define the **expectation of X**, $E[X]$, to be

$$\mathrm{E}[X] = \int X dP$$

.

3.2. Independence.

Definition 3.2.1. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $\mathcal{C} \subset \mathcal{F}$. Then $\mathcal{C}$ is said to be **independent** if for each $(A_i)_{i=1}^n \subset \mathcal{C}$,

$$P\bigg(\bigcap_{k=1}^n A_k\bigg) = \prod_{k=1}^n P(A_k)$$

Definition 3.2.2. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $\mathcal{C}_1, \cdots, \mathcal{C}_n \subset \mathcal{F}$. Then $\mathcal{C}_1, \cdots, \mathcal{C}_n$ are said to be **independent** if for each $A_1 \in \mathcal{C}_1, \cdots, A_n \in \mathcal{C}_n$, $A_1, \cdots, A_n$ are independent.

Note 3.2.3. We will explicitely say that for each $i = 1, \cdots, n$, $\mathcal{C}_i$ is independent when talking about the independence of the elements of $\mathcal{C}_i$ to avoid ambiguity.

Definition 3.2.4. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X_1, \cdots, X_2$ random variables on $(\Omega, \mathcal{F})$. Then $X_1, \cdots, X_n$ are said to be **independent** if for each $B_1, \cdots, B_n \in \mathcal{B}(\mathbb{R})$, $X_1^{-1}B_1, \cdots, X_n^{-1}B_n$ are independent.

Exercise 3.2.5. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X_1, \cdots, X_n$ random variables on $(\Omega, \mathcal{F})$. Then $X_1, \cdots, X_n$ are independent iff $\sigma(X_1), \cdots, \sigma(X_n)$ are independent.

Proof. Suppose that $X_1, \cdots, X_n$ are independent. Let $A_1, \in \sigma(X_1), \cdots, A_n \in \sigma(A_n)$. Then for each $i = 1, \cdots, n$, there exists $B_i \in \mathcal{B}(\mathbb{R})$ such that $A_i = X_i^{-1}(B_i)$. Then $A_1, \cdots, A_n$ are independent. Hence $\sigma(X_1), \cdots, \sigma(X_n)$ are independent. Conversely, suppose that $\sigma(X_1), \cdots, \sigma(X_n)$ are independent. Let $B_1, \cdots, B_n \in \mathcal{B}(\mathbb{R})$. Then for each $i = 1, \cdots, n$, $X_i^{-1}B_i \in \sigma(X_i)$. Then $X_1^{-1}B_1, \cdots, X_n^{-1}B_n$ are independent. Hence $X_1, \cdots, X_n$ are independent. □

Exercise 3.2.6. Let $(\Omega, \mathcal{F}, P)$ be a probability space, $X_1, \cdots, X_n$ random variables on $(\Omega, \mathcal{F})$ and $\mathcal{F}_1, \cdots, \mathcal{F}_n \subset \mathcal{F}$ a collection of σ-algebras on Ω. Suppose that for each $i = 1, \cdots, n$, X_i is $\mathcal{F}_i$-measurable. If $\mathcal{F}_1, \cdots, \mathcal{F}_n$ are independent, then $X_1, \cdots, X_n$ are independent.

Proof. For each $i = 1, \cdots, n$, $\sigma(X_i) \subset \mathcal{F}_i$. So $\sigma(X_1), \cdots, \sigma(X_n)$ are independent. Hence $X_1, \cdots, X_n$ are independent. □

Exercise 3.2.7. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $\mathcal{C}_1, \cdots, \mathcal{C}_n \subset \mathcal{F}$. Suppose that for each $i = 1, \cdots, n$, $\mathcal{C}_i$ is a π-system and $\mathcal{C}_1, \cdots, \mathcal{C}_n$ are independent, then $\sigma(\mathcal{C}_1), \cdots, \sigma(\mathcal{C}_n)$ are independent.

Proof. Let $A_2 \in \mathcal{C}_2$. Define $\mathcal{L} = \{A \in \mathcal{F} : P(A \cap A_2) = P(A)P(A_2)\}$. Then

(1) $\Omega \in \mathcal{L}$
(2) If $A \in \mathcal{L}$, then

$$\begin{aligned} P(A^c \cap A_2) &= P(A_2) - P(A_2 \cap A) \\ &= P(A_2) - P(A_2)P(A) \\ &= (1 - P(A))P(A_2) \\ &= P(A^c)P(A_2) \end{aligned}$$

So $A^c \in \mathcal{L}$

(3) If $(B_n)_{n\in\mathbb{N}} \subset \mathcal{L}$ is disjoint, then

$$\begin{aligned} P\bigg(\bigg[\bigcup_{n\in\mathbb{N}} B_n\bigg] \cap A_2\bigg) &= P\bigg(\bigcup_{n\in\mathbb{N}} B_n \cap A_2\bigg) \\ &= \sum_{n\in\mathbb{N}} P(B_n \cap A_2) \\ &= \sum_{n\in\mathbb{N}} P(B_n)P(A_2) \\ &= \bigg[\sum_{n\in\mathbb{N}} P(B_n)\bigg] P(A_2) \\ &= P\bigg(\bigcup_{n\in\mathbb{N}} A_n\bigg) P(A_2) \end{aligned}$$

So $\bigcup_{n\in\mathbb{N}} B_n \in \mathcal{L}$.

Thus $\mathcal{L}$ is a λ-system. Since $\mathcal{C}_1 \subset \mathcal{L}$ is a π-system, Dynkin's theorem tells us that $\sigma(\mathcal{C}_1) \subset \mathcal{L}$. Since $A_2 \in \mathcal{C}_2$ is arbitrary $\sigma(\mathcal{C}_1)$ and $\mathcal{C}_2$ are independent. The same reasoning implies that $\sigma(\mathcal{C}_1)$ and $\sigma(\mathcal{C}_2)$ are independent. Let $A_2 \in \mathcal{C}_1, \cdots, A_n \in \mathcal{C}_n$ We may do the same process with

$$\mathcal{L} = \left\{A \in \mathcal{F} : P\bigg(A \cap \bigg(\bigcap_{i=2}^{n} A_i\bigg)\bigg) = P(A)\prod_{i=2}^{n} P(A_i)\right\}$$

and conclude that $\sigma(\mathcal{C}_1), \mathcal{C}_2, \cdots, \mathcal{C}_n$ are independent. Which, using the same reasoning would imply that $\sigma(\mathcal{C}_1), \cdots, \sigma(\mathcal{C}_n)$ are independent. $\square$

Exercise 3.2.8. Let $(\Omega, \mathcal{F}, P)$ be a probability space, $X_1, \cdots, X_n$ random variables on $(\Omega, \mathcal{F})$. Then $X_1, \cdots, X_n$ are independent iff for each $x_1, \cdots, x_n \in \mathbb{R}$,

$$P(X_1 \leq x_1, \cdots, X_n \leq x_n) = \prod_{i=1}^{n} P(X_i \leq x_i)$$

Proof. Suppose that $X_1, \cdots, X_n$ are independent. Then $\sigma(X_1), \cdots, \sigma(X_n)$ are independent. Let $x_1, \cdots, x_n \in \mathbb{R}$. Then for each $i = 1, \cdots, n$, $\{X_i \leq x_i\} \in \sigma(X_i)$. Hence $P(X_1 \leq x_1, \cdots, X_n \leq x_n) = \prod_{i=1}^{n} P(X_i \leq x_i)$. Conversely, suppose that for each $x_1, \cdots, x_n \in \mathbb{R}$, $P(X_1 \leq x_1, \cdots, X_n \leq x_n) = \prod_{i=1}^{n} P(X_i \leq x_i)$. Define $\mathcal{C} = \{(-\infty, x] : x \in \mathbb{R}\}$. Then $\mathcal{B}(\mathbb{R}) = \sigma(\mathcal{C})$. For each $i = 1, \cdots, n$, define $\mathcal{C}_i = X_i^{-1}\mathcal{C}$. Then for each $i = 1, \cdots, n$, $\mathcal{C}_i$ is a π-system and

$$\begin{aligned} \sigma(\mathcal{C}_i) &= \sigma(X^{-1}(\mathcal{C})) \\ &= X_i^{-1}(\sigma(\mathcal{C})) \\ &= X_i^{-1}(\mathcal{B}(\mathbb{R})) \\ &= \sigma(X_i) \end{aligned}$$

By assumption, $\mathcal{C}_1, \cdots, \mathcal{C}_n$ are independent. The previous exercies tells us that $\sigma(X_1), \cdots, \sigma(X_n)$ are independent. Then $X_1, \cdots, X_n$ are independent. $\square$

Exercise 3.2.9. Let Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X_1, \cdots, X_n$ random variables on $(\Omega, \mathcal{F})$. Define $X = (X_1, \cdots, X_n)$. If $X_1, \cdots, X_n$ are independent, then

$$P_X = \prod_{i=1}^{n} P_{X_i}$$

.

Proof. Let $A_1, \cdots, A_n \in \mathcal{B}(\mathbb{R})$. Then

$$\begin{aligned} P_X(A_1 \times \cdots \times A_n) &= P(X \in A_1 \times \cdots \times \in A_n) \\ &= P(X_1 \in A_1, \cdots, X_n \in A_n) \\ &= P(X_1 \in A_1) \cdots P(X_n \in A_n) \\ &= P_{X_1}(A_1) \cdots P_{X_n}(A_n) \\ &= \prod_{i=1}^{n} P_{X_i}(A_1 \times \cdots \times A_n) \end{aligned}$$

Put

$$\mathcal{P} = \{A_1 \times \cdots \times A_n : A_1 \in \mathcal{B}(R), \cdots, A_n \in \mathcal{B}(R)\}$$

Then $\mathcal{P}$ is a π-system and

$$\sigma(\mathcal{P}) = \mathcal{B}(R) \otimes \cdots \otimes \mathcal{B}(R) = \mathcal{B}(\mathbb{R}^n)$$

A previous exercise then tells us that $P_X = \prod_{i=1}^{n} P_{X_i}$ $\square$

Exercise 3.2.10. Let Let $(\Omega, \mathcal{F}, P)$ be a probability space, $X_1, \cdots, X_n$ random variables on $(\Omega, \mathcal{F})$ and $f_1, \cdots, f_n : \mathbb{R} \to \mathbb{R} \in L^0$. Suppose that $f_1 \circ X_1, \cdots, f_n \circ X_n \in L^+(\Omega)$ or $f_1 \circ X_1, \cdots, f_n \circ X_n \in L^1(\Omega)$. If $X_1, \cdots, X_n$ are independent, then

$$E[f_1(X_1) \cdots f_n(X_n)] = \prod_{i=1}^{n} E[f_i(X_i)]$$

Proof. Define the random vector $X : \Omega \to \mathbb{R}^n$ by $X = (X_1, \cdots, X_n)$ and $g : \mathbb{R}^n \to \mathbb{R}$ by $g(x_1, \cdots, x_n) = f_1(x_1) \cdots f_n(x_n)$. Suppose that for each $i = 1, \cdots, n$, $f_i \in L^+(\mathbb{R})$. Then

$g \in L^+(\mathbb{R}^n)$ and by change of variables,

$$\begin{aligned}
E[f_1(X_1)\cdots f_n(X_n)] &= E[g(X)] \\
&= \int_\Omega g \circ X dP \\
&= \int_{\mathbb{R}^n} g(x) dP_X(x) \\
&= \int_{R^n} g(x) d\prod_{i=1}^n P_{X_i}(x) \\
&= \prod_{i=1}^n \int_{\mathbb{R}} f_i(x) dP_{X_i}(x) \\
&= \prod_{i=1}^n \int_\Omega f_i \circ X dP \\
&= \prod_{i=1}^n E[f_i(X_i)]
\end{aligned}$$

If for each $i = 1, \cdots, n$, $f_i \in L^1(\mathbb{R}, P_{X_i})$, then following the above reasoning with $|g|$ tells us that $g \in L^1(\mathbb{R}^n, P_X)$ and we use change of variables and Fubini's theorem to get the same result. □

3.3. L^p Spaces for Probability.

Note 3.3.1. Recall that for a probability space $(\Omega, \mathcal{F}, P)$ and $1 \le p \le q \le \infty$ we have $L^q \subset L^p$ and for each $X \in L^q$, $\|X\|_p \le \|X\|_q$. Also recall that for $X, Y \in Ł^2$, we have that $\|XY\|_1 \le \|X\|_2 \|X\|_2$.

Definition 3.3.2. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X \in L^2$. Define the **variance of X**, $Var(X)$, to be

$$Var(X) = \mathrm{E}\big[\big(X - E[X]\big)^2\big]$$

.

Definition 3.3.3. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X, Y \in L^2$. Define the

Definition 3.3.4. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X, Y \in L^2$. Define the **covariance of X and Y**, $Cov(X, Y)$, to be

$$Cov(X, Y) = E[(X - E[X])(Y - E[Y])]$$

Exercise 3.3.5. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X, Y \in L^2$. Then the covariance is well defined and $Cov(X, Y)^2 \le Var(X)Var(Y)$

Proof. By Holder's inequality,

$$\begin{aligned}|Cov(X,Y)| &= \left| \int (X-E[X])(Y-E[Y])dP \right| \\ &\leq \int |(X-E[X])(Y-E[Y])|dP \\ &= \|(X-E[X])(Y-E[Y])\|_1 \\ &\leq \|X-E[X]\|_2 \|(Y-E[Y]\|_2 \\ &= \left(\int |X-E[X]|^2 dP\right)^{\frac{1}{2}} \left(|Y-E[Y]|^2\right)^{\frac{1}{2}} \\ &= Var(X)^{\frac{1}{2}} Var(Y)^{\frac{1}{2}}\end{aligned}$$

So $Cov(X,Y)^2 \leq Var(X)Var(Y)$. □

Exercise 3.3.6. Let $(\Omega, \mathcal{F}, P)$ be a measure space and $X, Y \in L^2$. Then

(1) $Cov(X,Y) = E[XY] - E[X]E[Y]$
(2) If X, Y are independent, then $Cov(X,Y) = 0$
(3) $Var(X) = E[X^2] - E[X]^2$
(4) for each $a, b \in \mathbb{R}$, $Var(aX+b) = a^2 Var(X)$.
(5) $Var(X+Y) = Var(X) + Var(Y) + 2Cov(X,Y)$

Proof.

(1) We have that

$$\begin{aligned}Cov(X,Y) &= E[(X-E[X])(Y-E[Y])] \\ &= E[XY - E[Y]X - E[X]Y + E[X]E[Y]] \\ &= E[XY] - E[X]E[Y] - E[X]E[Y] + E[X]E[Y] \\ &= E[XY] - E[X]E[Y]\end{aligned}$$

(2) Suppose that X, Y are independent. Then $E[XY] = E[X]E[Y]$. Hence

$$\begin{aligned}Cov(X,Y) &= E[XY] - E[X]E[Y] \\ &= E[X]E[Y] - E[X]E[Y] \\ &= 0\end{aligned}$$

(3) Part (1) implies that

$$\begin{aligned}Var(X) &= Cov(X,X) \\ &= E[X^2] - E[X]^2\end{aligned}$$

(4) Let $a, b \in \mathbb{R}$. Then

$$\begin{aligned}Var(aX+b) &= E[(aX+b)^2] - E[aX+b]^2 \\ &= E[a^2X^2 + 2abX + b^2] - (aE[X]+b)^2 \\ &= a^2E[X^2] + 2abE[X] + b^2 - (a^2E[X]^2 + 2abE[X] + b^2) \\ &= a^2(E[X^2] - E[X]^2) \\ &= a^2 Var(X)\end{aligned}$$

(5) We have that

$$\begin{aligned}
Var(X+Y) &= E[(X+Y)^2] - E[X+Y]^2 \\
&= E[X^2 + 2XY + Y^2] - (E[X] + E[Y])^2 \\
&= E[X^2] + 2E[XY] + E[Y^2] - (E[X]^2 + 2E[X]E[Y] + E[Y]^2) \\
&= (E[X^2] - E[X]^2) + (E[Y^2] - E[Y]^2) + 2(E[XY] - E[X]E[Y]) \\
&= Var(X) + Var(Y) + 2Cov(X,Y)
\end{aligned}$$

□

Definition 3.3.7. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X, Y \in L^2$. The **correlation of X and Y**, $Cor(X,Y)$, is defined to be

$$Cor(X,Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}}$$

Exercise 3.3.8.

Exercise 3.3.9. Jensen's Inequality Let $(\Omega, \mathcal{F}, P)$ be a probability space, $X \in L^1$ and $\phi : \mathbb{R} \to \mathbb{R}$. If ϕ is convex, then

$$\phi(E[X]) \leq E[\phi(X)]$$

Proof. Put $x_0 = E[X]$. Since ϕ is convex, there exist $a, b \in \mathbb{R}$ such that $\phi(x_0) = ax_0 + b$ and for each $x \in \mathbb{R}$, $\phi(x) \geq ax + b$. Then

$$\begin{aligned}
E[\phi(X)] &= \int \phi(X) dP \\
&\geq \int [aX + b] dP \\
&= a \int X dP + b \\
&= aE[X] + b \\
&= ax_0 + b \\
&= \phi(x_0) \\
&= \phi(E[X])
\end{aligned}$$

□

Exercise 3.3.10. Markov's Inequality: Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X \in L^+$. Then for each $a \in (0, \infty)$,

$$P(X \geq a) \leq \frac{E[X]}{a}$$

Proof. Let $a \in (0, \infty)$. Then $a\mathbf{1}_{\{X \geq a\}} \leq X\mathbf{1}_{\{X \geq a\}}$. Thus

$$\begin{aligned} aP(X \geq a) &= \int a\mathbf{1}_{\{X \geq a\}} dP \\ &= \int X\mathbf{1}_{\{X \geq a\}} dP \\ &\leq \int X dP \\ &= E[X] \end{aligned}$$

Therefore

$$P(X \geq a) \leq \frac{E[X]}{a}$$

. □

Exercise 3.3.11. Chebychev's Inequality: Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X \in L^2$. Then for each $a \in (0, \infty)$,

$$P(|X - E[X]| \geq a) \leq \frac{Var(X)}{a^2}$$

Proof. Let $a \in (0, \infty)$. Then

$$\begin{aligned} P(|X - E[X]| \geq a) &= P((X - E[X])^2 \geq a^2) \\ &\leq \frac{E[(X - E[X])^2]}{a^2} \\ &= \frac{Var(X)}{a^2} \end{aligned}$$

□

Exercise 3.3.12. Chernoff's Bound: Let $(\Omega, \mathcal{F}, P)$ be a probability space and $X \in L^2$. Then for each $a, t \in (0, \infty)$,

$$P(X \geq a) \leq e^{-ta} E[e^{tX}]$$

Proof. Let $a, t \in (0, \infty)$. Then

$$\begin{aligned} P(X \geq a) &= P(tX \geq ta) \\ &= P(e^{tX} \geq e^{ta}) \\ &\leq e^{-ta} E[e^{tX}] \end{aligned}$$

□

Exercise 3.3.13. Weak Law of Large Numbers: Let $(\Omega, \mathcal{F}, P)$ be a probability space $(X_i)_{i \in \mathbb{N}} \subset L^2$. Suppose that $(X_i)_{i \in \mathbb{N}}$ are iid. Then

$$\frac{1}{n} \sum_{i=1}^{n} X_i \xrightarrow{P} E[X_1]$$

Proof. Put $\mu = E[X_1]$ and $\sigma^2 = Var(X_1)$. Then

$$\begin{aligned} E[\frac{1}{n}\sum_{i=1}^n X_i] &= \frac{1}{n}\sum_{i=1}^n E[X_i] \\ &= \frac{1}{n}\sum_{i=1}^n \mu \\ &= \mu \end{aligned}$$

and

$$\begin{aligned} Var(\frac{1}{n}\sum_{i=1}^n X_i) &= \frac{1}{n^2}Var(\sum_{i=1}^n X_i) \\ &= \frac{1}{n^2}\sum_{i=1}^n Var(X_i) \\ &= \frac{1}{n^2}\sum_{i=1}^n \sigma^2 \\ &= \frac{\sigma^2}{n} \end{aligned}$$

Let $\epsilon > 0$. Then

$$\begin{aligned} P\left(\left|\frac{1}{n}\sum_{i=1}^n X_i - E[X_1]\right| \geq \epsilon\right) &= P\left(\left|\frac{1}{n}\sum_{i=1}^n X_i - \mu\right| \geq \epsilon\right) \\ &= P\left(\left|\frac{1}{n}\sum_{i=1}^n X_i - \mathrm{E}\left[\frac{1}{n}\sum_{i=1}^n X_i\right]\right| \geq \epsilon\right) \\ &\leq \frac{Var(\frac{1}{n}\sum_{i=1}^n X_i)}{\epsilon^2} \\ &= \frac{\sigma^2/n}{\epsilon^2} \\ &= \frac{\sigma^2}{n\epsilon^2} \to 0 \end{aligned}$$

So

$$\frac{1}{n}\sum_{i=1}^n X_i \xrightarrow{P} E[X_1]$$

□

3.4. Borel Cantelli Lemma.

Exercise 3.4.1. Borel Cantelli Lemma: Let $(\Omega, \mathcal{F}, P)$ be a probability space and $(A_n)_{n\in\mathbb{N}} \subset \mathcal{F}$.

(1) If $\sum\limits_{n\in\mathbb{N}} P(A_n) < \infty$, then $P(\limsup\limits_{n\to\infty} A_n) = 0$.
(2) If $(A_n)_{n\in\mathbb{N}}$ are independent and $\sum\limits_{n\in\mathbb{N}} P(A_n) = \infty$, then $P(\limsup\limits_{n\to\infty} A_n) = 1$

Proof.

(1) Suppose that $\sum\limits_{n\in\mathbb{N}} P(A_n) < \infty$. Recall that

$$\limsup_{n\to\infty} A_n = \left\{\omega \in \Omega : \sum_{n\in\mathbb{N}} 1_{A_n}(\omega) = \infty\right\}$$

Then

$$\begin{aligned}\infty &> \sum_{n\in\mathbb{N}} P(A_n) \\ &= \sum_{n\in\mathbb{N}} \int 1_{A_n} dP \\ &= \int \sum_{n\in\mathbb{N}} 1_{A_n} dP\end{aligned}$$

Thus $\sum\limits_{n\in\mathbb{N}} 1_{A_n} < \infty$ a.e. and $P(\limsup\limits_{n\to\infty} A_n) = 0$.

(2) Suppose that $(A_n)_{n\in\mathbb{N}}$ are independent and $\sum\limits_{n\in\mathbb{N}} P(A_n) = \infty$.

□

Exercise 3.4.2. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $(X_n)_{n\in\mathbb{N}} \subset L^0$ and $X \in L^0$.

(1) If for each $\epsilon > 0$, $\sum\limits_{n\in\mathbb{N}} P(|X_n - X| \geq \epsilon) < \infty$, then $X_n \to X$ a.e.
(2) If $(X_n)_{n\in\mathbb{N}}$ are independent and there exists $\epsilon > 0$ such that $\sum\limits_{n\in\mathbb{N}} P(|X_n - X| \geq \epsilon) = \infty$, then $X_n \not\to X$ a.e.

Proof.

(1) For $\epsilon > 0$ and $n \in \mathbb{N}$, set $A_n(\epsilon) = \{\omega \in \Omega : |X_n(\omega) - X(\omega)| \geq \epsilon\}$. Suppose that for each $\epsilon > 0$, $\sum\limits_{n\in\mathbb{N}} P(|X_n - X| \geq \epsilon) < \infty$. The Borel-Cantelli lemma implies that for each $m \in \mathbb{N}$,

$$P(\limsup_{n\to\infty} A_n(1/m)) = 0$$

Let $\omega \in \Omega$. Then $X_n(\omega) \not\to X(\omega)$ iff

$$\omega \in \bigcup_{m\in\mathbb{N}} \limsup_{n\to\infty} A_n(1/m)$$

So

$$\begin{aligned} P(X_n \not\to X) &= P\bigg(\bigcup_{m \in \mathbb{N}} \limsup_{n \to \infty} A_n(1/m) \bigg) \\ &\leq \sum_{m \in \mathbb{N}} P(\limsup_{n \to \infty} A_n(1/m)) \\ &= 0 \end{aligned}$$

Hence $X_n \to X$ a.e.

(2)

$\square$

4. Conditional Expectation and Probability

4.1. **Conditional Expectation.**

Exercise 4.1.1. Let $(\Omega, \mathcal{F}, P)$ be a probability space, $\mathcal{G}$ a sub σ-alg of $\mathcal{F}$ and $X \in L^1(\Omega, \mathcal{F}, P)$. Define $P_{\mathcal{G}} = P|_{\mathcal{G}}$ and $Q : \mathcal{G} \to [0, \infty)$ by $Q(G) = \int_G X dP$. Then Q is finite. and $Q \ll P_{\mathcal{G}}$.

Proof. Since $X \in L^1$, for each $G \in \mathcal{G}$,

$$\begin{aligned} |Q(G)| &= \left| \int_G X dP \right| \\ &\leq \int_G |X| dP \\ &< \infty \end{aligned}$$

So Q is finite. Let $G \in \mathcal{G}$. Suppose that $P_{\mathcal{G}}(G) = 0$. By definition then, $P(G) = 0$. So $Q(G) = 0$ and $Q \ll P_{\mathcal{G}}$. □

Definition 4.1.2. Let $(\Omega, \mathcal{F}, P)$ be a probability space, $\mathcal{G}$ a sub σ-alg of $\mathcal{F}$ and $X, Y \in L^1(\Omega, \mathcal{F}, P)$. Then Y is said to be a **conditional expectation of** X **given** $\mathcal{G}$ if

(1) Y is $\mathcal{G}$-measurable
(2) for each $G \in \mathcal{G}$,

$$\int_G Y dP = \int_G X dP$$

To denote this, we write $Y = E[X|\mathcal{G}]$

Exercise 4.1.3. Let $(\Omega, \mathcal{F}, P)$ be a probability space, $\mathcal{G}$ a sub σ-alg of $\mathcal{F}$ and $X \in L^1(\Omega, \mathcal{F}, P)$. Define Q and $P_{\mathcal{G}}$ as in the previous exercise. Define $Y = dQ/dP_{\mathcal{G}}$. Then Y is a conditional expectation of X given $\mathcal{G}$.

Proof. By definition of the Radon-Nikodym derivative, Y is $\mathcal{G}$-measurable and by the Radon-Nikodym theorem, $X \in L^1(\Omega, \mathcal{F}, P)$ imples that $Y \in L^1(\Omega, \mathcal{G}, P_{\mathcal{G}})$. An exercies in section 3.3 of [**?**], implies that for each $G \in \mathcal{G}$

$$\int_G Y dP = \int_G X dP$$

□

Exercise 4.1.4. (Doob–Dynkin Lemma)
Let Ω be a nonempty set, $(\Omega', \mathcal{F}')$ a measurable space $X : \Omega \to \Omega'$ and $Z : \Omega \to \mathbb{R}^n$. Suppose that $\operatorname{Im} X \in \mathcal{F}'$. Then Z is $\sigma(X)$-$\mathcal{B}(\mathbb{R}^n)$ measurable iff there exists $\phi : \Omega' \to \mathbb{R}^n$ such that ϕ is $\mathcal{F}'$-$\mathcal{B}(\mathbb{R}^n)$ measurable and $Z = \phi \circ X$.

Proof. Suppose that there exists $\phi : \Omega' \to \mathbb{R}^n$ such that ϕ is $\mathcal{F}'$-$\mathcal{B}(\mathbb{R}^n)$ measurable and $Z = Y \circ X$. Since X is $\sigma(X)$-$\mathcal{F}'$ measurable, $Z = \phi \circ X$ is $\sigma(X)$-$\mathcal{B}(\mathbb{R}^n)$ measurable. Conversely, suppose that Z is $\sigma(X)$-$\mathcal{B}(\mathbb{R}^n)$ measurable. For now, suppose that $n = 1$ and Z is simple. Then there exists a partition $(A_i)_{i=1}^k \subset \sigma(X)$ of Ω and $(a_i)_{i=1}^k \in \mathbb{R}$ such that

$$Z = \sum_{i=1}^k a_i 1_{A_i}$$

By definition of $\sigma(X)$, there exists a partition $(B_i)_{i=1}^k \subset \mathcal{F}'$ such that for each $i = 1, \cdots, k$, $A_i = X^{-1}(B_i)$. Define

$$\phi = \sum_{i=1}^k a_i 1_{B_i}$$

Since $(B_i)_{i=1}^k$ partitions Ω',

$$\begin{aligned} \phi \circ X &= \sum_{i=1}^k a_i 1_{X^{-1}(B_i)} \\ &= \sum_{i=1}^k a_i 1_{A_i} \\ &= Z \end{aligned}$$

More generally, if Z is $\sigma(X)$-$\mathcal{B}(\mathbb{R})$ measurable, there exits a sequence $(Z_j)_{j\in\mathbb{N}}$ of simple $\sigma(X)$-$\mathcal{B}(\mathbb{R})$ measurable functions such that for each $j \in N$ $0 \le |Z_j| \le |Z_{j+1}| \le |Z|$ and $Z_j \xrightarrow{\text{p.w.}} Z$.

Therefore, as shown previously, there exists a sequence $(\phi_j)_{j\in\mathbb{N}}$ of $\mathcal{F}'$-$\mathcal{B}(\mathbb{R})$-measurable simple functions such that for each $j \in \mathbb{N}$, $Z_j = \phi_j \circ X$. Let $b \in \operatorname{Im} X$. Then there exists $a \in \Omega$ such that $X(a) = b$. So

$$\begin{aligned} \phi_j(b) &= \phi_j \circ X(a) \\ &= Z_j(a) \\ &\to Z(a) \end{aligned}$$

Thus we may define $\phi : \Omega' \to \mathbb{R}$ by

$$\phi = \lim_{j\to\infty} \phi_j 1_{\operatorname{Im} X}$$

Then ϕ is measurable since $\operatorname{Im} X \in \mathcal{F}'$ and $Z = \phi \circ X$. For $n \ge 1$, we may write $Z = (Z_1, \cdots, Z_n)$ where for each $i = 1, \cdots, n$, Z_i is $\sigma(X)$-$\mathcal{B}(\mathbb{R})$ measurable and apply the result from above to obtain $\phi = (\phi_1, \cdots, \phi_n)$ where for each $i = 1, \cdots, n$, ϕ_i is $\mathcal{F}'$-$\mathcal{B}(\mathbb{R})$ measurable and $Z_i = \phi_i \circ X$. Then $Z = \phi \circ X$. □

4.2. **Conditional Probability.**

Definition 4.2.1. Let $(A, \mathcal{A})$ be a measurable space, $(B, \mathcal{B}, P_Y)$ a probability space and $Q : B \times \mathcal{A} \to [0, 1]$. Then Q is said to be a **stochastic transition kernel from** $(B, \mathcal{B}, P)$ **to** $(A, \mathcal{A})$ if

1. for each $E \in \mathcal{A}$, $Q(\cdot, E)$ is $\mathcal{B}$-measurable
2. for P-a.e. $b \in B$, $Q(b, \cdot)$ is a probability measure on $(A, \mathcal{A})$

Definition 4.2.2. Let $(\Omega, \mathcal{F}, P)$ be a probability space, $X, Y \in L^0_n(\Omega, \mathcal{F}, P)$ and $Q : \mathbb{R}^n \times \mathcal{F} \to [0, 1]$. Then Q is said to be a **conditional probability distribution of** X **given** Y if

1. Q is a stochastic transition kernel from $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), P_Y)$ to $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$
2. for each $A, B \in \mathcal{F}$,

$$\int_B Q(y, A) dP_Y(y) = P(X \in A, Y \in B)$$

Note 4.2.3. It is helpful to connect this notion of conditional probability with the elementary one by writing $Q(y, A) = P(X \in A|Y = y)$. If $P_Y \ll \mu$, then property (2) in the definition becomes

$$\begin{aligned} P(X \in A, Y \in B) &= \int_B Q(y, A) dP_Y(y) \\ &= \int_B P(X \in A|Y = y) f_Y(y) d\mu(y) \end{aligned}$$

as in a first course on probability.

Exercise 4.2.4. Let $(\Omega, \mathcal{F}, P)$ be a probability space, $X, Y \in L_n^0$ and $Q : \mathbb{R}^n \times \mathcal{F} \to [0, 1]$. Suppose that for each $A \in \mathcal{F}$, $Q(\cdot, A)$ is $\mathcal{B}(\mathbb{R}^n)$-measurable, for P_Y-a.e. $y \in \mathbb{R}^n$, $P_{X|Y}(y, \cdot)$ is a probability measure on $(\Omega, \mathcal{F})$ and $Q(Y, A) = P(X \in A|Y)$ a.e. Then Q is a conditional probability of X given Y.

Proof. By assumption, for each $A \in \mathcal{F}$, $Q(\cdot, A)$ is $\mathcal{B}(\mathbb{R}^n)$-measurable and for P_Y-a.e. $y \in \mathbb{R}^n$, $Q(y, \cdot)$ is a probability measure on $(\Omega, \mathcal{F})$. Let $A, B \in \mathcal{F}$. Then

$$\begin{aligned} \int_B Q(y, A) dP_Y(y) &= \int_{Y^{-1}(B)} Q(Y(\omega), A) dP(\omega) \\ &= \int_{Y^{-1}(B)} P(X \in A|Y) dP \\ &= \int_{Y^{-1}(B)} E[1_{X^{-1}(A)}|Y] dP \\ &= \int_{Y^{-1}(B)} 1_{X^{-1}(A)} dP \\ &= \int 1_{X^{-1}(A)} 1_{Y^{-1}(B)} dP \\ &= \int 1_{X^{-1}(A) \cap Y^{-1}(B)} dP \\ &= P(X \in A, Y \in B) \end{aligned}$$

So Q is a conditional probability distribution of X given Y. $\square$

Definition 4.2.5. Let $(\Omega, \mathcal{F}, P)$ be a probability space, $X, Y \in L_n^0$ and μ a σ-finite measure on $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$. Suppose that $P_X, P_Y \ll \mu$. Then $P_{X,Y} \ll \mu^2$. Let $f_X = dP_X/d\mu$, $f_Y = dP_Y/d\mu$ and $f_{X,Y} = dP_{X,Y}/d\mu^2$. Define $f_{X|Y} : \mathbb{R}^n \times \mathbb{R}^n$ by

$$f_{X|Y}(x, y) = \begin{cases} \frac{f_{X,Y}(x,y)}{f_Y(y)}, & y \in \operatorname{supp} Y \\ 0, & y \notin \operatorname{supp} Y \end{cases}$$

Then $f_{X|Y}$ is called the **conditional probability density of X given Y.**

Exercise 4.2.6. Let $(\Omega, \mathcal{F}, P)$ be a probability space, $X, Y \in L_n^0$ and μ a σ-finite measure on $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$. Suppose that $P_X, P_Y \ll \mu$. Define $Q : \mathbb{R}^n \times \mathcal{F} \to [0, 1]$ by

$$Q(y, A) = \int_A f_{X|Y}(x, y) d\mu(x)$$

Then Q is a conditional probability distribution of X given Y.

Proof. By the Fubini-Tonelli Theorem, for each $A \in \mathcal{F}$, $Q(\cdot, A)$ is $\mathcal{B}(\mathbb{R}^n)$-measurable and for P_Y-a.e. $y \in \mathbb{R}^n$, $Q(y, \cdot)$ is a probability measure on $(\Omega, \mathcal{F})$. Let $A, B \in \mathcal{F}$. Then

$$\begin{aligned}
\int_B Q(y,A)dP_Y(y) &= \int_B \bigg[\int_A f_{X|Y}(x,y)d\mu(x)\bigg]dP_Y(y) \\
&= \int_{B\cap \operatorname{supp} Y} \bigg[\int_{A\cap \operatorname{supp} Y} \frac{f_{X,Y}(x,y)}{f_Y(y)}d\mu(x)f_Y(y)\bigg]d\mu(y) \\
&= \int_{B\cap \operatorname{supp} Y} \bigg[\int_A f_{X,Y}(x,y)d\mu(x)\bigg]d\mu(y) \\
&= P(X \in A, Y \in B \cap \operatorname{supp} Y) \\
&= P(X \in A, Y \in B)
\end{aligned}$$

□

Theorem 4.2.7. Let $(\Omega, \mathcal{F}, P)$ be a probability space, $X, Y \in L^1_n(\Omega, \mathcal{F}, P)$. Suppose that $\operatorname{Im} X \in \mathcal{B}(\mathbb{R}^n)$. Then there exists a conditional probability distribution of Y given X.

5. Markov Chains

Definition 5.0.1. Let $(\Omega, \mathcal{F}, P)$ be a probability space and $(X_n)_{n\in\mathbb{N}_0} \in L_n^0$. Then $(X_n)_{n\in\mathbb{N}_0}$ is said to be a **homogeneous Markov chain** if for each $A \in \mathcal{F}$ and $n \in \mathbb{N}$, $P(X_n \in A|X_1, \cdots, X_{n-1}) = P(X_1 \in A|X_0)$ a.e.

6. Stochastic Integration

Exercise 6.0.1. Let $(\Omega, \mathcal{F}, P)$ be a probability space, X a set $\mathcal{A}_0$ an algebra, $\mu_0 : \mathcal{A}_0 \to \mathbb{C}$ and $B : \mathcal{A}_0 \to L^2(\Omega, \mathcal{F}, P)$. Suppose that

1. $B(\varnothing) = 0$
2. for each $E, F \in \mathcal{A}_0$, if $E \cap F = \varnothing$, then $B(E \cup F) = B(E) + B(F)$
3. $\mathrm{E}[B(E)B(F)^*] = \mu_0(E \cap F)$

Then

1. for each $E \in \mathcal{A}_0$, $\mu_0(E) = \mathrm{E}[|B(E)|^2]$.
2. for each $E \in \mathcal{A}_0$, $0 \leq \mu_0(E) < \infty$
3. for each $E, F \in \mathcal{A}_0$, if $E \cap F = \varnothing$, then $\mu_0(E \cup F) = \mu_0(E) + \mu_0(F)$

Proof.

1. Clear
2. Clear
3. Let $E, F \in \mathcal{A}_0$. Suppose that $E \cap F = \varnothing$. Then
$$\begin{aligned} \mathrm{E}[B(E)B(F)^*] &= \mu_0(E \cap F) \\ &= \mu_0(\varnothing) \\ &= \mathrm{E}[|B(\varnothing)|^2] \\ &= \mathrm{E}[0] \\ &= 0 \end{aligned}$$
This implies that
$$\begin{aligned} \mu_0(E \cup F) &= \mathrm{E}[|B(E \cup F)|^2] \\ &= \mathrm{E}[|B(E) + B(F)|^2] \\ &= \mathrm{E}[|B(E)|^2] + \mathrm{E}[|B(F)|^2] + 2\mathrm{Re}\mathrm{E}[B(E)B(F)^*] \\ &= \mu_0(E) + \mu_0(F) + 0 \\ &= \mu_0(E) + \mu_0(F) \end{aligned}$$

$\square$

Definition 6.0.2. Let $(\Omega, \mathcal{F}, P)$ be a probability space, X a set $\mathcal{A}_0$ an algebra, $\mu_0 : \mathcal{A}_0 \to [0, \infty)$ a premeasure and $B : \mathcal{A}_0 \to L^2(\Omega, \mathcal{F}, P)$. Suppose that

1. $B(\varnothing) = 0$
2. for each $E, F \in \mathcal{A}_0$, if $E \cap F = \varnothing$, then $B(E \cup F) = B(E) + B(F)$
3. $\mathrm{E}[B(E)B(F)^*] = \mu_0(E \cap F)$

Then B is said to be a **stochastic premeasure with sturcture** μ_0