

This set of notes aims to provide complete proofs of a number of asymptotic results regarding the Bootstrap [4] contained in Bickel and Freedman [1].

## 1 Bootstrap asymptotics for the I.I.D. sample mean

**Theorem 1.1 (Bootstrap Central Limit Theorem for I.I.D. sample mean, Theorem 2.1 [1])**

Let  $(\Omega, \mathcal{A}, \nu)$  be a probability space. Let  $X, X_1, X_2, \dots : \Omega \rightarrow \mathbb{R}$  be a sequence of independent and identically distributed  $\mathbb{R}$ -valued random variables defined on  $\Omega$  *with finite expectation value  $\mu_X \in \mathbb{R}$  and variance  $\sigma_X^2 < \infty$* . For each  $m \in \mathbb{N}$ , define:

$$\bar{X}^{(m)} : \Omega \rightarrow \mathbb{R} : \omega \mapsto \frac{1}{m} \sum_{i=1}^m X_i(\omega).$$

For  $n, m \in \mathbb{N}$ , define  $\mathcal{S}_n^{(m)}$  to be the set of all functions from  $\{1, 2, \dots, m\} \rightarrow \{1, 2, \dots, n\}$ . Thus, each

$$s = (s(1), s(2), \dots, s(m)) \in \mathcal{S}_n^{(m)}$$

can be regarded as a length- $m$  finite (ordered) sequence of positive integers between 1 and  $n$ , inclusive. Note that  $\mathcal{S}_n^{(m)}$  is a finite set with  $|\mathcal{S}_n^{(m)}| = n^m$ . Endow  $\mathcal{S}_n^{(m)}$  with the probability space structure induced by the uniform probability function:

$$P_{\mathcal{S}_n^{(m)}}(s) := \frac{1}{n^m}, \quad \text{for each } s \in \mathcal{S}_n^{(m)}.$$

Let  $\Omega \times \mathcal{S}_n^{(m)}$  be the product probability space of  $\Omega$  and  $\mathcal{S}_n^{(m)}$ . Define:

$$\bar{X}_n^{(m)} : \Omega \times \mathcal{S}_n^{(m)} \rightarrow \mathbb{R} : (\omega, s) \mapsto \frac{1}{m} \sum_{j=1}^m X_{s(j)}(\omega).$$

For each  $\omega \in \Omega$ , define:

$$Y_{n,\omega}^{(m)} : \mathcal{S}_n^{(m)} \rightarrow \mathbb{R} : s \mapsto \sqrt{m} \left( \bar{X}_n^{(m)}(\omega, s) - \bar{X}_n(\omega) \right)$$

Then,

$$P \left( Y_{n,\omega}^{(m)} \xrightarrow{d} N(0, \sigma_X^2), \text{ as } n, m \rightarrow \infty \right) = \nu \left( \left\{ \omega \in \Omega \mid Y_{n,\omega}^{(m)} \xrightarrow{d} N(0, \sigma_X^2), \text{ as } n, m \rightarrow \infty \right\} \right) = 1.$$

**Remark 1.2**

For each fixed  $\omega \in \Omega$ ,  $\left\{ Y_{n,\omega}^{(m)} : \mathcal{S}_n^{(m)} \rightarrow \mathbb{R} \right\}_{n,m \in \mathbb{N}}$  is a doubly indexed sequence of  $\mathbb{R}$ -valued random variables. Note that their respective domains  $\mathcal{S}_n^{(m)}$  are pairwise distinct probability spaces. The **Bootstrap Central Limit Theorem for I.I.D. sample mean** asserts that for almost every  $\omega \in \Omega$ , the doubly indexed sequence  $\left\{ Y_{n,\omega}^{(m)} \right\}$  of  $\mathbb{R}$ -valued random variables converges in distribution to  $N(0, \sigma_X^2)$  as  $n, m \rightarrow \infty$ .

**Remark 1.3** The following results are well known from classical asymptotic theory:

By the **Weak Law of Large Numbers**,  $\bar{X}_n$  converges in probability to  $\mu_X$ , as  $n \rightarrow \infty$ ; in other words,

$$\lim_{n \rightarrow \infty} P \left( |\bar{X}_n - \mu_X| > \varepsilon \right) = \lim_{n \rightarrow \infty} \nu \left( \left\{ \omega \in \Omega : |\bar{X}_n(\omega) - \mu_X| > \varepsilon \right\} \right) = 0, \quad \text{for each } \varepsilon > 0.$$

By the **Strong Law of Large Numbers**,  $\bar{X}_n$  converges almost surely to  $\mu_X$ , as  $n \rightarrow \infty$ ; in other words,

$$P \left( \lim_{n \rightarrow \infty} \bar{X}_n = \mu_X \right) = \nu \left( \left\{ \omega \in \Omega \mid \lim_{n \rightarrow \infty} \bar{X}_n(\omega) = \mu_X \right\} \right) = 1.$$

By the **Central Limit Theorem**,  $\sqrt{n}(\bar{X}_n - \mu_X)$  converges in distribution to  $N(0, \sigma_X^2)$ .

PROOF Let  $\mathcal{M}_1(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  denotes the set of probability measures on  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ . Let

$$\mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R})) := \left\{ G \in \mathcal{M}_1(\mathbb{R}, \mathcal{B}(\mathbb{R})) \mid \int_{\mathbb{R}} x^2 dG(x) < \infty \right\}.$$

denote the Wasserstein space (Definition A.2) of order 2 of the measurable space  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ , whose underlying topological space (1-dimensional Euclidean space) is a Polish space (i.e. separable complete metric space). Let

$$W_2 : \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R})) \times \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R})) \longrightarrow \mathbb{R} : (G, G') \longmapsto \inf \left\{ \sqrt{E(|X - Y|^2)} \mid (X, Y) \in \Pi(G, G') \right\}$$

denote the Wasserstein metric (Theorem A.3) on  $\mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ .

For each  $m \in \mathbb{N}$ , let  $F^{(m)} \in \mathcal{M}_1(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  denote the distribution of

$$Y^{(m)} : \Omega \longrightarrow \mathbb{R} : \omega \longmapsto \sqrt{m} \left( \bar{X}^{(m)}(\omega) - \mu_X \right).$$

And, for each  $\omega \in \Omega$ , and each  $m, n \in \mathbb{N}$ , let  $F_n^{(m)}(\omega) \in \mathcal{M}_1(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  denote the distribution of

$$Y_{n,\omega}^{(m)} : \mathcal{S}_n^{(m)} \longrightarrow \mathbb{R} : s \longmapsto \sqrt{m} \left( \bar{X}_n^{(m)}(\omega, s) - \bar{X}^{(n)}(\omega) \right).$$

Note that  $N(0, \sigma_X^2) \in \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ . By hypothesis,  $F^{(m)} \in \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  for each  $m \in \mathbb{N}$ . And, for each  $\omega \in \Omega$ ,  $m, n \in \mathbb{N}$ , we have  $F_n^{(m)}(\omega) \in \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ , since  $\mathcal{S}_n^{(m)}$  is a finite probability space. Therefore, by Theorem A.3 and Claim 3 below, the following inequalities hold: For each  $\omega \in \Omega$  and  $m, n \in \mathbb{N}$ ,

$$\begin{aligned} W_2 \left( F_n^{(m)}(\omega), N(0, \sigma_X^2) \right) &\leq W_2 \left( F_n^{(m)}(\omega), F^{(m)} \right) + W_2 \left( F^{(m)}, N(0, \sigma_X^2) \right) \\ &\leq W_2(F_n(\omega), F) + W_2(F^{(m)}, N(0, \sigma_X^2)). \end{aligned}$$

Thus, the present Theorem follows by Theorem A.6 and the following two claims:

**Claim 1:**  $W_2(F^{(m)}, N(0, \sigma_X^2)) \longrightarrow 0$ , as  $m \longrightarrow \infty$ .

**Claim 2:**  $\nu \left( \left\{ \omega \in \Omega \mid W_2(F_n(\omega), F) \longrightarrow 0, \text{ as } n \longrightarrow \infty \right\} \right) = 1$ .

Proof of Claim 1: By the Classical Central Limit Theorem,  $F^{(m)} \xrightarrow{w} N(0, \sigma_X^2)$ . Since  $E[Y^{(m)}] = 0$ , we have

$$\begin{aligned} \int_{\mathbb{R}} y^2 dF^{(m)}(y) &= E \left[ \left( Y^{(m)} \right)^2 \right] = \text{Var} \left[ Y^{(m)} \right] = m \cdot \text{Var} \left[ \left( \frac{1}{m} \sum_{i=1}^m X_i \right) - \mu_X \right] \\ &= \frac{m}{m^2} \cdot \sum_{i=1}^m \text{Var}[X_i] = \frac{1}{m} \cdot m \cdot \sigma_X^2 = \sigma_X^2, \end{aligned}$$

which is the second moment of  $N(0, \sigma_X^2)$ . Hence, by Definition A.5, we have  $F^{(m)} \xrightarrow{\mathcal{W}_1^2} N(0, \sigma_X^2)$ , and by Theorem A.6, we have  $W_2(F^{(m)}, N(0, \sigma_X^2)) \longrightarrow 0$ , as  $m \longrightarrow \infty$ . This completes the proof of Claim 1.

Proof of Claim 2: By hypothesis  $\mu_X := E[X] \in \mathbb{R}$  and  $\sigma_X^2 := \text{Var}[X] < \infty$ . Hence  $E[X^2] = \text{Var}[X] + E[X]^2 < \infty$ . Thus, by the Strong Law of Large Numbers, we have:

$$\int_{\mathbb{R}} x^2 dF_n(\omega)(x) = \frac{1}{n} \sum_{i=1}^n X_i(\omega)^2 \xrightarrow{\text{a.e.}} E[X^2] = \int_{\mathbb{R}} x^2 dF(x),$$

equivalently,

$$\nu\left(\left\{\omega \in \Omega \mid \int_{\mathbb{R}} x^2 dF_n(\omega)(x) \longrightarrow \int_{\mathbb{R}} x^2 dF(x) \right\}\right) = 1.$$

On the other hand, by the Glivenko-Cantelli Theorem, we have:

$$\nu\left(\left\{\omega \in \Omega \mid \lim_{n \rightarrow \infty} \sup_{t \in \mathbb{R}} |F_n(\omega)(t) - F(t)| = 0 \right\}\right) = 1,$$

which implies trivially

$$\nu\left(\left\{\omega \in \Omega \mid \lim_{n \rightarrow \infty} F_n(\omega)(t) = F(t), \text{ for each } t \in \mathbb{R} \right\}\right) = 1,$$

which in turn implies

$$\nu\left(\left\{\omega \in \Omega \mid F_n(\omega) \xrightarrow{w} F \right\}\right) = 1.$$

Note that in the above assertion, we used the slight abuse of notation that  $F_n(\omega)$  represents both the distribution (measure)  $F_n(\omega) \in \mathcal{M}_1(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  as well as its cumulative distribution function defined on  $\mathbb{R}$ . Thus, we see that Theorem A.6, the Glivenko-Cantelli Theorem, and the Strong Law of Large Numbers together imply:

$$\begin{aligned} & \nu\left(\left\{\omega \in \Omega \mid W_2(F_n(\omega), F) \longrightarrow 0 \right\}\right) \\ &= \nu\left(\left\{\omega \in \Omega \mid F_n(\omega) \xrightarrow{\mathcal{W}_2^2} F \right\}\right) \\ &= \nu\left(\left\{\omega \in \Omega \mid F_n(\omega) \xrightarrow{w} F \text{ and } \int_{\mathbb{R}} x^2 dF_n(\omega)(x) \longrightarrow \int_{\mathbb{R}} x^2 dF(x) \right\}\right) \\ &= \nu\left(\left\{\omega \in \Omega \mid F_n(\omega) \xrightarrow{w} F \right\} \cap \left\{\omega \in \Omega \mid \int_{\mathbb{R}} x^2 dF_n(\omega)(x) \longrightarrow \int_{\mathbb{R}} x^2 dF(x) \right\}\right) \\ &= 1. \end{aligned}$$

This completes the proof of Claim 2.

**Claim 3:** Let  $G \in \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  and  $m \in \mathbb{N}$ . Suppose  $Z_1^{(G)}, Z_2^{(G)}, \dots, Z_m^{(G)}$  are independent and identically distributed random variables, each having distribution  $G$ . Let  $G^{(m)} \in \mathcal{M}_1(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  be the (empirical) measure of the random variable

$$Y_m^{(G)} := \frac{1}{m^{1/2}} \sum_{i=1}^m (Z_i^{(G)} - \mu_G) : \Omega \longrightarrow \mathbb{R},$$

where  $\mu_G := \int_{\mathbb{R}} x dG(x)$  is the expectation value of the distribution  $G$ . Then, for any  $G, H \in \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ , we have

$$W_2(G^{(m)}, H^{(m)}) \leq W_2(G, H).$$

Proof of Claim 3:

□

## A Wasserstein Spaces

Proofs of results mentioned in this section can be found in Chapters 1 and 6 of [6].

Suppose  $(S, \mathcal{S})$  and  $(T, \mathcal{T})$  are two measurable spaces. We will use the following notations:

- $(S \times T, \mathcal{S} \otimes \mathcal{T})$  denotes their product measurable space (see Chapter 10, [5]).
- $\mathcal{M}_1(S, \mathcal{S})$ ,  $\mathcal{M}_1(T, \mathcal{T})$ , and  $\mathcal{M}_1(S \times T, \mathcal{S} \otimes \mathcal{T})$  denote the sets of probability measures on the respective measurable spaces.
- $\Pi^S : S \times T \longrightarrow S : (s, t) \longmapsto s$  and  $\Pi^T : S \times T \longrightarrow T : (s, t) \longmapsto t$  are the canonical projection maps, and

$$\Pi_*^S : \mathcal{M}_1(S \times T, \mathcal{S} \otimes \mathcal{T}) \longrightarrow \mathcal{M}_1(S, \mathcal{S}) : \pi \longmapsto \left( A \in \mathcal{S} \longmapsto \pi[(\Pi^S)^{-1}(A)] \right),$$

$$\Pi_*^T : \mathcal{M}_1(S \times T, \mathcal{S} \otimes \mathcal{T}) \longrightarrow \mathcal{M}_1(T, \mathcal{T}) : \pi \longmapsto \left( B \in \mathcal{T} \longmapsto \pi[(\Pi^T)^{-1}(B)] \right)$$

are the corresponding push-forward maps of measures.

## Definition A.1 (Coupling measures and couplings (Definition 1.1, [6]))

Let  $(S, \mathcal{S})$  and  $(T, \mathcal{T})$  be two measurable spaces. Let  $\mu \in \mathcal{M}_1(S, \mathcal{S})$  and  $\nu \in \mathcal{M}_1(T, \mathcal{T})$ .

- A **coupling (probability) measure** of  $\mu$  and  $\nu$  is a probability measure  $\pi \in \mathcal{M}_1(S \times T, \mathcal{S} \otimes \mathcal{T})$  whose push-forwards under the canonical projection maps are  $\mu$  and  $\nu$  respectively; in other words  $\pi \in \mathcal{M}_1(S \times T, \mathcal{S} \otimes \mathcal{T})$  is a coupling measure of  $(\mu, \nu) \in \mathcal{M}_1(S, \mathcal{S}) \times \mathcal{M}_1(T, \mathcal{T})$  if  $\pi$  satisfies:

$$\Pi_*^S(\pi) = \mu \quad \text{and} \quad \Pi_*^T(\pi) = \nu.$$

In this case,  $\mu$  and  $\nu$  are called the **marginal (probability) measures** of  $\pi$ . We denote by  $\Pi(\mu, \nu)$  the subset of  $\mathcal{M}_1(S \times T, \mathcal{S} \otimes \mathcal{T})$  of all coupling probability measures of  $\mu$  and  $\nu$ .

- A **coupling** of  $\mu$  and  $\nu$  is an  $(S \times T)$ -valued random variable

$$Z = (X, Y) : (\Omega, \mathcal{A}, P_\Omega) \longrightarrow (S \times T, \mathcal{S} \otimes \mathcal{T})$$

whose induced measure on  $(S \times T, \mathcal{S} \otimes \mathcal{T})$  is a coupling probability measure of  $\mu$  and  $\nu$ . More precisely,

$$\mu(A) = P_X(A) = P_\Omega(X^{-1}(A)) = P_\Omega((\Pi^S \circ Z)^{-1}(A)) = P_\Omega(Z^{-1}[(\Pi^S)^{-1}(A)]), \quad \text{for each } A \in \mathcal{S}$$

$$\nu(B) = P_Y(B) = P_\Omega(Y^{-1}(B)) = P_\Omega((\Pi^T \circ Z)^{-1}(B)) = P_\Omega(Z^{-1}[(\Pi^T)^{-1}(B)]), \quad \text{for each } B \in \mathcal{T}$$

## Definition A.2 (Wasserstein distances and Wasserstein spaces (Definitions 6.1 and 6.4, [6]))

Let  $p \in [1, \infty)$ . Let  $(S, \rho)$  be a Polish space (i.e. separable complete metric space), and  $\mathcal{S}$  its Borel  $\sigma$ -algebra.

- The **Wasserstein distance of order  $p$**  is, by definition, the map  $W_p : \mathcal{M}_1(S, \mathcal{S}) \times \mathcal{M}_1(S, \mathcal{S}) \longrightarrow \mathbb{R} \cup \{+\infty\}$  given by:

$$\begin{aligned} W_p(\mu, \nu) &:= \inf_{\pi \in \Pi(\mu, \nu)} \left\{ \left( \int_{S \times S} \rho(x, y)^p \, d\pi(x, y) \right)^{1/p} \right\} \\ &= \inf \left\{ (E[\rho(X, Y)^p])^{1/p} \in \mathbb{R} \cup \{+\infty\} \mid \begin{array}{l} X, Y : (\Omega, \mathcal{A}, \pi) \longrightarrow (S, \mathcal{S}) \text{ are } S\text{-valued} \\ \text{random variables with } X^*(\pi) = \mu, Y^*(\pi) = \nu \end{array} \right\}. \end{aligned}$$

- The **Wasserstein space of order  $p$**  is defined to be:

$$\mathcal{W}_1^p(S, \mathcal{S}) := \left\{ \mu \in \mathcal{M}_1(S, \mathcal{S}) \mid \int_S \rho(x_0, x)^p \, d\mu(x) < \infty \right\},$$

where  $x_0 \in S$  is an arbitrary point in  $S$  ( $\mathcal{W}_1^p(S, \mathcal{S})$  is independent of the choice of  $x_0 \in S$ ). Thus,  $\mathcal{W}_1^p(S, \mathcal{S})$  is the set of probability measures on  $(S, \mathcal{S})$  with finite moment of order  $p$ .

**Theorem A.3 (Wasserstein metrics (Definition 6.4 and Theorem 6.18, [6]))**

- The Wasserstein space  $\mathcal{W}_1^p(S, \mathcal{S})$  is independent of the choice of the point  $x_0 \in S$  in its definition.
- The Wasserstein distance  $W_p$  restricts to a metric on  $\mathcal{W}_1^p(S, \mathcal{S}) \times \mathcal{W}_1^p(S, \mathcal{S})$ .
- For a Polish space (i.e. separable complete metric space)  $(S, \rho)$  with Borel  $\sigma$ -algebra  $\mathcal{S}$ , the Wasserstein space  $\mathcal{W}_1^p(S, \mathcal{S})$ , when metrized by the Wasserstein metric  $W_p$ , is itself a Polish space.

**Definition A.4 (Weak convergence in metric spaces (Chapter 1, [3]))**

Suppose:

- $(S, \rho)$  is a metric space and  $\mathcal{S}$  is its Borel  $\sigma$ -algebra.
- $\mathcal{M}_1(S, \mathcal{S})$  denotes the set of probability measures defined on  $(S, \mathcal{S})$ .
- $\mu \in \mathcal{M}_1(S, \mathcal{S})$  and  $\{\mu_k\}_{k \in \mathbb{N}} \subset \mathcal{M}_1(S, \mathcal{S})$ .

Then,  $\{\mu_k\}_{k \in \mathbb{N}}$  is said to **converge weakly** to  $\mu$  if, for each  $f \in C_b(S, \mathbb{R})$ ,

$$\int_S f(x) d\mu_k(x) \longrightarrow \int_S f(x) d\mu(x), \text{ as } k \longrightarrow \infty,$$

where  $C_b(S, \mathbb{R})$  denotes the set of all bounded continuous  $\mathbb{R}$ -valued functions on  $S$ . We write  $\mu_k \xrightarrow{w} \mu$  for  $\mu_k$  converging weakly to  $\mu$ .

**Definition A.5 (Weak convergence in Wasserstein spaces (Definition 6.8, [6]))**

Suppose:

- $(X, \rho)$  is a Polish space, and  $\mathcal{S}$  is its Borel  $\sigma$ -algebra.
- $p \in [1, \infty)$  and  $\mathcal{W}_1^p(S, \mathcal{S})$  is the corresponding Wasserstein space of order  $p$ .
- $\mu \in \mathcal{W}_1^p(S, \mathcal{S})$  and  $\{\mu_k\}_{k \in \mathbb{N}} \subset \mathcal{W}_1^p(S, \mathcal{S})$ .

Then,  $\{\mu_k\}_{k \in \mathbb{N}}$  is said to **converge weakly in  $\mathcal{W}_1^p(S, \mathcal{S})$**  to  $\mu$  if, for some (hence any)  $x_0 \in S$ , we have:

$$\mu_k \xrightarrow{w} \mu \quad \text{and} \quad \int_S \rho(x_0, x)^p d\mu_k(x) \longrightarrow \int_S \rho(x_0, x)^p d\mu(x), \text{ as } k \longrightarrow \infty.$$

We write  $\mu_k \xrightarrow{\mathcal{W}_1^p} \mu$  for  $\mu_k$  converging weakly to  $\mu$  in  $\mathcal{W}_1^p(S, \mathcal{S})$ .

**Theorem A.6 (Wasserstein metrics metrize weak convergence in Wasserstein spaces (Theorem 6.9, [6]))**

Suppose:

- $(X, \rho)$  is a Polish space, and  $\mathcal{S}$  is its Borel  $\sigma$ -algebra.
- $p \in [1, \infty)$ ,  $(\mathcal{W}_1^p(S, \mathcal{S}), W_p)$  is the corresponding Wasserstein space of order  $p$ , metrized by the Wasserstein metric  $W_p$  defined on it.
- $\mu \in \mathcal{W}_1^p(S, \mathcal{S})$  and  $\{\mu_k\}_{k \in \mathbb{N}} \subset \mathcal{W}_1^p(S, \mathcal{S})$ .

Then,

$$\mu_k \xrightarrow{\mathcal{W}_1^p} \mu \quad \text{if and only if} \quad W_p(\mu_k, \mu) \longrightarrow 0.$$

To conclude this Appendix, we present several technical results regarding  $\mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  that are used in the main text.

**Lemma A.7**

Suppose:

- $m \in \mathbb{N}$  is a positive integer.
- $X_1, X_2, \dots, X_m : \Omega_X \rightarrow \mathbb{R}$  are independent and identically distributed  $\mathbb{R}$ -valued random variables defined on the same probability space  $\Omega_X$  such that  $E[X_i] = 0$ , for each  $i = 1, 2, \dots, m$ .
- $Y_1, Y_2, \dots, Y_m : \Omega_Y \rightarrow \mathbb{R}$  are independent and identically distributed  $\mathbb{R}$ -valued random variables defined on the same probability space  $\Omega_Y$  such that  $E[Y_i] = 0$ , for each  $i = 1, 2, \dots, m$ .
- $G^{(1)} \in \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  denotes the common probability distribution of  $X_i$ , for  $i = 1, 2, \dots, m$ , and  $G^{(m)} \in \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  denotes the probability distribution on  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  induced by:

$$\frac{1}{\sqrt{m}} \sum_{i=1}^m X_i : \Omega_X \rightarrow \mathbb{R}.$$

- $H^{(1)} \in \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  denotes the common probability distribution of  $Y_i$ , for  $i = 1, 2, \dots, m$ , and  $H^{(m)} \in \mathcal{W}_1^2(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  denotes the probability distribution on  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  induced by:

$$\frac{1}{\sqrt{m}} \sum_{i=1}^m Y_i : \Omega_Y \rightarrow \mathbb{R}.$$

Then,

$$W_2(G^{(m)}, H^{(m)}) \leq W_2(G^{(1)}, H^{(1)}).$$

PROOF

$$\begin{aligned}
 & W_2(G^{(m)}, H^{(m)}) \\
 = & \inf \left\{ \int_{\mathbb{R}^2} (x - y)^2 d\mu(x, y) \in [0, \infty) \mid \mu \in \Pi(G^{(m)}, H^{(m)}) \right\} \\
 \leq & \inf \left\{ \int_{\mathbb{R}^{2m}} \left( \frac{1}{\sqrt{m}} \sum_{i=1}^m x_i - \frac{1}{\sqrt{m}} \sum_{i=1}^m y_i \right)^2 d\mu_1(x_1, y_1) \cdots d\mu_m(x_m, y_m) \mid (\mu_1, \dots, \mu_m) \in \Pi(G^{(1)}, H^{(1)})^m \right\} \\
 & \vdots \\
 = & \dots\dots\dots \\
 & \vdots \\
 = & \inf \left\{ \frac{1}{m} \sum_{i=1}^m \int_{\mathbb{R}^2} (x_i - y_i)^2 d\mu_i(x_i, y_i) \mid (\mu_1, \dots, \mu_m) \in \Pi(G^{(1)}, H^{(1)})^m \right\} \\
 = & \frac{1}{m} \cdot \sum_{i=1}^m \inf \left\{ \int_{\mathbb{R}^2} (x_i - y_i)^2 d\mu_i(x_i, y_i) \mid \mu_i \in \Pi(G^{(1)}, H^{(1)}) \right\} \\
 = & \frac{1}{m} \cdot \sum_{i=1}^m W_2(G^{(1)}, H^{(1)}) \\
 = & W_2(G^{(1)}, H^{(1)}),
 \end{aligned}$$

where the inequality follows from ... the ellipses follow from the following arithmetic:

$$\begin{aligned}
 & \int_{\mathbb{R}^{2m}} \left( \frac{1}{\sqrt{m}} \sum_{i=1}^m x_i - \frac{1}{\sqrt{m}} \sum_{i=1}^m y_i \right)^2 d\mu_1(x_1, y_1) \cdots d\mu_m(x_m, y_m) \\
 &= \frac{1}{m} \int_{\mathbb{R}^{2m}} \left[ \sum_{i=1}^m (x_i - y_i) \right]^2 d\mu_1(x_1, y_1) \cdots d\mu_m(x_m, y_m) \\
 &= \frac{1}{m} \int_{\mathbb{R}^{2m}} \left[ \sum_{i=1}^m (x_i - y_i)^2 + \sum_{i \neq j} \sum (x_i - y_i)(x_j - y_j) \right] d\mu_1(x_1, y_1) \cdots d\mu_m(x_m, y_m) \\
 &= \frac{1}{m} \cdot \sum_{i=1}^m \int_{\mathbb{R}^2} (x_i - y_i)^2 d\mu_i(x_i, y_i) + \frac{1}{m} \cdot \sum_{i \neq j} \sum \left( \int_{\mathbb{R}^2} (x_i - y_i) d\mu_i(x_i, y_i) \right) \cdot \left( \int_{\mathbb{R}^2} (x_j - y_j) d\mu_j(x_j, y_j) \right) \\
 &= \frac{1}{m} \sum_{i=1}^m \int_{\mathbb{R}^2} (x_i - y_i)^2 d\mu_i(x_i, y_i) + \frac{1}{m} \cdot \sum_{i \neq j} \sum (E[X_i] - E[Y_i]) \cdot (E[X_j] - E[Y_j]) \\
 &= \frac{1}{m} \sum_{i=1}^m \int_{\mathbb{R}^2} (x_i - y_i)^2 d\mu_i(x_i, y_i).
 \end{aligned}$$

□

## B A stochastic process $\{X_t : \Omega \longrightarrow V\}_{t \in T}$ and its equivalent $V^T$ -valued random variable $X : \Omega \longrightarrow V^T$

Let  $\Omega$ ,  $T$ , and  $V$  be non-empty sets. Let  $\{X_t : \Omega \longrightarrow V\}_{t \in T}$  be a  $T$ -index family of maps, each of which maps from  $\Omega$  into  $V$ . Note that this family of maps is set-theoretically equivalent (in the sense that either one completely determines the other) to the following  $(V^T)$ -valued map defined on  $\Omega$ :

$$X : \Omega \longrightarrow V^T : \omega \longmapsto (t \longmapsto X_t(\omega)),$$

where  $V^T = \prod_{t \in T} V$  denotes the set of all (arbitrary)  $V$ -valued functions defined on  $T$ . In this section, we aim to establish the following two results:

- Suppose  $(\Omega, \mathcal{A})$  and  $(V, \mathcal{F})$  are measurable space structures on  $\Omega$  and  $V$ , respectively. Then,  $X : \Omega \longrightarrow V^T$  is  $(\mathcal{A}, \sigma[(V, \mathcal{F})^T])$ -measurable if and only if  $X_t : \Omega \longrightarrow V$  is  $(\mathcal{A}, \mathcal{F})$ -measurable for each  $t \in T$ . Here,  $\sigma[(V, \mathcal{F})^T]$  denotes the product  $\sigma$ -algebra on  $V^T$ , which is by definition the smallest  $\sigma$ -algebra on  $V^T$  such that, for each  $t \in T$ , the projection map (or evaluation map)

$$\pi_t : V^T \longrightarrow V : x \longmapsto x(t)$$

is  $(\sigma[(V, \mathcal{F})^T], \mathcal{F})$ -measurable.

- An immediate corollary of the above result is that: Suppose  $(\Omega, \mathcal{A}, \mu)$  is a probability space structure on  $\Omega$ ,  $(V, \mathcal{F})$  is a measurable space structure on  $V$ , and  $\sigma[(V, \mathcal{F})^T]$  is the product  $\sigma$ -algebra on  $V^T$ . Then,  $X : (\Omega, \mathcal{A}, \mu) \longrightarrow (V^T, \sigma[(V, \mathcal{F})^T])$  is  $V^T$ -valued random variable if and only if  $\{X_t : (\Omega, \mathcal{A}, \mu) \longrightarrow (V, \mathcal{F})\}_{t \in T}$  is a stochastic process.

### Definition B.1 (The product $\sigma$ -algebra of a Cartesian product of measurable spaces)

Let  $T$  be an arbitrary non-empty set. For each  $t \in T$ , let  $(V_t, \mathcal{F}_t)$  be a measurable space (in particular,  $V_t \neq \emptyset$ ). Let  $\prod_{t \in T} V_t$  be the Cartesian product of  $\{V_t\}_{t \in T}$ . In other words,

$$\prod_{t \in T} V_t := \left\{ v : T \longrightarrow \bigsqcup_{t \in T} V_t \mid v(t) \in V_t, \text{ for each } t \in T \right\}.$$

That  $\prod_{t \in T} V_t \neq \emptyset$  follows from the Axiom of Choice. For each  $t \in T$ , let

$$\pi_t : \prod_{\tau \in T} V_\tau \longrightarrow V_t : v \longmapsto v(t)$$

be the projection map from  $\prod_{\tau \in T} V_\tau$  onto  $V_t$ . The **product  $\sigma$ -algebra** on  $\prod_{t \in T} V_t$  is the following:

$$\sigma \left( \left\{ \pi_t^{-1}(F) \subset \prod_{\tau \in T} V_\tau \mid F \in \mathcal{F}_t, t \in T \right\} \right) \subset \text{PowerSet} \left( \prod_{t \in T} V_t \right).$$

Clearly, it is the smallest  $\sigma$ -algebra on  $\prod_{t \in T} V_t$  with respect to which each projection map  $\pi_t : \prod_{t \in T} V_t \longrightarrow (V_t, \mathcal{F}_t)$  is measurable. We denote the product  $\sigma$ -algebra on  $\prod_{t \in T} V_t$  by

$$\sigma \left( \prod_{t \in T} (V_t, \mathcal{F}_t) \right).$$

## Theorem B.2

Suppose  $\Omega$ ,  $T$ , and  $V$  are non-empty sets. Let  $\{X_t : \Omega \longrightarrow V\}_{t \in T}$  be a  $T$ -indexed family of  $V$ -valued maps defined on  $\Omega$ . Then, the following statements are true:

1. The family  $\{X_t : \Omega \longrightarrow V\}_{t \in T}$  of maps is set-theoretically equivalent (in the sense that either completely determines the other) to the following  $(V^T)$ -valued map defined on  $\Omega$ :

$$X : \Omega \longrightarrow V^T : \omega \longmapsto (t \longmapsto X_t(\omega)),$$

where  $V^T = \prod_{t \in T} V$  denotes the set of all (arbitrary)  $V$ -valued functions defined on  $T$ .

2. Suppose:

- $(\Omega, \mathcal{A})$  and  $(V, \mathcal{F})$  are measurable space structures on  $\Omega$  and  $V$ , respectively.
- $W \subset V^T$  is a subset of  $V^T$  such that  $X(\Omega) = \bigcup_{t \in T} X_t(\Omega) \subset W$ .
- $(W, \mathcal{G})$  is a measurable space structure on  $W$  such that, for each  $t \in T$ , the projection map

$$\pi_t : W \longrightarrow V : w \longmapsto w(t)$$

is  $(\mathcal{G}, \mathcal{F})$ -measurable.

Then,  $(\mathcal{A}, \mathcal{G})$ -measurability of  $X : \Omega \longrightarrow W$  implies  $(\mathcal{A}, \mathcal{F})$ -measurability of  $X_t : \Omega \longrightarrow V$  for each  $t \in T$ .

3. Suppose:

- $(\Omega, \mathcal{A})$  and  $(V, \mathcal{F})$  are measurable space structures on  $\Omega$  and  $V$ , respectively.
- $\sigma[(V, \mathcal{F})^T]$  is the product  $\sigma$ -algebra on  $V^T = \prod_{t \in T} V$  generated by the collection of projection maps

$$\left\{ \pi_t : V^T = \prod_{\tau \in T} V \longrightarrow V : w \longmapsto w(t) \right\}_{t \in T}.$$

Then,  $X : \Omega \longrightarrow V^T$  is  $(\mathcal{A}, \sigma[(V, \mathcal{F})^T])$ -measurable if and only if  $X_t : \Omega \longrightarrow V$  is  $(\mathcal{A}, \mathcal{F})$ -measurable for each  $t \in T$ .

PROOF



1. The proof of this result is routine and we omit it.
2. Suppose  $X : \Omega \longrightarrow W$  is  $(\mathcal{A}, \mathcal{G})$ -measurable. Note that  $X_t = \pi_t \circ X$ , where

$$\pi_t : V^T = \prod_{t \in T} V \longrightarrow V : v \longrightarrow v(t)$$

is the projection from  $V^T = \prod_{t \in T} V$  onto the  $t$ -th factor. By hypothesis,  $\pi_t : W \longrightarrow V$  is  $(\mathcal{G}, \mathcal{F})$ -measurable for each  $t \in T$ . This implies, for each  $t \in T$ ,  $X_t = \pi_t \circ X$  is  $(\mathcal{A}, \mathcal{F})$ -measurable, being a composition of two measurable maps.

3. Since, for each  $t \in T$ , the projection map  $\pi_t : V^T \longrightarrow V$  is  $(\sigma[(V, \mathcal{F})^T], \mathcal{F})$ -measurable (by construction of the  $\sigma$ -algebra  $\sigma[(V, \mathcal{F})^T]$  on  $V^T$ ), the preceding result immediately implies the following implication:

$$(\mathcal{A}, \sigma[(V, \mathcal{F})^T])\text{-measurability of } X : \Omega \longrightarrow V^T \implies (\mathcal{A}, \mathcal{F})\text{-measurability of } X_t : \Omega \longrightarrow V, \text{ for each } t \in T.$$

Conversely, suppose  $X_t$  is  $(\mathcal{A}, \mathcal{F})$ -measurable for each  $t \in T$ . Recall that the product  $\sigma$ -algebra on  $V^T$  is generated by sets of the form:

$$\pi_t^{-1}(F), \text{ for some } t \in T \text{ and } F \in \mathcal{F}.$$

It follows that, for each  $t \in T$  and each  $F \in \mathcal{F}$ , we have

$$X^{-1}(\pi_t^{-1}(F)) = (X^{-1} \circ \pi_t^{-1})(F) = (\pi_t \circ X)^{-1}(F) = X_t^{-1}(F) \subset \Omega$$

is  $\mathcal{A}$ -measurable, since  $X_t : (\Omega, \mathcal{A}) \longrightarrow (V, \mathcal{F})$  is  $(\mathcal{A}, \mathcal{F})$ -measurable by hypothesis. This proves that  $X : \Omega \longrightarrow V^T$  is  $(\mathcal{A}, \sigma[(V, \mathcal{F})^T])$ -measurable.  $\square$

### Definition B.3 (Stochastic processes)

A **stochastic process** is a family, indexed by some non-empty set  $T$ ,

$$\{ X_t : (\Omega, \mathcal{A}, \mu) \longrightarrow (V, \mathcal{F}) \}_{t \in T}$$

of  $(\mathcal{A}, \mathcal{F})$ -measurable maps, where the common domain  $(\Omega, \mathcal{A}, \mu)$  is a probability space and the common codomain  $(V, \mathcal{F})$  is a measurable space. The common codomain  $(V, \mathcal{F})$  is called the **state space** of the stochastic process.

### Corollary B.4

Suppose:

- $(\Omega, \mathcal{A}, \mu)$  is a probability space and  $(V, \mathcal{F})$  is a measurable space.
- $T$  is a non-empty set and  $W \subset V^T = \prod_{t \in T} V$ .
- $(W, \mathcal{G})$  is a measurable space structure on  $W$  such that, for each  $t \in T$ , the projection map

$$\pi_t : W \longrightarrow V : w \longmapsto w(t)$$

is  $(\mathcal{G}, \mathcal{F})$ -measurable.

If  $X : (\Omega, \mathcal{A}, \mu) \longrightarrow (V^T, \sigma[(V, \mathcal{F})^T])$  is a  $V^T$ -valued random variable (i.e.  $X$  is  $(\mathcal{A}, \sigma[(V, \mathcal{F})^T])$ -measurable), then its set-theoretically equivalent  $T$ -indexed family of  $V$ -valued maps defined on  $\Omega$

$$\left\{ \begin{array}{lll} X_t & : & (\Omega, \mathcal{A}, \mu) \longrightarrow (V, \mathcal{F}) \\ \omega & \longmapsto & (\pi_t \circ X)(\omega) = \pi_t(X(\omega)) = X(\omega)(t) \end{array} \right\}_{t \in T}$$

is a stochastic process (i.e.  $X_t$  is  $(\mathcal{A}, \mathcal{F})$ -measurable for each  $t \in T$ ).

## Corollary B.5

Suppose:

- $T, \Omega, V$  are non-empty sets.
- $(\Omega, \mathcal{A}, \mu)$  is a probability space structure on  $\Omega$ ,  $(V, \mathcal{F})$  is a measurable space structure on  $V$ .
- $\sigma[(V, \mathcal{F})^T]$  denotes the corresponding product  $\sigma$ -algebra on  $V^T = \prod_{t \in T} V$ .

Let  $\{X_t : \Omega \rightarrow V\}_{t \in T}$  be a  $T$ -indexed family of  $V$ -valued maps defined on  $\Omega$ , and let

$$X : \Omega \rightarrow V^T : \omega \mapsto (t \mapsto X_t(\omega))$$

be its set-theoretically equivalent  $(V^T)$ -valued map defined on  $\Omega$ . Then,

$$\{X_t : (\Omega, \mathcal{A}, \mu) \rightarrow (V, \mathcal{F})\}_{t \in T}$$

is a stochastic process if and only if

$$X : (\Omega, \mathcal{A}, \mu) \rightarrow (V^T, \sigma[(V, \mathcal{F})^T])$$

is a  $(V^T)$ -valued random variable.

## C Uniqueness of the “full distribution” of a stochastic process $\{X_t : \Omega \rightarrow V\}_{t \in T}$ given its finite-dimensional distributions

### Definition C.1 (Finite-dimensional distributions of a stochastic process)

Let  $\{X_t : (\Omega, \mathcal{A}, \mu) \rightarrow (V, \mathcal{F})\}_{t \in T}$  be a stochastic process. Let  $n \in \mathbb{N}$  and  $t_1, t_2, \dots, t_n \in T$  be distinct elements of  $T$ . Let  $\mathcal{P}_{(X_{t_1}, \dots, X_{t_n})} \in \mathcal{M}_1(V^n, \mathcal{F}^{\otimes n})$  denote the probability measure induced on the product measurable space  $(V^n, \mathcal{F}^{\otimes n})$  by the random variable

$$(X_{t_1}, X_{t_2}, \dots, X_{t_n}) : (\Omega, \mathcal{A}, \mu) \rightarrow (V^n, \mathcal{F}^{\otimes n})$$

$\mathcal{P}_{(X_{t_1}, \dots, X_{t_n})}$  is called a **finite-dimensional distribution** of the stochastic process.

### Theorem C.2

Let  $(V, \mathcal{F})$  be a measurable space, and  $\sigma[(V, \mathcal{F})^T]$  the product  $\sigma$ -algebra on  $V^T = \prod_{t \in T} V$ . Let

$$\{X_t : (\Omega_X, \mathcal{A}_X, \mu_X) \rightarrow (V, \mathcal{F})\}_{t \in T} \quad \text{and} \quad \{Y_t : (\Omega_Y, \mathcal{A}_Y, \mu_Y) \rightarrow (V, \mathcal{F})\}_{t \in T}$$

be two stochastic processes with the same index set  $T$  and the same state space  $(V, \mathcal{F})$ . Let

$$X : (\Omega_X, \mathcal{A}_X, \mu_X) \rightarrow (V^T, \sigma[(V, \mathcal{F})^T]) \quad \text{and} \quad Y : (\Omega_Y, \mathcal{A}_Y, \mu_Y) \rightarrow (V^T, \sigma[(V, \mathcal{F})^T])$$

be their respective  $(V^T, \sigma[(V, \mathcal{F})^T])$ -valued random variables. Let  $\mathcal{P}_X, \mathcal{P}_Y \in \mathcal{M}_1(V^T, \sigma[(V, \mathcal{F})^T])$  be the probability measures induced on  $(V^T, \sigma[(V, \mathcal{F})^T])$  by  $X$  and  $Y$ , respectively. Then,

$$\mathcal{P}_X = \mathcal{P}_Y \in \mathcal{M}_1(V^T, \sigma[(V, \mathcal{F})^T])$$

if and only if

$$\mathcal{P}_{(X_{t_1}, X_{t_2}, \dots, X_{t_n})} = \mathcal{P}_{(Y_{t_1}, Y_{t_2}, \dots, Y_{t_n})} \in \mathcal{M}_1(V^n, \mathcal{F}^{\otimes n}), \quad \text{for each } n \in \mathbb{N} \text{ and pairwise distinct } t_1, t_2, \dots, t_n \in T.$$

PROOF

□

## D Existence of a stochastic process given its finite-dimensional distributions: Komolgorov's Existence Theorem

### Definition D.1 (Stochastic processes)

Suppose  $(\Omega, \mathcal{A}, \mu)$  is a probability space,  $(V, \mathcal{F})$  is a measurable space, and  $T$  is an arbitrary non-empty set. A **stochastic process** indexed by  $T$  defined on  $\Omega$  with codomain  $V$  is a family  $\{X_t : \Omega \rightarrow V\}_{t \in T}$  indexed by  $T$  of  $V$ -valued random variables defined on  $\Omega$ .

### Definition D.2 (Finite-dimensional distributions of a stochastic processes)

Let  $\{X_t : \Omega \rightarrow (V, \mathcal{F})\}_{t \in T}$  be a stochastic process. Let  $n \in \mathbb{N}$  and  $t_1, t_2, \dots, t_n \in T$  be distinct elements of  $T$ . The probability distribution induced on the product measurable space  $(V^n, \mathcal{F}^{\otimes n})$  by  $(X_{t_1}, X_{t_2}, \dots, X_{t_n}) : \Omega \rightarrow V^n$  is called a **finite-dimensional distribution** of the stochastic process.

### Definition D.3 (Komolgorov systems of finite-dimensional distributions & Komolgorov consistency)

Let  $T$  be an arbitrary non-empty set, and  $\mathcal{D}(T)$  the set of all finite ordered sequences of elements of  $T$  whose elements are pairwise distinct; in other words,

$$\mathcal{D}(T) := \left\{ (t_1, t_2, \dots, t_n) \in \bigcup_{k=1}^{\infty} T^k \mid n \in \mathbb{N}, t_i \neq t_j, \text{ whenever } i \neq j \right\}.$$

For each  $n \in \mathbb{N}$ , let  $\mathcal{M}_1(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$  be the set of all probability measures defined on the product measurable space  $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$ . A **Komolgorov system of finite-dimensional distributions** is a  $\mathcal{D}(T)$ -indexed family  $\mathcal{P}$  of probability measures of the following form:

$$\mathcal{P} = \{ P_{(t_1, \dots, t_n)} \in \mathcal{M}_1(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n)) \mid (t_1, \dots, t_n) \in \mathcal{D}(T) \}.$$

Furthermore,  $\mathcal{P}$  is said to be **Komolgorov consistent** if it satisfies both of the following conditions:

- **permutation invariance:** For any  $n \in \mathbb{N}$ , any  $(t_1, \dots, t_n) \in \mathcal{D}(T)$ , any  $B_1, \dots, B_n \in \mathcal{B}(\mathbb{R})$ , and any permutation  $\pi : \{1, \dots, n\} \rightarrow \{1, \dots, n\}$ , the following equality holds:

$$P_{(t_1, \dots, t_n)}(B_1 \times \dots \times B_n) = P_{(t_{\pi(1)}, \dots, t_{\pi(n)})}(B_{\pi(1)} \times \dots \times B_{\pi(n)}).$$

- **projection invariance:** For any  $n \in \mathbb{N}$ , any  $(t_1, \dots, t_{n+1}) \in \mathcal{D}(T)$ , and any  $B_1, \dots, B_n \in \mathcal{B}(\mathbb{R})$ , the following equality holds:

$$P_{(t_1, \dots, t_n, t_{n+1})}(B_1 \times \dots \times B_n \times \mathbb{R}) = P_{(t_1, \dots, t_n)}(B_1 \times \dots \times B_n).$$

### Remark D.4

It is obvious that the collection of finite-dimensional distributions of any  $\mathbb{R}$ -valued stochastic process is a Komolgorov consistent Komolgorov system of finite-dimensional distributions.

### Definition D.5

Let  $\{X_t : \Omega \rightarrow \mathbb{R}\}_{t \in T}$  be an  $\mathbb{R}$ -valued stochastic process, and

$$\mathcal{P} = \{ P_{(t_1, \dots, t_n)} \in \mathcal{M}_1(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n)) \mid (t_1, \dots, t_n) \in \mathcal{D}(T) \}$$

be a Komolgorov system of finite-dimensional distributions. We say that **the stochastic process  $\{X_t\}$  admits  $\mathcal{P}$  as its collection of finite-dimensional distributions** if, for each  $n \in \mathbb{N}$  and any  $(t_1, t_2, \dots, t_n) \in \mathcal{D}(T)$ , the probability distribution induced on  $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$  by the map

$$(X_{t_1}, \dots, X_{t_n}) : \Omega \rightarrow \mathbb{R}^n$$

equals  $P_{(t_1, \dots, t_n)} \in \mathcal{P}$ .

## Theorem D.6 (Komolgorov's Existence Theorem, Theorem 36.2, [2])

Let

$$\mathcal{P} = \{ P_{(t_1, \dots, t_n)} \in \mathcal{M}_1(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n)) \mid (t_1, \dots, t_n) \in \mathcal{D}(T) \}.$$

be a Komolgorov system of finite-dimensional distributions. Then, there exists a stochastic process

$$\{ X_t : (\Omega, \mathcal{A}, \mu) \longrightarrow (\mathbb{R}, \mathcal{B}(\mathbb{R})) \}_{t \in T}$$

which admits  $\mathcal{P}$  as its collection of finite-dimensional distributions if and only if  $\mathcal{P}$  is Komolgorov consistent.

## E Gaussian Processes

### Definition E.1 (Gaussian processes)

An  $\mathbb{R}$ -valued stochastic process  $\{ X_t : \Omega \longrightarrow \mathbb{R} \}_{t \in T}$  is said to be **Gaussian** if each of its finite-dimensional distribution is a (univariate or multivariate) Gaussian distribution.

### Definition E.2 (Mean and covariance functions of $\mathbb{R}$ -valued stochastic processes)

Let  $\{ X_t : \Omega \longrightarrow \mathbb{R} \}_{t \in T}$  be an  $\mathbb{R}$ -valued stochastic process.

- If, for each  $t \in T$ , we have  $E(X_t) \in \mathbb{R}$ , then the function

$$a_X : T \longrightarrow \mathbb{R} : t \longmapsto E(X_t)$$

is called the **mean** function of the  $\mathbb{R}$ -valued stochastic process  $\{ X_t \}$ .

- In addition, if, for each  $t_1, t_2 \in T$ , we have  $0 \leq \text{Cov}(X_{t_1}, X_{t_2}) < \infty$ , then the function

$$\Sigma_X : T \times T \longrightarrow \mathbb{R} : (t_1, t_2) \longmapsto \text{Cov}(X_{t_1}, X_{t_2})$$

is called the **covariance** function of the  $\mathbb{R}$ -valued stochastic process  $\{ X_t \}$ .

### Theorem E.3

Let  $T$  be an arbitrary non-empty set,  $a : T \longrightarrow \mathbb{R}$  an arbitrary  $\mathbb{R}$ -valued function defined on  $T$ , and  $\Sigma : T \times T \longrightarrow [0, \infty)$  a non-negative  $\mathbb{R}$ -valued function defined on  $T \times T$ . Then, there exists a Gaussian process whose mean and covariance functions are  $a$  and  $\Sigma$ , respectively.

### Theorem E.4

The mean and covariance functions of a Gaussian process together completely determine its collection of finite-dimensional distributions.

### Definition E.5 (Brownian motion, a.k.a. Wiener process)

A **Brownian motion**, or **Wiener process**, is a stochastic process  $\{ W_t : (\Omega, \mathcal{A}, \mu) \longrightarrow \mathbb{R} \}_{t \geq 0}$  indexed by the non-negative real line satisfying the following conditions:

- At  $t = 0$ , the process takes value 0 with probability 1; more precisely:

$$P(W_0 = 0) = \mu(\{ \omega \in \Omega \mid W_0(\omega) = 0 \}) = 1.$$

- The process  $\{ W_t \}$  has independent increments; more precisely: for any  $0 \leq t_1 \leq t_2 \leq \dots \leq t_n < \infty$ ,

$$W_{t_n} - W_{t_{n-1}}, \quad W_{t_{n-1}} - W_{t_{n-2}}, \quad \dots, \quad W_{t_2} - W_{t_1} : \Omega \longrightarrow \mathbb{R}$$

are independent random variables.

- For  $0 \leq t_1 < t_2 < \infty$ , the increment  $W_{t_2} - W_{t_1}$  follows a Gaussian distribution with mean 0 and variance  $t_2 - t_1$ .

## Definition E.6 (Brownian bridge)

A **Brownian bridge** is a Gaussian process  $\{W_t^\circ : (\Omega, \mathcal{A}, \mu) \longrightarrow \mathbb{R}\}_{t \in [0,1]}$  indexed by the closed unit interval in  $\mathbb{R}$  satisfying the following conditions:

- For each  $t \in [0, 1]$ , we have  $E(W_t^\circ) = 0$ .
- For any  $t_1, t_2 \in [0, 1]$ , we have  $\text{Cov}(W_{t_1}^\circ, W_{t_2}^\circ) = \min\{t_1, t_2\} - t_1 t_2$ .

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