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# Random Fields I

Lecture Notes  
(Draft)

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# 1 Basic notions of the theory of random functions

## 1.1 Random functions

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space,  $\Omega \neq \emptyset$ , and  $(S, \mathcal{B})$  be a measurable space constructed upon an abstract set  $S \neq \emptyset$ .

Definition 1.1.1

A random element  $X : \Omega \rightarrow S$  is an  $\mathcal{F}|\mathcal{B}$ -measurable mapping of  $(\Omega, \mathcal{F})$  into  $(S, \mathcal{B})$ , i.e.

$$X^{-1}(B) := \{\omega \in \Omega : X(\omega) \in B\} \in \mathcal{F} \text{ for all } B \in \mathcal{B}.$$

We write  $X \in \mathcal{F}|\mathcal{B}$ .

Later on,  $S$  will often be a topological space or even a metric space. Then,  $\mathcal{B}$  will be chosen to be the Borel  $\sigma$ -algebra  $\mathcal{B}(S)$ , i.e. the  $\sigma$ -algebra generated by all open subsets of  $S$ :  $\mathcal{B}(S) = \sigma(\mathcal{M})$ , where  $\mathcal{M}$  is the class of all open subsets of  $S$ . "generated by  $\mathcal{M}$ " means:  $\mathcal{B}_S$  is the smallest  $\sigma$ -Algebra on  $S$  containing  $\mathcal{M}$ :

$$\mathcal{B}_S = \bigcap_{\substack{\mathcal{A}: \sigma\text{-Algebra} \\ \text{containing } \mathcal{M}}} \mathcal{A}.$$

Example 1.1.1 1.  $S = \mathbb{R} \implies X$  is a random variable.

2.  $S = \mathbb{R}^k, k \geq 1 \implies X$  is a random vector.

3.  $S = \{\text{functions } f : T \rightarrow E\}$ , where  $T$  and  $E$  are two abstract spaces  $\implies X$  is a random ( $E$ -valued) function with index space  $T$ . If  $E = \mathbb{R}$ , then the notation  $S = \mathbb{R}^T$  is used.

4. Let  $\mathbb{N}$  be the set of all locally finite simple point patterns  $\varphi = \{x_i\}_{i=1}^{\infty}$  in  $\mathbb{R}^d$ . This means

- $\varphi(B) := |\varphi \cap B| < \infty$  for all bounded subsets  $B \in \mathcal{B}(\mathbb{R}^d)$  (write  $B \in \mathcal{B}_o(\mathbb{R}^d)$ ), where  $|A|$  denotes the cardinality of  $A$
- $x_i \neq x_j, i \neq j$  for all  $\varphi \in \mathbb{N}$

Let  $\mathcal{N}$  be the minimal  $\sigma$ -algebra generated by all sets of the form  $\{\varphi \in \mathbb{N} : \varphi(B) = k\}$ , where  $k \in \mathbb{N}_0$  and  $B$  an open relatively compact subset of  $\mathbb{R}^d$ . Then  $(\mathbb{N}, \mathcal{N})$  is a measurable space. The point process  $\Phi$  is a random element  $(\Omega, \mathcal{F}) \rightarrow (\mathbb{N}, \mathcal{N})$ .

Another possibility to define  $\Phi$  is to see it as a random counting measure:  $\Phi(B) = \sum_{i=1}^{\infty} \delta_{x_i}(B)$ , or shortly  $\Phi = \text{supp } \Phi$ . The point process  $\Phi$  is called homogeneous Poisson process on  $\mathbb{R}^d$  with intensity  $\lambda$ , if  $\varphi(B) \sim \text{Poi}(\lambda \nu_d(B))$  for all  $B \in \mathcal{B}_o(\mathbb{R}^d)$ , where  $\nu_d(\cdot)$  is the  $d$ -dimensional Lebesgue measure. One can show that  $\Phi(B_1), \dots, \Phi(B_n)$  are independent random variables, if  $B_1, \dots, B_n \in \mathcal{B}_o(\mathbb{R}^d)$  are disjoint sets. Moreover,  $\lambda \nu_d(B)$  is the mean number of points of  $\Phi$  in the window  $B$ .

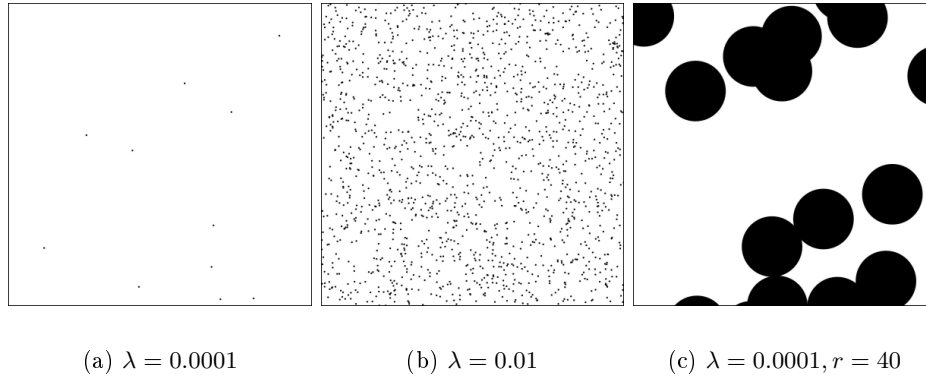


Fig. 1.1: A realization of a homogeneous Poisson point process with intensity  $\lambda = 0.0001$  (left),  $\lambda = 0.01$  (middle) and a germ-grain model of equal discs based on a homogeneous Poisson point process with intensity  $\lambda = 0.0001$

5. Let  $\mathbf{G}$  be the set of all closed sets in  $\mathbb{R}^d$ . Introduce the minimal  $\sigma$ -Algebra  $\mathcal{G}$ , which is generated by the class of sets  $\{A \in \mathbf{G} : A \cap B \neq \emptyset\}$ , where  $B \subset \mathbb{R}^d$  is compact. The random closed set (RACS) is a random element  $\Xi : (\Omega, \mathcal{F}) \rightarrow (\mathbf{G}, \mathcal{G})$ . As an example take  $\Xi = \bigcup_{i=1}^n B_r(x_i)$ ,  $r > 0$ , for any point process  $\varphi = \{x_i\}_{i=1}^\infty$ , which is a special case of the so called germ-grain models.

If  $T = \mathbb{R}$ ,  $\mathbb{R}_+ = [0; \infty)$  or  $[a; b] \subset \mathbb{R}$ , then  $X$  is called a random process with continuous time. If  $T = \mathbb{N}$  or  $\mathbb{Z}$ , it is called a random process with discrete time. For  $T = \mathbb{R}^d$  ( $\mathbb{Z}^d$ ),  $d > 1$  or a (finite) subset of these spaces, we call  $X$  a random field. To stress that  $S$  depends on  $T$ , we will sometimes use the notation  $S_T$ .

#### Definition 1.1.2

The distribution of a random element  $X : \Omega \rightarrow S$  is a probability measure  $P_X$  defined on the measurable space  $(S, \mathcal{B})$  by

$$P_X(B) = P(X^{-1}(B)), \quad B \in \mathcal{B}.$$

#### Lemma 1.1.1

Any probability measure  $\mu$  on  $(S, \mathcal{B})$  can be considered as a distribution of some random element  $X$ .

Proof Take  $\Omega = S$ ,  $\mathcal{F} = \mathcal{B}$ ,  $P = \mu$  and  $X(\omega) = \omega$ . □

Let us give a more intuitive definition of random functions:

#### Definition 1.1.3

Let  $T$  be an abstract index space<sup>1</sup> and  $(S, \mathcal{B})$  a measurable space. A family  $X = \{X(t), t \in T\}$  of random elements  $X(t) : \Omega \rightarrow S$  defined on a probability space  $(\Omega, \mathcal{F}, P)$  is called a random function. Evidently,  $X = X(\omega, t)$  is a mapping of  $\Omega \times T$  onto  $S$ , which is  $\mathcal{F}|\mathcal{B}$ -measurable for each  $t \in T$ . For any fixed  $\omega \in \Omega$ , the function  $\{X(t, \omega), t \in T\}$  is called a realization (trajectory) of  $X$ .

<sup>1</sup>The notation  $T$  comes from "time", since for random processes  $t \in T$  is often interpreted as the time parameter.

Let us ask the question of existence of random functions with some predefined properties. First of all, we mention the existence result for random functions  $X = \{X(t), t \in T\}$ , where all  $X(t)$  have given distributions and are independent.

Theorem 1.1.1 (Z. Lomnicki, S. Ulam (1934)):

Let  $(S_t, \mathcal{B}_t)_{t \in T}$  be a sequence of arbitrary measurable spaces equipped with a probability measure  $\mu_t$  for every  $t \in T$  in an index space  $T$ . Then there exists a probability space  $(\Omega, \mathcal{F}, P)$  and a random function  $X = \{X(t) : \Omega \rightarrow S_t, t \in T\}$  such that

1.  $X(t)$  is  $\mathcal{F}|\mathcal{B}_t$ -measurable for all  $t \in T$ .
2. the random elements  $X(t)$  are independent for all  $t \in T$ .
3.  $P_{X(t)} = \mu_t$  on  $\mathcal{B}_t$  for all  $t \in T$ .

Many meaningful classes of random functions are constructed on the basis of independent ones, see examples in Section 1.2.

Definition 1.1.4

For  $n \in \mathbb{N}$  and  $t_1, \dots, t_n \in T$  we call the distribution of the random vector  $(X(t_1), \dots, X(t_n))^\top$  a finite-dimensional distribution of random function  $X = \{X(t), t \in T\}$ . For  $n = 1$ , the distribution of  $X(t)$  is called marginal. We write

$$P_{t_1, \dots, t_n}(B_{t_1}, \dots, B_{t_n}) = P(X(t_1) \in B_{t_1}, \dots, X(t_n) \in B_{t_n}),$$

where  $B_{t_k} \in \mathcal{B}_{t_k}$ ,  $k = 1, \dots, n$ .

Let us analyze the question of equivalence of Definition 1.1.1, Example 1.1.1 3) and Definition 1.1.3. For that, one has to solve the problem of measurability of a mapping  $\omega \mapsto X(\omega, \cdot)$ ,  $\omega \in \Omega$ . Let  $S = \{\text{functions } f : T \rightarrow E\} := E^T$ . Let us consider a more general space  $S$  by admitting  $S = \{\text{functions } f \text{ on } T : f(t) \in E_t\}$  for a family of measurable spaces  $(E_t, \mathcal{E}_t)_{t \in T}$ .

Introduce the class  $\mathcal{M}$  of elementary cylinder sets  $C(t, B_t)$  of  $S$ , i.e.  $\mathcal{M}$  contains sets of the form  $\{f \in S : f(t) \in B_t\}$ , where  $t \in T$  and  $B_t \in \mathcal{E}_t$ . These sets contain all functions  $f$  with trajectories  $f(\cdot)$  that go through the "gate"  $B_t$ .

Definition 1.1.5

The  $\sigma$ -algebra  $\mathcal{B}_T$  on  $S$  generated by  $\mathcal{M}$  is called a cylindric  $\sigma$ -algebra  $\mathcal{B}_T = \sigma(\mathcal{M})$ . Notation:  $\mathcal{B}_T = \bigotimes_{t \in T} \mathcal{E}_t$ . For  $E_t = E$  for all  $t \in T$  one can use  $\mathcal{B}_T = \mathcal{E}^T$ .

Let us prove the following result:

Proposition 1.1.1

A family  $X = \{X(\omega, t) : t \in T\}$ , i.e. the family of  $\mathcal{F}|\mathcal{E}_t$ -measurable random elements is a random function if and only if the mapping  $\omega \mapsto X(\omega, \cdot)$ ,  $\omega \in \Omega$  is  $\mathcal{F}|\mathcal{B}_T$ -measurable.

Proof " $\Rightarrow$ " If  $X^{-1}(B_t) \in \mathcal{F}$  for all  $B_t \in \mathcal{E}_t$ ,  $t \in T$ , then  $\{\omega \in \Omega : X(\omega, \cdot) \in C(t, B_t)\} \in \mathcal{F}$ , thus  $X^{-1}(\mathcal{M}) \subseteq \mathcal{F}$  and  $X$  is  $\mathcal{F}|\mathcal{B}_T$ -measurable, because  $\mathcal{B}_T$  is generated by  $\mathcal{M}$ .

" $\Leftarrow$ " Let  $X$  be  $\mathcal{F}|\mathcal{B}_T$ -measurable. Introduce the coordinate projection  $\pi_{T,t} : S_T \rightarrow E_t$  by  $\pi_{T,t}f = f(t)$  for  $f \in S_T$ ,  $t \in T$ .  $\pi_{T,t}$  is  $\mathcal{B}_T|\mathcal{E}_t$ -measurable, since for all  $B_t \in \mathcal{E}_t$  we have  $\pi_{T,t}^{-1}(B_t) = C(t, B_t) \in \mathcal{B}_T$ . It is clear that  $X(\omega, t) = \pi_{T,t}X(\omega)$ . Since  $\pi_{T,t}$  is  $\mathcal{B}_T|\mathcal{E}_t$ -measurable and  $X$  is  $\mathcal{F}|\mathcal{B}_T$ -measurable, then  $X(\omega, t)$  is  $\mathcal{F}|\mathcal{E}_t$ -measurable for all  $t$  as a composition of two measurable mappings.  $\square$

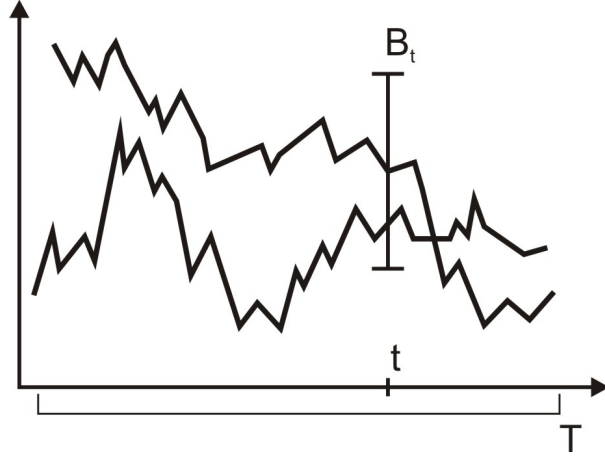


Fig. 1.2: Trajectories going through a "gate"  $B_t$

Now let us consider the question whether a random function  $X$  is defined by all its finite-dimensional distributions. To be more concrete, for all  $t_1, \dots, t_n \in T$  introduce the space  $E_{t_1, \dots, t_n} := E_{t_1} \times \dots \times E_{t_n}$  as a phase space of the random vector  $X_{t_1, \dots, t_n} := (X(t_1), \dots, X(t_n))^T$ . Let  $\mathcal{E}_{t_1, \dots, t_n} := \mathcal{E}_{t_1} \otimes \dots \otimes \mathcal{E}_{t_n}$  be the  $\sigma$ -Algebra on  $E_{t_1, \dots, t_n}$  generated by all "parallelepipeds"  $B_{t_1} \times \dots \times B_{t_n}$ ,  $B_{t_k} \in \mathcal{E}_{t_k}$  for all  $k = 1, \dots, n$ . Then the vector  $X_{t_1, \dots, t_n}$  is  $\mathcal{F}|_{\mathcal{E}_{t_1, \dots, t_n}}$ -measurable, since

$$X_{t_1, \dots, t_n}^{-1}(B_{t_1} \times \dots \times B_{t_n}) = \bigcap_{k=1}^n \{X(t_k) \in B_{t_k}\} \in \mathcal{F}.$$

Then, the finite-dimensional distribution  $P_{t_1, \dots, t_n}$  of  $X$  at "time" points  $t_1, \dots, t_n$  is a probability measure on  $(E_{t_1, \dots, t_n}, \mathcal{E}_{t_1, \dots, t_n})$ . For parallelepipeds  $B = B_{t_1} \times \dots \times B_{t_n}$  it holds

$$P_{t_1, \dots, t_n}(B) = P(X(t_1) \in B_{t_1}, \dots, X(t_n) \in B_{t_n}). \quad (1.1.1)$$

The finite-dimensional distributions of a random function  $X$  have the following important properties:

For all  $n \geq 2$ ,  $t_1, \dots, t_n \in T$ ,  $B_{t_k} \in \mathcal{E}_{t_k}$ ,  $k = 1, \dots, n$  and an arbitrary permutation  $(i_1, \dots, i_n)$  of  $(1, \dots, n)$  the following two conditions are satisfied:

1. Symmetry:

$$P_{t_1, \dots, t_n}(B_{t_1} \times \dots \times B_{t_n}) = P_{t_{i_1}, \dots, t_{i_n}}(B_{t_{i_1}}, \dots, B_{t_{i_n}})$$

2. Consistency:

$$P_{t_1, \dots, t_n}(B_{t_1} \times \dots \times B_{t_{n-1}} \times E_{t_n}) = P_{t_1, \dots, t_{n-1}}(B_{t_1}, \dots, B_{t_{n-1}})$$

They are evident considering (1.1.1) and  $\{X(t_n) \in E_{t_n}\} = \Omega$ . The consistency condition can be equivalently written as

$$P_{t_1, \dots, t_m, \dots, t_n}(B_{t_1} \times \dots \times E_{t_m} \times \dots \times B_{t_n}) = P_{t_1, \dots, t_{m-1}, t_{m+1}, \dots, t_n}(B_{t_1} \times \dots \times B_{t_{m-1}} \times B_{t_{m+1}} \times \dots \times B_{t_n})$$

for any  $m \in \{1, \dots, n\}$ . In the above conditions, only  $n$ -tuples of  $t_1, \dots, t_n$  are meaningful with  $t_i \neq t_j, i \neq j$ . Otherwise if say  $t_1 = t_2 = t$ , one could write  $P_{t_1, t_2}(B_1 \times B_2) = P(X(t) \in B_1, X(t) \in B_2) = P(X(t) \in B_1 \cap B_2) = P_t(B_1 \cap B_2)$  for all  $B_1, B_2 \in \mathcal{E}_t$ .

To formulate the basic theorem of Kolmogorov on the existence of a random function with given finite-dimensional distributions, we need the following

**Definition 1.1.6**

Two measurable spaces  $(C, \mathcal{C})$  and  $(D, \mathcal{D})$  are called isomorphic  $((C, \mathcal{C}) \sim (D, \mathcal{D}))$  if there exists a one-to-one mapping  $h : C \rightarrow D$  such that  $h \in \mathcal{C}|\mathcal{D}$  and  $h^{-1} \in \mathcal{D}|\mathcal{C}$ . If  $D$  is a Borel subset of  $[0; 1]$  and  $\mathcal{D}$  is the  $\sigma$ -Algebra of Borel subsets of  $D$  (i.e.  $\mathcal{D} = D \cap \mathcal{B}([0; 1])$ ) we call a measurable space  $(C, \mathcal{C})$ , which is isomorphic to  $(D, \mathcal{D})$ , a Borel space.

For instance, if  $C$  is a Borel subset of a Polish space<sup>2</sup>  $\mathcal{P}$  with  $\sigma$ -Algebra  $\mathcal{C} = C \cap \mathcal{B}(\mathcal{P})$ , then it can be shown that  $(C, \mathcal{C})$  is a Borel space. A natural choice of  $\mathcal{P}$  can be e.g.  $\mathbb{R}^k, k \geq 1$ .

**Theorem 1.1.2 (A. N. Kolmogorov, 1933):**

Let  $(E_t, \mathcal{E}_t)_{t \in T}$  be a family of Borel spaces. For any  $n \in \mathbb{N}$  and  $t_1, \dots, t_n \in T, t_i \neq t_j, i \neq j$  let measures  $P_{t_1, \dots, t_n}$  be given on spaces  $(E_{t_1, \dots, t_n}, \mathcal{E}_{t_1, \dots, t_n})$  such that they satisfy the conditions of symmetry and consistency. Then there exists a probability space  $(\Omega, \mathcal{F}, P)$  and a random function  $X = \{X(t) : t \in T\}$  defined on it such that its finite-dimensional distributions coincide with the measures  $P_{t_1, \dots, t_n}$ .

**Remark 1.1.1**

In Definition 1.1.6 (and consequently the formulation of Kolmogorov's Theorem) it is required that  $E_t$  is isomorphic to a Borel subset of  $[0; 1]$  and not to the whole  $[0; 1]$ . It was done to admit finite and countable spaces  $E_t$  as the following result shows:

**Theorem 1.1.3**

The Borel space  $(D, \mathcal{D})$  is isomorphic to

$$(D, \mathcal{D}) \sim \begin{cases} (K, \mathcal{B}(K)) & \text{if } D \text{ is non-countable,} \\ (\mathbb{N}, 2^{\mathbb{N}}) & \text{if } D \text{ is countable,} \\ ((1, \dots, |D|), \mathcal{A}(1, \dots, |D|)) & \text{if } D \text{ is finite,} \end{cases}$$

where  $|D|$  is the number of elements of  $D$ ,  $\mathcal{A}(1, \dots, |D|)$  is the  $\sigma$ -algebra of all subsets of  $D$ , and  $2^D$  is the  $\sigma$ -algebra of all subsets of  $D$ . The space  $(K, \mathcal{B}(K))$  is defined as follows: take the Polish space  $\{0, 1\}$  with metric  $d(x, y) = 1\{x \neq y\}, x, y \in \{0, 1\}$ , set  $K = \{0, 1\}^{\mathbb{N}}$  and introduce the metric  $d_K$  on that space by

$$d_K(x, y) = \sum_{n=1}^{\infty} 2^{-n} \frac{d(x_n, y_n)}{1 + d(x_n, y_n)} \text{ for } x = \{x_n\}_{n=1}^{\infty}, y = \{y_n\}_{n=1}^{\infty} \in K. \quad (1.1.2)$$

Then  $K$  is a measurable space by taking its  $\sigma$ -algebra  $\mathcal{B}(K)$  of Borel sets in this metric.

The proof of Kolmogorov's theorem will be given in Section 1.6. Now let us formulate an equivalent statement in terms of characteristic functions of random measures for the special case  $E_t = \mathbb{R}, \mathcal{E}_t = \mathcal{B}(\mathbb{R})$ , for all  $t \in T$ .

<sup>2</sup>A Polish space is a separable complete metric space.

Definition 1.1.7

Let  $\mu$  be a finite measure on  $(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$ . Its characteristic function  $\varphi_\mu(s)$  is defined by

$$\varphi_\mu(s) = \int_{\mathbb{R}^d} \exp(i \langle s, t \rangle) \mu(dt), \quad s \in \mathbb{R}^d,$$

where  $\langle s, t \rangle = \sum_{k=1}^d s_k t_k$  is the scalar product of vectors  $s$  and  $t$  in  $\mathbb{R}^d$ .

If  $\mu$  is a probability measure, it obviously coincides with the characteristic function of a  $d$ -dimensional random vector  $Y$  with distribution  $\mu$ . It is known that  $\varphi_\mu(\cdot)$  determines the measure  $\mu$  uniquely.

Proposition 1.1.2

The family of measures  $P_{t_1, \dots, t_d}$  on  $(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$ ,  $(t_1, \dots, t_d) \in T^d$ ,  $d \geq 1$ , satisfies the conditions of symmetry and consistency if and only if for all  $d \geq 2$ ,  $s = (s_1, \dots, s_d) \in \mathbb{R}^d$  and  $t = (t_1, \dots, t_d) \in T^d$  it holds

1.

$$\varphi_{P_{t_1, \dots, t_d}}((s_1, \dots, s_d)) = \varphi_{P_{t_{i_1}, \dots, t_{i_d}}}((s_{i_1}, \dots, s_{i_d}))$$

for any permutation  $(1, \dots, d) \mapsto (i_1, \dots, i_d)$

2.

$$\varphi_{P_{t_1, \dots, t_{d-1}}}((s_1, \dots, s_{d-1})) = \varphi_{P_{t_1, \dots, t_d}}((s_1, \dots, s_{d-1}, 0))$$

Exercise 1.1.1

Prove Proposition 1.1.2.

As all stochastic objects are defined up to a set of zero probability it can happen that for a random function  $X(t)$  these "exception sets" are quite different. In such case, it would be useless to speak of different realizations of  $X(t)$ . That is why a convention is accepted that all  $X(t)$ ,  $t \in T$  are defined simultaneously on one single set  $\Omega_0 \subseteq \Omega$ ,  $\Omega_0 \in \mathcal{F}$  of probability one. In this case, the random function  $\tilde{X} : \Omega_0 \times T \rightarrow \mathbb{R}$  is called a modification of  $X$ , where  $X : \Omega \times T \rightarrow \mathbb{R}$ . The difference between  $X(t)$  and  $\tilde{X}(t)$  is that they may take different values on a set of zero probability. But such a difference can make the realizations of  $X$  possess some "nice" properties such as continuity or differentiability. Later on, if we say that "random function  $X$  has property  $A$ " we mean that a modification of  $X$  is considered which has this property  $A$ . Similar ideas lead to the notion of equivalence of two random functions.

Definition 1.1.8

Random functions  $X = \{X(t), t \in T\}$  and  $Y = \{Y(t), t \in T\}$ , defined on a common probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  with values in  $(E_t, \mathcal{E}_t)$  are (stochastically) equivalent, if

$$\{\omega \in \Omega : X(\omega, t) \neq Y(\omega, t)\} \in \mathcal{F}, \quad t \in T \quad \text{and}$$

$$\mathbb{P}(\{\omega \in \Omega : X(\omega, t) \neq Y(\omega, t)\}) = 0, \quad t \in T.$$

It is clear that all modifications of  $X$  are equivalent to  $X$ .

Example 1.1.2

Let  $X(\omega, t) \equiv 0$ ,  $t \in [0; 1]$  be a random function defined on  $([0; 1], \mathcal{B}([0; 1]), \lambda_1)$ , where  $\lambda_1$  is the Lebesgue measure on  $[0; 1]$ . Define  $Y(\omega, t) = I_{\{t\}}(\omega)$  on the same probability space. Then,  $X$  and  $Y$  are stochastically equivalent, i.e.  $Y$  is a modification of  $X$ . Note that all trajectories of  $X$  are continuous, but all trajectories of  $Y$  are discontinuous.



## Definition 1.1.9

Random functions  $X = \{X(t), t \in T\}$  and  $Y = \{Y(t), t \in T\}$  (not necessarily defined on the same probability space) with values in  $(E_t, \mathcal{E}_t)$ ,  $t \in T$  are equivalent in distribution if their probability laws are identical:  $P_X = P_Y$  on  $(S_T, \mathcal{B}_T)$ .

By Kolmogorov's theorem, such processes must have the same finite-dimensional distributions. It is clear that equivalence in the stochastic sense implies equivalence in distribution, but not vice versa. Equivalence in distribution is often used in coupling arguments which play an important role in the theory of Markov processes.

## Definition 1.1.10

Random functions  $X = \{X(t), t \in T\}$  and  $Y = \{Y(t), t \in T\}$  defined on the same probability space  $(\Omega, \mathcal{F}, P)$  with values in  $(E_t, \mathcal{E}_t)$ ,  $t \in T$  have equivalent trajectories if

$$\{\omega \in \Omega : X(\omega, t) \neq Y(\omega, t) \text{ for some } t \in T\} \in \mathcal{F} \quad \text{and} \\ P(\{\omega \in \Omega : X(\omega, t) \neq Y(\omega, t) \text{ for some } t \in T\}) = 0.$$

It means that the realizations of  $X$  and  $Y$  coincide with probability one. It is clear that for all  $s \in T$  we have  $\{\omega \in \Omega : X(\omega, s) \neq Y(\omega, s)\} \subset \{\omega \in \Omega : X(\omega, s) \neq Y(\omega, s) \text{ for some } s \in T\}$ . Hence, for a complete<sup>3</sup> probability space  $(\Omega, \mathcal{F}, P)$  processes with equivalent trajectories are stochastically equivalent.

Let us return to the question of measurability of a random function  $X$ . Let  $(T, \mathcal{A})$  be a measurable space as well. It is known from the definition of a random function that for all  $t \in T$   $X(t)$  is  $\mathcal{F}|\mathcal{E}_t$ -measurable. But nobody guarantees the measurability of  $X(\omega, t)$  as a function of  $(\omega, t)$ .

## Definition 1.1.11

Let  $X = \{X(t), t \in T\}$  be a random function defined on the probability space  $(\Omega, \mathcal{F}, P)$  with values in  $(E, \mathcal{E})$  for all  $t \in T$ .  $X$  is said to be measurable if the mapping

$$X : (\omega, t) \longmapsto X(\omega, t) \in E, \quad (\omega, t) \in \Omega \times T$$

is  $\mathcal{F} \otimes \mathcal{A}|\mathcal{E}$ -measurable as a mapping of  $\Omega \times T$  onto  $E$ .

## 1.2 Elementary examples

## §1. White noise

## Definition 1.2.1

A random function  $X = \{X(t), t \in T\}$  defined on  $(\Omega, \mathcal{F}, P)$  is called white noise, if  $X(t), t \in T$  are independent and identically distributed.

As a special case, one has  $T = \mathbb{Z}^d$  or  $\mathbb{R}^d$ ,  $d \geq 1$ . White noise is used to model noise in images, such as salt-and-pepper noise  $X(t) \sim \text{Ber}(p), t \in T$ , for binary images or Gaussian white noise  $X(t) \sim \mathcal{N}(0, \sigma^2), \sigma^2 > 0$ , for greyscale images.

Because of mutual independence of  $X(t)$  for every  $t \in T$  all finite-dimensional distributions are product distributions that obviously satisfy the conditions of Theorem 1.1.2. Hence, the white noise exists, compare also Theorem 1.1.1.

<sup>3</sup>The probability space  $(\Omega, \mathcal{F}, P)$  is complete if for all  $A \in \mathcal{F} : P(A) = 0$  it follows that for all  $B \subset A$  we have  $B \in \mathcal{F}$  (and hence  $P(B) = 0$  as well).

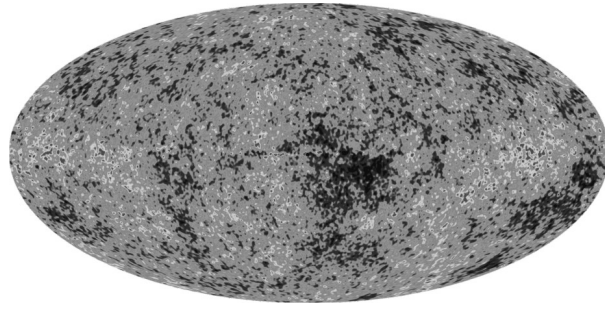


Fig. 1.3: WMAP (Wilkinson Microwave Anisotropy Probe) cosmic microwave fluctuations over the full sky with five years of data.

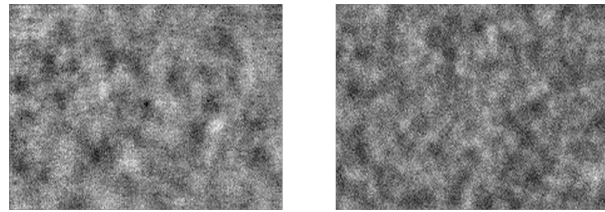


Fig. 1.4: Paper surface (left) and Simulated Gaussian random field based on the estimated data  $EX(t) = 126$ ,  $\text{cov}(X(0), X(t)) = 491 \exp\left(-\frac{|t|}{56}\right)$  (right)

## §2. Gaussian random functions

Another famous simple example of a random function given by all its finite-dimensional distributions explicitly is that of a Gaussian random function.

### Definition 1.2.2

The random function  $X = \{X(t), t \in T\}$  is called Gaussian if all its finite-dimensional distributions  $P_{t_1, \dots, t_n}$  are Gaussian, i.e. for all  $n \geq 1$  and all  $t_1, \dots, t_n \in T$  the distribution of the random vector  $X_{t_1, \dots, t_n} = (X(t_1), \dots, X(t_n))^T$  is an  $n$ -dimensional normal distribution with expectation  $\mu_{t_1, \dots, t_n} = (\mu(t_1), \dots, \mu(t_n))^T$  and a covariance matrix  $\Sigma_{t_1, \dots, t_n} = (\text{cov}(X(t_i), X(t_j)))_{i, j=1}^n$ :  $X_{t_1, \dots, t_n} \sim \mathcal{N}(\mu_{t_1, \dots, t_n}, \Sigma_{t_1, \dots, t_n})$ . This means that for any vector  $c \in \mathbb{R}^n$  the random variable  $\langle c, X_{t_1, \dots, t_n} \rangle$  is normally distributed. If  $\Sigma_{t_1, \dots, t_n}$  is non-degenerate, then  $P_{t_1, \dots, t_n}$  has the density

$$f_{t_1, \dots, t_n}(y) = \frac{1}{(2\pi)^{n/2} \sqrt{\det \Sigma_{t_1, \dots, t_n}}} \exp \left\{ -\frac{1}{2} (y - \mu_{t_1, \dots, t_n})^T \Sigma_{t_1, \dots, t_n}^{-1} (y - \mu_{t_1, \dots, t_n}) \right\}, \quad y \in \mathbb{R}^n.$$

### Exercise 1.2.1

Show that any Gaussian function  $X$  is uniquely defined by its expectation (or mean value) function  $\mu(t) = EX_t$ ,  $t \in T$  and its (non-centered) covariance function  $C(s, t) = E[X_s X_t]$ ,  $s, t \in T$ .

Gaussian random functions are widely used in applications starting with modelling the microstructure of surfaces in material science (e.g. metal surfaces or paper, see Figure 1.4) up to models of fluctuations of microwave cosmic background radiation (see Figure 1.3).

For the construction of many other random functions, Theorem 1.1.2 cannot be used directly as their finite-dimensional distribution cannot be written down explicitly in a convenient way. In such cases, explicit constructions of the form  $X(t) = g(t, Y_1, \dots, Y_n)$ ,  $t \in T$  are used, where  $g$  is measurable and  $Y_1, \dots, Y_n$ ,  $n \in \mathbb{N}$  are some random elements whose existence has been already proved. Let us give corresponding examples:

### §3. Lognormal fields

A random function  $X = \{X(t), t \in T\}$  is called lognormal if  $X(t) = e^{Y(t)}$ , where  $Y = \{Y(t), t \in T\}$  is a Gaussian random field.

### §4. $\chi^2$ -fields

A random function  $X = \{X(t), t \in \mathbb{R}^d\}$  is called  $\chi^2$ -field if  $X(t) = |Y(t)|^2$ ,  $t \in \mathbb{R}^d$ , where  $Y = \{Y(t), t \in \mathbb{R}^d\}$  is an  $n$ -dimensional vector-valued random field such that  $Y(t) \sim \mathcal{N}(0, I)$ ,  $t \in \mathbb{R}^d$ .  $I$  denotes the identity matrix. It is clear that  $X(t)$  is  $\chi_n^2$ -distributed for all  $t \in \mathbb{R}^d$ .

### §5. Cosine fields

Let  $Y_1$  be a random variable,  $Y_2$  a random vector on  $(\Omega, \mathcal{F}, \mathbb{P})$ ,  $\dim Y_2 = \dim T$ , where  $Y_1$  and  $Y_2$  are independent. Consider a random field  $X = \{X(t), t \in \mathbb{R}^d\}$ ,  $d \geq 1$  defined by  $X(t) = \sqrt{2} \cos(2\pi Y_1 + \langle t, Y_2 \rangle)$ . For instance, we can put  $Y_1$  to be uniformly distributed on  $[0; 1]$  (notation:  $Y_1 \sim U[0; 1]$ ). Each realization of  $X$  is a cosine wave surface. If  $X_1, \dots, X_n$  are independent cosine waves with covariance function  $\text{cov}$  of the Gaussian random field  $Z$ , then by the central limit theorem we have

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i(t) \xrightarrow{d} Z(t)$$

as  $n \rightarrow \infty$ , where  $\xrightarrow{d}$  denotes convergence in distribution. In this case, the distribution of  $Y_2$  is chosen to be the spectral measure  $\mu$  of  $\text{cov}$ , confer Definition 2.1.2. This is the so called spectral method for the simulation of  $X$ . For more details on it, see e.g. [Lantuejoul].

### §6. Empirical random measures

Let  $\{Y_i\}_{i \in \mathbb{N}}$  be a sequence of independent identically distributed (iid)  $d$ -dimensional random vectors defined on  $(\Omega, \mathcal{F}, \mathbb{P})$ . Fix some  $n \in \mathbb{N}$ .

#### Definition 1.2.3

For any Borel set  $B \in \mathcal{B}(\mathbb{R}^d)$  define the empirical random measure  $\mu_n(B, \omega)$  as

$$\mu_n(B, \omega) := \frac{1}{n} \sum_{i=1}^n 1\{Y_i(\omega) \in B\}, \quad (1.2.1)$$

or shortly,  $\mu_n(B) = \frac{1}{n} \sum_{i=1}^n 1\{Y_i \in B\}$ . This is obviously a random function indexed by Borel sets  $B$ . It is used in statistics to estimate the (unknown) distribution  $P_Y(B) = P(Y_i \in B)$ ,  $B \in \mathcal{B}(\mathbb{R}^d)$  of  $Y_i$ . For instance, in the special case of  $d = 1$  and  $B = (-\infty; x]$ ,  $x \in \mathbb{R}$  one gets the well known empirical distribution function  $\hat{F}_n(x) = \mu_n((-\infty; x])$ . It is clear that by the strong law of large numbers it holds  $\mu_n(B) \rightarrow P_Y(B)$  in the almost-sure sense as  $n \rightarrow \infty$ ,  $B \in \mathcal{B}(\mathbb{R}^d)$ . That means  $\mu_n(B)$  is a reasonable approximation of  $P_Y(\cdot)$  for sufficiently large  $n$ .

§7. Partial sums of a random field  $Y$ 

Let  $Y = \{Y(t), t \in \mathbb{Z}^d\}$  be a white noise on the lattice  $\mathbb{Z}^d$ ,  $d \geq 1$ . Let  $(\mu_n)_{n \in \mathbb{N}}$  be a sequence of  $\sigma$ -finite measures on  $\mathcal{B}(\mathbb{R}^d)$ .

## Definition 1.2.4

The random function  $S = \{S_n(B), B \in \mathcal{B}((0; 1]^d), n \in \mathbb{N}\}$  defined by

$$S_n(B) = \sum_{t \in \mathbb{Z}^d} Y(t) \mu_n((t-1; t] \cap nB)$$

for all  $B \in \mathcal{B}((0; 1]^d)$  and  $n \in \mathbb{N}$  is called the process of partial (weighted) sums of  $Y$ . Here  $(t-1; t] = \bigotimes_{j=1}^d (t_j - 1; t_j]$ ,  $t = (t_1, \dots, t_d)^\top$  is a unit cube with left lower vertex  $t-1$  and  $nB = \{nb : b \in B\}$ .

The measures  $\mu_n$  give particular weights to any cell  $(t-1; t]$ . Thus, for  $B = (0; 1]^d$  and

$$\mu_n((t; t+1] \cap [0; n]^d) = \begin{cases} \frac{1}{n^{d/2}} & \text{if } (t; t+1] \cap [0; n]^d \neq \emptyset, \\ 0 & \text{otherwise,} \end{cases}$$

we would get

$$S_n([0; 1]^d) = \frac{1}{n^{d/2}} \sum_{t \in \mathbb{Z}^d \cap [0; n]^d} Y(t),$$

which corresponds to partial sums used in the central limit theorem. Under some additional assumptions we have  $S_n([0; 1]^d) \xrightarrow{d} \mathcal{N}(\cdot, \cdot)$ .

## §8. Shot noise random fields and moving averages

Let  $\Phi = \{x_i, i \in \mathbb{N}\}$  be a homogeneous Poisson point process with intensity  $\lambda > 0$  (see Example 1.1.1, 4.). Let  $g : \mathbb{R}^d \rightarrow \mathbb{R}$  be a deterministic function, for which  $\int_{\mathbb{R}^d} g(x) dx < \infty$  and  $\int_{\mathbb{R}^d} g^2(x) dx < \infty$  hold. Introduce a random field  $X = \{X(t), t \in \mathbb{R}^d\}$  by  $X(t) = \sum_{x \in \Phi} g(t-x)$ ,  $t \in \mathbb{R}^d$ . Due to local finiteness of the point process and the integrability conditions of  $g$  it can be shown that  $X$  is a well-defined random field with finite first two moments.

## Exercise 1.2.2

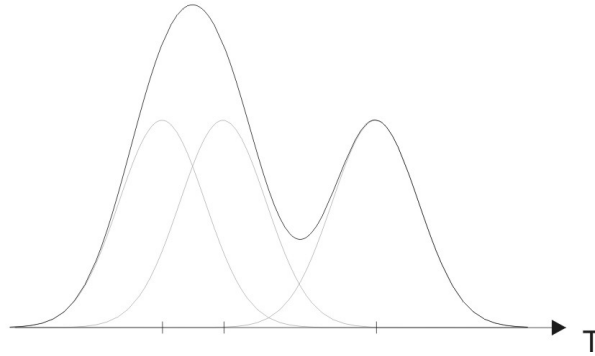
Please, show this!

## Definition 1.2.5

The random field  $X$  introduced above is called a shot-noise field. The function  $g$  is called response function.

Which response functions  $g : \mathbb{R}^d \rightarrow \mathbb{R}$  are used in applications to model real phenomena by Poisson shot-noise random fields? A large class of response functions can be constructed as follows: take  $g(x) = K(\frac{|x|}{a})$ , where  $|x|$  is the Euclidean norm of  $x \in \mathbb{R}^d$  and  $K : \mathbb{R} \rightarrow \mathbb{R}$ , the so-called kernel, is a probability density function with compact support  $\text{supp}K = \{x \in \mathbb{R}^d : K(x) > 0\}$ . For instance,  $K$  can be chosen to be the Epanechnikov kernel  $K(x) = \frac{3}{4}(1-x^2)1\{x \in [-1; 1]\}$  or the bisquare kernel  $K(x) = \frac{15}{16}(1-x^2)^2 1\{x \in [-1; 1]\}$ . Alternatively, kernels with unbounded support such as the Gaussian kernel  $K(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$  can be used as well.

Strictly speaking, we have thus defined a special case of shot-noise fields. This definition can be generalized if we use random response functions (see [40], p. 31) or allow other (non-)

Fig. 1.5: Construction of a shot-noise process in  $\mathbb{R}$ 

homogeneous point processes for  $\Phi$ . Formally, a shot-noise field can be written as a stochastic integral  $X(t) = \int_{\mathbb{R}^d} g(t-x)\Phi(dx)$  if  $\Phi(\cdot)$  is interpreted as a random Poisson counting measure (see [52], ch. 7). This means that it is a special case of a very general class of moving averages:  $X(t) = \int_E g(t,x)\mu(dx)$ , where  $\mu(\cdot)$  is a random independently scattered measure on some measurable space  $(E, \mathcal{E})$ , i.e.

$$B_1, \dots, B_n \in \mathcal{E}, B_i \cap B_j = \emptyset, i \neq j \implies \mu(B_1), \dots, \mu(B_n) \text{ are independent,}$$

and  $g: \mathbb{R}^d \times E \rightarrow \mathbb{R}$  is a deterministic function.

Example 1.2.1 1.  $\mu$  is the Poisson counting measure  $\Phi$ .

2.  $\mu$  is the Gaussian white noise measure:  $\mu(B) \sim \mathcal{N}(0, \lambda_d(B))$ , if  $(E, \mathcal{E}) = (\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$ , where  $\lambda_d(B)$  denotes the volume of  $B$ .

Of course, one has to make it more precise, in which sense this stochastic integral is understood. Depending on the context, it can be defined in  $L^p$ -sense ( $p \in (0; 2]$ ), in probability or almost surely. More details will be given in Chapter 3.

Example 1.2.2 1.  $\mu$  - Gaussian: Existence of the integral in the  $L^2$ -sense:

$$\mathbb{E} \left| \sum_{i=1}^n g(t, \xi_i^n) \mu(B_i^n) - \int_E g(t, x) \mu(dx) \right|^2 \xrightarrow{n \rightarrow \infty} 0.$$

2.  $\mu$  - stable: Existence of the integral in probability:

$$\mathbb{P} \left( \left| \sum_{i=1}^n g(t, \xi_i^n) \mu(B_i^n) - \int_E g(t, x) \mu(dx) \right| > \varepsilon \right) \xrightarrow{n \rightarrow \infty} 0, \varepsilon > 0.$$

## §9. Finite Markov random fields

Let  $T$  be the vertex set of a finite non-oriented graph  $(T, \mathcal{T})$ , where  $\mathcal{T}$  is the edge set of the graph constructed by some neighborhood relation  $\sim$ :

$$\forall s, t \in T : (s, t) \in \mathcal{T} \text{ iff } s \sim t.$$

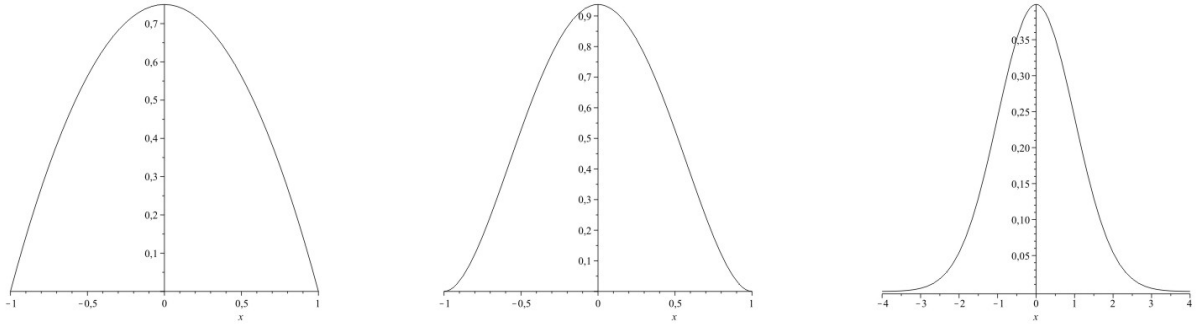


Fig. 1.6: The Epanechnikov kernel (left), Bisquare kernel (middle) and Gaussian kernel (right)

Then, the neighborhood  $\partial s$  of  $s \in T$  is given by  $\partial s = \{t \in T : t \neq s, s \sim t\}$ . Let  $E = \{e_1, \dots, e_m\}$  be a finite space,  $\mathcal{E} = 2^E$ .

**Definition 1.2.6**

The random function  $X = \{X(t), t \in T\}$  such that  $X(t) : \Omega \rightarrow E$  for all  $t \in T$  and  $T, (E, \mathcal{E})$  introduced as above is called a (finite) Markov random field with respect to the neighborhood relation  $\sim$  if for all  $x = (x_t)_{t \in T} \in S = E^T$ :

$$P(X(s) = x_s | X(t) = x_t, t \neq s) = P(X(s) = x_s | X(t) = x_t, t \in \partial s). \quad (1.2.2)$$

Relation (1.2.2) is called Markov property.

Obviously, any finite random field  $X$  on  $T, E$  is a Markov random field with respect to some neighborhood relation. In applications however, Markov random fields  $X$  with respect to small neighborhoods are sought.

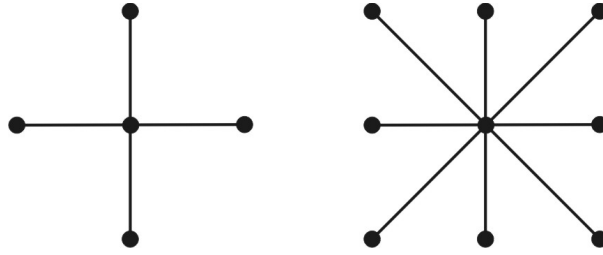
The distribution of a finite random field  $X = \{X(t), t \in T\}$  is given by  $P(X = x)$ ,  $x \in S$ . As a distribution of a finite vector of dimension  $|T|$  it always exists. To give examples of  $T$  and  $E$  let  $T = T_N = \mathbb{Z}^d \cap [-N; N]$ . In image analysis we have  $d = 2$  (3) and  $t \in T_N$  are pixels (voxels). We distinguish between binary images ( $E = \{0, 1\}$ ,  $0 \hat{=}$  white pixel,  $1 \hat{=}$  black pixel) and greyscale images ( $E = \{0, \dots, 255\}$ ,  $0 \hat{=}$  white pixel,  $\dots$ ,  $255 \hat{=}$  black pixel). In physics, if  $d = 3$ , a finite random field with index space  $T_N$  and  $E = \{-1, 1\}$  describes the distribution of dipole directions (spins) at lattice points of a crystal lattice.

How can the neighborhood relation  $\sim$  be defined on  $T_N$ ? Two canonical ways are the so-called 4- and 8-neighborhoods (write  $\sim_4, \sim_8$ ):

- $s \sim_4 t$  iff  $\|s - t\|_1 = 1$  ( $2d$  neighbors),
- $s \sim_8 t$  iff  $\|s - t\|_\infty = 1$  ( $3^d - 1$  neighbors),

where  $\|\cdot\|_1$  is the  $L^1$ -norm and  $\|\cdot\|_\infty$  is the maximum norm. Accordingly, for  $d = 2$  a lattice point has 4 (resp. 8) neighbors.

More generally, if  $T$  is any finite vertex set with a given metric  $\rho$ , then the nearest-neighbor relation  $\sim$  on  $T$  is defined as  $s \sim t$ ,  $s, t \in T$  iff  $\rho(s, t)$  is the smallest distance within the class of all pairs  $(s, u)$ ,  $u \in T, u \neq s$  or  $(v, t)$ ,  $v \in T, v \neq t$ . Then  $\sim$  generates the nearest-neighbor

Fig. 1.7: 4-neighborhood and 8-neighborhood in  $\mathbb{Z}^2$ 

graph out of the vertex set  $T$ .

A prominent example of finite Markov random fields yields the Ising model proposed by the German physicists W. Lenz and E. Ising in the 1920s. It describes ferromagnetic properties of a crystal lattice  $T_N$ .

Example 1.2.3 (Ising model):

The Ising model is given by a finite random field  $X = \{X(t), t \in T_N\}$  on the phase space  $S = E^{T_N}$ ,  $E = \{-1, 1\}$  with

$$P_X(x) = P(X = x) = P(X(s) = x_s, s \in T_N) = \frac{1}{c_x} \exp(-H(x)), \quad x = (x_t)_{t \in T_N},$$

where  $H(x) \in (-\infty; +\infty]$  is the energy functional

$$H(x) = -\frac{1}{kt_0} \left( -mB \sum_{s \in T_N} x_s + J \sum_{\substack{s, t \in T_N \\ s \sim t}} x_s x_t \right).$$

The parameters have the following meanings:

- $t_0 > 0$  - absolute temperature
- $k$  - Boltzmann constant
- $B \in \mathbb{R}$  - intensity of the external ferromagnetic field
- $m > 0$  - material constant
- $J \in \mathbb{R}$  - interaction parameter ( $J > 0$ : ferromagnetic case,  $J < 0$ : antiferromagnetic case,  $J = 0$ : no interaction)

$c_x = \sum_{z \in S} \exp(-H(z))$  is a normalizing constant. Normally, the sum  $\sum_{z \in S}$  runs  $|S| = 2^{|T_N|} = 2^{(2N+1)^d}$  components and (for large  $N$  and  $d$ ) is practically not computable. For  $\sim$  one can take a 4-neighborhood relation.

#### §10. Gibbs random fields

Let  $(T, \mathcal{T})$  be a finite non directed graph with neighborhood relation  $\sim$  and  $E$  a finite state space. For any random field  $X = \{X(t), t \in T\}$  with state space  $E$ , i.e.  $X(t) : \Omega \rightarrow E$ ,  $t \in T$ ,

and distribution  $P_X(x) = P(X = x)$ ,  $x \in S = E^T$ ,  $P_X(x)$  can be written in the so-called Gibbs form:

$$P_X(x) = \frac{1}{c_x} \exp(-H(x)),$$

where  $H(x) = -\log P_X(x) - \log c_x$  is the energy function,  $H(x) \in (-\infty, +\infty]$ , and  $c_x = \sum_{z \in S} \exp(-H(z))$  is the partition function. The definition of  $H(x)$  is unique up to an additive constant. One can achieve uniqueness by setting e.g.  $H(x_0) = 0$  for some  $x_0 \in S$ .

As all Gibbs fields are Markov with respect to some neighborhood relation  $\sim$  on  $T$ , their consideration in this form adds nothing new to the subject, apart from the problem of the existence (and uniqueness) of infinite Gibbs random fields, i.e. fields defined as a limit of  $X$  as  $T$  expands, for instance,  $T = T_N$ ,  $T_N \nearrow \mathbb{Z}^d$  as  $N \rightarrow \infty$ . Does there exist a random field on  $\mathbb{Z}^d$  such that it is a weak limit of finite Gibbs random fields on  $T_N$  as introduced in Examples 6 and 7 of §1.7? In general, this problem is quite complicated. Its solutions can be found in the book [39]. In particular, for the case of the Ising model it can be shown that this thermodynamic limit (as  $N \rightarrow \infty$ ) exists for all parameters  $J > 0$  (see [39], pp. 3-4).

### 1.3 Moments and covariance

Let  $X = \{X(t), t \in T\}$  be a random function,  $X(t) : \Omega \rightarrow \mathbb{R}$ ,  $t \in T$  and  $T$  be an arbitrary index space.

#### Definition 1.3.1

The (mixed) moment  $\mu^{(j_1, \dots, j_n)}(t_1, \dots, t_n)$  of  $X$  of orders  $j_1, \dots, j_n \in \mathbb{N}$  at index values  $t_1, \dots, t_n \in T$  is defined by

$$\mu^{(j_1, \dots, j_n)}(t_1, \dots, t_n) = E [X^{j_1}(t_1) \cdot \dots \cdot X^{j_n}(t_n)],$$

provided that this expectation exists and is finite. For that, it is sufficient to require  $E|X(t)|^j < \infty$  for all  $t \in T$ , where  $j = j_1 + \dots + j_n$ . Special cases are

1.  $\mu(t) = \mu^{(1)}(t) = EX(t)$ ,  $t \in T$  - mean value function
2.  $\mu^{(1,1)}(s, t) = E[X(s)X(t)]$ ,  $s, t \in T$  - (non-centered) covariance function
3.  $C(s, t) = \text{cov}(X(s), X(t)) = \mu^{(1,1)}(s, t) - \mu^{(1)}(s)\mu^{(1)}(t)$ ,  $s, t \in T$  - (centered) covariance function

#### Exercise 1.3.1

Prove that the covariance function  $C(s, t)$  of a random field  $X$

1. is symmetric, i.e.  $C(s, t) = C(t, s)$ ,  $s, t \in T$ .
2. fulfills  $C(t, t) = \text{var}X(t)$ ,  $t \in T$ .
3. is positive semi-definite, i.e. for all  $n \in \mathbb{N}$ ,  $t_1, \dots, t_n \in T$ ,  $z_1, \dots, z_n \in \mathbb{C}$  it holds that

$$\sum_{i=1}^n \sum_{j=1}^n C(t_i, t_j) z_i \bar{z}_j \geq 0.$$



As opposed to the restrictions of positive semi-definiteness in Exercise 1.3.1, the mean value function can be arbitrary. It shows the (deterministic) trend of the random function  $X$ .

The correlation coefficient  $R(s, t) = \frac{C(s, t)}{\sqrt{C(s, s)C(t, t)}}$  is sometimes called the correlation function of  $X$ . It holds  $|R(s, t)| \leq 1$ ,  $s, t \in T$  by the inequality of Cauchy-Schwarz.

#### Exercise 1.3.2

Prove that both non-centered covariance function and correlation function are positive semi-definite.

Exercise 1.3.3 1. Prove that for any positive semi-definite function  $K : T \times T \rightarrow \mathbb{R}$  there exists a centered random function  $X$  such that  $C(s, t) = K(s, t)$ ,  $s, t \in T$ .

2. Let  $K : T \times T \rightarrow \mathbb{R}$  be a positive semi-definite function and  $m : T \rightarrow \mathbb{R}$  be any function with the property:  $K(s, t) - m(s)m(t)$  is positive semi-definite. Show that there exists a random function  $X : \Omega \times T \rightarrow \mathbb{R}$  such that  $\mu(t) = m(t)$  and  $C(s, t) = K(s, t) - m(s)m(t)$ .

#### Exercise 1.3.4

Give examples of two different random functions  $X$  and  $Y$  with  $\mathbf{E}X(t) = \mathbf{E}Y(t)$ ,  $t \in T$  and  $\mathbf{E}[X(s)X(t)] = \mathbf{E}[Y(s)Y(t)]$ ,  $s, t \in T$ .

From the solution of the above exercise it is clear that  $\mu$  and  $C$  (as well as any first  $k$  moments of  $X$ ) do not specify the distribution of  $X$  uniquely.

#### Definition 1.3.2

For any  $t_1, \dots, t_n \in T$ ,  $n \in \mathbb{N}$ , let

$$\varphi(\lambda) = \varphi_{X_{t_1, \dots, t_n}}(\lambda) = \mathbf{E} \exp\{i \langle \lambda, X_{t_1, \dots, t_n} \rangle\}, \quad \lambda = (\lambda_1, \dots, \lambda_n) \in \mathbb{R}^n$$

be the characteristic function of the random vector  $X_{t_1, \dots, t_n} = (X(t_1), \dots, X(t_n))^\top$  (or, equivalently, of the finite-dimensional distribution  $\mathbf{P}_{t_1, \dots, t_n}$  of  $X$ ). For any  $r = (r_1, \dots, r_n) \in \mathbb{N}^n$  let  $|r| = \sum_{j=1}^n r_j$ . The semi-invariant (cumulant, truncated correlation function) is defined by

$$s_X(t_1, \dots, t_n, r) = \frac{1}{i^{|r|}} \cdot \left. \frac{\partial^{|r|} \log \varphi(\lambda)}{\partial \lambda_1^{r_1} \dots \partial \lambda_n^{r_n}} \right|_{\lambda=0}.$$

Sometimes, the notation  $\langle X(t_1)^{r_1}, \dots, X(t_n)^{r_n} \rangle$  for  $s_X(t_1, \dots, t_n, r)$  will be used. In particular,  $\langle X(t_1), \dots, X(t_n) \rangle = s_X(t_1, \dots, t_n, \mathbf{e})$  for  $\mathbf{e} = (1, \dots, 1)^\top$ .

#### Exercise 1.3.5

Show that  $\log \varphi(\lambda) \in C^\infty(\mathbb{R}^n)$ , and thus  $s_X(t_1, \dots, t_n, r)$  is well-defined for all  $t_1, \dots, t_n \in T$ ,  $r \in \mathbb{N}$ , if

$$\mathbf{E}|X(t)|^k < \infty, \quad t \in T, \quad k \in \mathbb{N}. \quad (1.3.1)$$

For later considerations, suppose (1.3.1) to hold true. The properties of  $s_X$  follow directly from the corresponding properties of characteristic functions:

1. Symmetry: for any permutation  $\sigma : (1, \dots, n) \mapsto (\sigma(1), \dots, \sigma(n))$  it holds

$$s_X(t_1, \dots, t_n, r) = s_X(t_{\sigma(1)}, \dots, t_{\sigma(n)}, r_{\sigma(1), \dots, \sigma(n)}), \quad n \in \mathbb{N}, \quad t_1, \dots, t_n \in T.$$

2. Multilinearity: for any  $a, b \in \mathbb{R}$ ,  $n \in \mathbb{N}$ ,  $t_0, \dots, t_n \in T$  it holds

$$\begin{aligned} & \langle aX(t_0) + bX(t_1), X(t_2), \dots, X(t_n) \rangle \\ &= a \langle X(t_0), X(t_2), \dots, X(t_n) \rangle + b \langle X(t_1), X(t_2), \dots, X(t_n) \rangle. \end{aligned}$$

3. Let  $A \cup B = \{t_1, \dots, t_n\}$  be a non-empty partition of  $\{t_1, \dots, t_n\}$  into two disjoint subsets. If  $\{X(t), t \in A\}$  and  $\{X(t), t \in B\}$  are independent, then  $s_X(t_1, \dots, t_n, r) = 0$  for all  $r \in \mathbb{N}^n$ . Hence, semi-invariants characterize the degree of dependence of  $X(t_1), \dots, X(t_n)$ .
4. It holds  $C(s, t) = s_X(s, t, (1, 1)) = \langle X(s), X(t) \rangle$ ,  $s, t \in T$ .

Exercise 1.3.6

Prove the properties 1), 2), 3), 4) of the semi-invariant  $s_X$ .

Let us formulate a generalization of this result:

Theorem 1.3.1

It holds

1.

$$\mu^{(e)}(t_1, \dots, t_n) = \sum_{P_n} \prod_{\{t_{i_1}, \dots, t_{i_k}\} \in P_n} \langle X(t_{i_1}), \dots, X(t_{i_k}) \rangle,$$

where  $P_n$  is any partition of the set  $\{t_1, \dots, t_n\}$  into mutually disjoint non-empty blocks, and  $\{t_{i_1}, \dots, t_{i_k}\}$  is one of such blocks.

2.

$$s_X(t_1, \dots, t_n, e) = \sum_{P_n} (-1)^{|P_n|-1} (|P_n| - 1)! \prod_{\{t_{i_1}, \dots, t_{i_k}\} \in P_n} \mu^{(e)}(t_{i_1}, \dots, t_{i_k}).$$

Proof See [39], p. 30. The idea consists is to compare the coefficients of the Taylor series of  $\varphi(\lambda)$  and  $\log \varphi(\lambda)$ .  $\square$

Cumulants are used not only for the description of the dependence structure of the random vector  $X_{t_1, \dots, t_n}$ , but also for the characterization of its distribution.

Corollary 1.3.1

A random function  $X$  is Gaussian iff  $s_X(t_1, \dots, t_n, e) = 0$  for all  $n > 2$ ,  $t_1, \dots, t_n \in T$ . This holds since the multivariate Gaussian distribution is the only one with  $\log \varphi(\lambda) =$  polynomial of second order.

Example 1.3.1 ([42]): 1.  $X \equiv a$  a.s.  $\iff \langle X^r \rangle = \begin{cases} a, & r = 1, \\ 0, & r > 1 \end{cases}$

2.  $X \sim \text{Poi}(\lambda) \iff \langle X^r \rangle = \lambda, r \in \mathbb{N}$

3.  $X \sim \text{Exp}(\lambda) \iff \langle X^r \rangle = (r-1)! \lambda^{-r}, r \in \mathbb{N}$

Definition 1.3.3

For any  $s, t \in T$  consider the increment  $X(t) - X(s)$  and suppose that  $E|X(t)|^k < \infty$ ,  $t \in T$ ,  $k \in \mathbb{N}$ .

1.  $\gamma_k(s, t) = E[X(t) - X(s)]^k$  is called the mean increment of order  $k \in \mathbb{N}$ .

2. In particular,  $\gamma(s, t) = \frac{1}{2} \gamma_2(s, t) = \frac{1}{2} E[X(t) - X(s)]^2$  is called the variogram of  $X$ .

Variograms are frequently used in geostatistics. One can easily see that the following relationship holds:

$$\gamma(s, t) = \frac{C(s, s) + C(t, t)}{2} - C(s, t) + \frac{1}{2}(\mu(s) - \mu(t))^2, \quad s, t \in T.$$

## 1.4 Stationarity and isotropy

In this section, we introduce the notions of spatial homogeneity of the distribution of random functions. Let the index space  $T$  be a linear vector space with operations  $+$  and  $\cdot$ .

### Definition 1.4.1

The random function  $X = \{X(t), t \in T\}$  is called (strictly) stationary if for any  $n \in \mathbb{N}$ ,  $\tau, t_1, \dots, t_n \in T$  it holds  $P_{t_1+\tau, \dots, t_n+\tau} = P_{t_1, \dots, t_n}$ , i.e. all finite-dimensional distributions of  $X$  are invariant with respect to shifts in  $T$ .

### Definition 1.4.2

Let  $X = \{X(t), t \in T\}$  be a random function with  $E|X(t)|^2 < \infty$ ,  $t \in T$ .  $X$  is called stationary (in the wide sense) if  $\mu(t) \equiv \mu$ ,  $t \in T$  and  $C(s, t) = C(s + \tau, t + \tau)$  ( $:= C(s - t)$ ),  $\tau, s, t \in T$ .

Notice that both definitions of stationarity do not imply each other. However, it is clear that if  $X$  is strictly stationary with finite second moment, then it is stationary in the wide sense.

### Definition 1.4.3

The random function  $X = \{X(t), t \in T\}$  is intrinsically stationary of order two if its mean increments  $\gamma_i(s, t)$ ,  $s, t \in T$  exist up to the order 2, and

1.  $\gamma_1(s, t) = 0$ ,  $s, t \in T$ .
2.  $\gamma_2(s, t) = \gamma_2(s + \tau, t + \tau)$ ,  $s, t, \tau \in T$ .

It is clear that intrinsic stationarity of order two (which is widely used in practice) is a little bit more general than stationarity in the wide sense, because we require the existence of moments of increments of  $X$  and not of  $X(t)$  itself. However, this distinction is of superficial nature, as most random functions which are of practical interest are stationary in the wide sense (and hence intrinsically stationary of order two).

Exactly as in the case of stationarity, the notion of isotropy can be introduced in the strict or wide sense. In order to define it, we need to assume that  $T = \mathbb{R}^d$ ,  $d \geq 2$ . Isotropy can be easily explained as independence of the probabilistic properties of a random field  $X$  of a chosen observation direction. It is often required that isotropic processes are also stationary. However, we shall not do it in the following definition, as there are examples of isotropic non-stationary random fields, see Figure 1.8.

### Definition 1.4.4

The random field  $X = \{X(t), t \in \mathbb{R}^d\}$  is said to be isotropic

1. in the strict sense, if for any  $n \in \mathbb{N}$ ,  $t_1, \dots, t_n \in \mathbb{R}^d$ ,  $A \in \text{SO}(d)$ <sup>4</sup>:

$$(X(At_1), \dots, X(At_n))^\top \stackrel{d}{=} (X(t_1), \dots, X(t_n))^\top.$$

2. in the wide sense, if for any  $s, t \in \mathbb{R}^d$ ,  $A \in \text{SO}(\mathbb{R}^d)$ :

$$\mu(At) = \mu(t), \quad C(As, At) = C(s, t).$$

### Definition 1.4.5

The random field  $X$  is motion invariant if it is stationary and isotropic (both either in the strict or wide sense).

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<sup>4</sup>denotes the special orthogonal group in  $\mathbb{R}^d$



Fig. 1.8: Two realizations of isotropic non-stationary random fields

We shall mostly consider stationarity, isotropy and invariance with respect to rigid motions in the wide sense. This means that  $\mu(t) = \mu$ ,  $t \in \mathbb{R}^d$  and  $C(s, t) = C_0(|t - s|)$  for such random fields, where  $C_0 : \mathbb{R}_+ \rightarrow \mathbb{R}$  is a function of the distance between the points  $s$  and  $t$ .

#### Definition 1.4.6

The random function  $X = \{X(t), t \in T\}$  on an index space  $T$  (which is a linear vector space) has stationary increments, if for all  $n \in \mathbb{N}$  and  $t, t_1, \dots, t_n \in T$

$$(X(t_2) - X(t_1), \dots, X(t_n) - X(t_1))^\top \stackrel{d}{=} (X(t_2 + t) - X(t_1 + t), \dots, X(t_n + t) - X(t_1 + t))^\top.$$

In what follows (here and in §1.5) we suppose that  $X = \{X(t), t \in T\}$  is a centered (i.e.  $\mu(t) = 0, t \in T$ ) random function with values in a Banach<sup>5</sup> space  $E$  and index space  $T$  which is a Banach space as well. If  $X$  is not centered, it can be made so by considering the new random field  $Y = \{Y(t) = X(t) - \mu(t), t \in T\}$ . Sometimes we shall assume that  $X$  is wide sense stationary. In this case, its covariance function  $C(h) = E[X(t)X(t+h)]$ ,  $h \in T$  satisfies obvious properties:

1.  $C(0) = \text{var}X(t) \geq 0$
2. Symmetry:  $C(h) = C(-h)$ ,  $h \in T$
3. Boundedness:  $|C(h)| \leq C(0)$ ,  $h \in T$

Further properties of stationary covariance functions will be considered in Chapter 2.

## 1.5 Continuity and differentiability

We consider different notions of continuity and differentiability of random functions which correspond to the respective convergence types in probability theory. As above, let  $X$  be a centered random function with index space  $T$  and phase space  $E$  (both being Banach spaces with norms  $|\cdot|_T$  and  $|\cdot|_E$ ).

#### Definition 1.5.1

The random function  $X = \{X(t), t \in T\}$  is

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<sup>5</sup>A Banach space is a complete normed vector space.

1. stochastically continuous at  $t \in T$ , if  $X(s) \xrightarrow{p} X(t)$  as  $s \rightarrow t$ , where  $\xrightarrow{p}$  means the convergence in probability, i.e.

$$\mathbb{P}(|X(s) - X(t)|_E > \varepsilon) \rightarrow 0, \quad \varepsilon > 0 \quad \text{as } s \rightarrow t.$$

2. continuous in  $p$ -mean ( $p \geq 1$ ) at  $t \in T$ , if  $X(s) \xrightarrow{L^p} X(t)$  as  $s \rightarrow t$ , i.e.

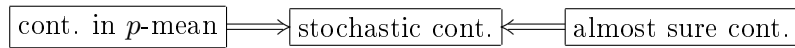
$$\mathbb{E}|X(s) - X(t)|_E^p \rightarrow 0, \quad \text{as } s \rightarrow t.$$

In particular, the case  $p = 2$  has a special name: continuity in quadratic mean, which holds if  $\gamma(s, t) \rightarrow 0$  as  $s \rightarrow t$ .

3. almost surely continuous at  $t \in T$ , if  $X(s) \xrightarrow{a.s.} X(t)$  as  $s \rightarrow t$ , i.e.

$$\mathbb{P}\left(\lim_{s \rightarrow t} X(s) = X(t)\right) = 1.$$

In applications, the most interesting case is certainly the a.s. continuity, and an even stronger property of the continuity of almost all realizations of  $X$ . The weakest (and actually less meaningful) notion is the stochastic continuity:



As it is shown on the above diagram, a random function is stochastically continuous if it is continuous a.s. or in  $p$ -mean,  $p \geq 1$ .

Let us investigate the properties of these three types of continuity in more detail. As it will follow from the next lemma, stochastic continuity is defined by the properties of the two-dimensional distribution  $\mathbb{P}_{s,t}$  of  $X$ .

Lemma 1.5.1

The following statements are equivalent:

- 1.

$$X(s) \xrightarrow{p} Y \quad \text{as } s \rightarrow t_0$$

- 2.

$$\mathbb{P}_{s,t} \xrightarrow{\omega} \mathbb{P}_{(Y,Y)} \quad \text{as } s, t \rightarrow t_0$$

for  $t_0 \in T$  and a random variable  $Y$ . Here  $\xrightarrow{\omega}$  denotes the weak convergence of probability measures. For  $X$  to be stochastically continuous at  $t_0$ , set  $Y = X(t_0)$ .

Proof  $1 \Rightarrow 2$  :  $X(s) \xrightarrow{p} Y$  as  $s \rightarrow t_0$  implies  $(X(s), X(t))^\top \xrightarrow{p} (Y, Y)^\top$  as  $s, t \rightarrow t_0$ . Thus  $\mathbb{P}_{s,t} \xrightarrow{\omega} \mathbb{P}_{(Y,Y)}$  as  $s, t \rightarrow t_0$ , since convergence in probability implies weak convergence.

$2 \Rightarrow 1$  : For any  $\varepsilon > 0$ , take a function  $g_\varepsilon : \mathbb{R} \rightarrow [0; 1]$ , which is continuous on  $\mathbb{R}$ ,  $g_\varepsilon(0) = 0$  and  $g_\varepsilon(x) = 1$  if  $x \notin B_\varepsilon(0)$ . For any  $s, t \in T$  it holds

$$\begin{aligned} & \mathbb{E} g_\varepsilon(|X(s) - X(t)|_E) \\ &= \mathbb{P}(|X(s) - X(t)|_E > \varepsilon) + \mathbb{E} [g_\varepsilon(|X(s) - X(t)|_E) \cdot \mathbf{1}\{|X(s) - X(t)|_E \leq \varepsilon\}], \end{aligned}$$

hence

$$\begin{aligned} \mathbb{P}(|X(s) - X(t)|_E > \varepsilon) &\leq \mathbb{E} g_\varepsilon(|X(s) - X(t)|_E) \\ &= \int_{E \times E} g_\varepsilon(|x - y|_E) \mathbb{P}_{s,t}(d(x, y)) \rightarrow \int_{E \times E} g_\varepsilon(|x - y|_E) \mathbb{P}_{(Y,Y)}(d(x, y)) = 0 \end{aligned}$$

as  $s, t \rightarrow t_0$ , since  $\mathbb{P}_{(Y,Y)}$  is concentrated on  $\{(x, y) \in E \times E : x = y\}$  and  $g_\varepsilon(0) = 0$ . Hence  $\{X(s)\}_{s \rightarrow t_0}$  is a fundamental sequence in probability, and then  $X(s) \xrightarrow{p} Y$  as  $s \rightarrow t_0$ .  $\square$

It can happen that  $X$  is stochastically continuous whereas all its realizations are discontinuous (in the sense that  $X$  does not have an a.s. continuous modification).

#### Exercise 1.5.1

Show this property for the homogeneous Poisson process on the real line.

The explanation of this fact is easy: the probability to have a discontinuity at a concrete  $t \in T$  is zero; hence discontinuities happen at different  $t \in T$  for all realizations of  $X$ .

#### Exercise 1.5.2

Let  $T$  be compact. Prove that if  $X$  is stochastically continuous on  $T$  (i.e. for all  $t \in T$ ), then it is uniformly stochastically continuous on  $T$ , which means that for all  $\varepsilon, \eta > 0$  there exists a  $\delta > 0$  such that for all  $s, t \in T$  with  $|s - t|_T < \delta$ , it holds that

$$\mathbb{P}(|X(s) - X(t)|_E > \varepsilon) < \eta.$$

Let us turn to the continuity in quadratic mean. In order to state further results, suppose that  $E = \mathbb{R}$  and  $\mathbb{E}X^2(t) < \infty$ ,  $t \in T$ . Since  $X$  is centered, it holds  $C(s, t) = \mathbb{E}[X(s)X(t)]$ .

#### Lemma 1.5.2

For any  $t_0 \in T$  and some random variable  $Y$  with  $\mathbb{E}Y^2 < \infty$ , the following statements are equivalent:

1.

$$X(s) \xrightarrow{L^2} Y \text{ as } s \rightarrow t_0$$

2.

$$C(s, t) \rightarrow \mathbb{E}Y^2 \text{ as } s, t \rightarrow t_0$$

Remark 1.5.1 1. For the mean quadratic continuity of  $X$  at  $t_0$  just set  $Y = X(t_0)$ . Then,  $\mathbb{E}Y^2 = C(t_0, t_0)$ , i.e.  $C$  must be continuous at  $(t_0, t_0)$ .

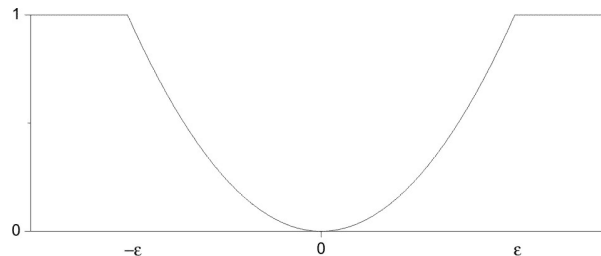


Fig. 1.9: The function  $g_\varepsilon(x)$

2. If  $X$  is not centered, it is enough to require  $\mu(s) \rightarrow \mu(t_0)$  as  $s \rightarrow t_0$  alongside with  $C(s, t) \rightarrow C(t_0, t_0)$  as  $s, t \rightarrow t_0$  for the  $L^2$ -continuity of  $X$  at  $t_0 \in T$ .

Proof of Lemma 1.5.2.  $1 \Rightarrow 2$ : First prove the following general fact: If  $\lim_{n \rightarrow \infty} X_n \stackrel{L^2}{=} X$  and  $\lim_{n \rightarrow \infty} Y_n \stackrel{L^2}{=} Y$  for some sequences  $\{X_n\}_{n \in \mathbb{N}}$  and  $\{Y_n\}_{n \in \mathbb{N}}$  of random variables  $X$  and  $Y$ , then  $E[X_m Y_n] \rightarrow E[XY]$  as  $n, m \rightarrow \infty$ . Indeed, it holds

$$\begin{aligned} & |E[X_m Y_n] - E[XY]| \\ &= |E[(X_m - X + X)(Y_n - Y + Y)] - E[XY]| \\ &\leq E|(X_m - X)(Y_n - Y)| + E|(X_m - X)Y| + E|(Y_n - Y)X| \\ &\leq \sqrt{E(X_m - X)^2 E(Y_n - Y)^2} + \sqrt{EY^2 E(X_m - X)^2} + \sqrt{EX^2 E(Y_n - Y)^2} \rightarrow 0 \end{aligned}$$

as  $m, n \rightarrow \infty$  by the inequality of Cauchy-Schwarz. Hence, from  $X(s) \stackrel{L^2}{\rightarrow} Y$  as  $s \rightarrow t_0$  and  $X(t) \stackrel{L^2}{\rightarrow} Y$  as  $t \rightarrow t_0$  it follows

$$C(s, t) = E[X(s)X(t)] \rightarrow EY^2$$

as  $s, t \rightarrow t_0$ .

$2 \Rightarrow 1$ : Use the relation in Definition 1.3.3 for  $\gamma(s, t)$ :

$$\begin{aligned} E[X(s) - X(t)]^2 &= 2\gamma(s, t) = C(s, s) + C(t, t) - 2C(s, t) \\ &\rightarrow 2EY^2 - 2EY^2 = 0 \end{aligned} \tag{1.5.1}$$

as  $s, t \rightarrow t_0$ . Hence  $\{X(s)\}_{s \rightarrow t_0}$  is a fundamental sequence in the mean quadratic sense, and it follows  $X(s) \stackrel{L^2}{\rightarrow} Y$  as  $s \rightarrow t_0$ .  $\square$

A mean-square continuous random function  $X$  can still have discontinuous realizations. Still in all cases of practical relevance (i.e., except for some "pathologic" random functions  $X$ ) mean-square continuous random functions have an a.s. continuous modification. Later on, this statement will be made more precise.

### Exercise 1.5.3

Construct a stationary shot-noise process with a.s. discontinuous realizations which is continuous in quadratic mean.

Let us consider the special case of a stationary centered random function  $X$ . In this case, the property in Definition 1.3.3 reads

$$\gamma(s, t) = \gamma(s - t) = C(0) - C(s - t), \quad s, t \in T$$

or

$$\gamma(h) = C(0) - C(h), \quad h \in T, \tag{1.5.2}$$

where  $C(0) = \text{var}X(t)$ . This allows us to state the following

Corollary 1.5.1 1. A stationary random function  $X$  is mean-square continuous iff its covariance function is continuous at the origin, i.e.  $\lim_{h \rightarrow 0} C(h) = C(0)$ .

2. If  $C(h)$  is continuous at the origin, then it is continuous everywhere on  $T$ .

Proof 1. This follows directly from Remark 1.5.1, 1) and Lemma 1.5.2 with  $C(h) = C(s, t)$ ,  $s - t = h$ .

2. Prove that  $\lim_{h \rightarrow 0} C(h + h_0) = C(h_0)$  for all  $h_0 \in T$  if it holds for  $h_0 = 0$ . Indeed, for any  $h \in T$  it holds

$$\begin{aligned} |C(h + h_0) - C(h_0)| &= |\mathbb{E}[X(t + h)X(t - h_0)] - \mathbb{E}[X(t)X(t - h_0)]| \\ &\leq \mathbb{E}|(X(t + h) - X(t))X(t - h_0)| \leq \sqrt{2\gamma(h)}\sqrt{\mathbb{E}X^2(t - h_0)} \\ &= \sqrt{2(C(0) - C(h))C(0)} \rightarrow 0 \end{aligned}$$

as  $h \rightarrow 0$  by the inequality of Cauchy-Schwarz and relation (1.5.2). □

Now let us turn to the property of a.s. continuity. If we are looking for a condition imposed on the finite-dimensional distributions of  $X$  assuring the a.s. continuity of its realizations, it is clear that any such condition can guarantee only the existence of a modification of the random function  $X$  with a.s. continuous paths. There are many such sufficient conditions (see e.g [13], [19], v. 1., pp. 192-193, for Gaussian random functions see [1], pp. 11-19 and [11], pp. 170-171). Let us give only one example of those (attributed to N.A. Kolmogorov) in the case of  $X$  being a stochastic process defined on  $T = [a; b] \subset \mathbb{R}$ .

Theorem 1.5.1

The stochastic process  $X = \{X(t), t \in [a; b]\}$  is a.s. continuous if for some  $\alpha, c, \delta > 0$  and sufficiently small  $h$  it holds that

$$\mathbb{E}|X(t + h) - X(t)|^\alpha < c|h|^{1+\delta}, \quad t \in (a; b).$$

Proof See [11], pp. 63-65. □

The above condition of  $X$  is a condition on its two-dimensional distributions  $\mathbb{P}_{t, t+h}$ .

Definition 1.5.2

The random function  $X = \{X(t), t \in T\}$  is differentiable at  $t \in T$  in direction  $h$  stochastically, in  $p$ -mean ( $p \geq 1$ ) or almost surely, if there exists

$$\lim_{l \rightarrow 0} \frac{X(t + hl) - X(t)}{l} := X'_h(t)$$

in the corresponding sense, i.e. in probability, in  $L^p$  or with probability one.

One says that  $X$  is differentiable on  $T$  if it is differentiable at any  $t \in T$ . The differentiability of order  $k$  is defined accordingly in the iterative way.

By Lemmas 1.5.1 and 1.5.2 it is easy to see that the stochastic differentiability is defined by the properties of the three-dimensional distributions of  $X$  (as the joint distribution of  $\frac{X(t+hl) - X(t)}{l}$  and  $\frac{X(s+hl') - X(s)}{l'}$  should weakly converge), whereas the differentiability in quadratic mean is regulated by the properties of the covariance function  $C(s, t)$  (hence, of the two-dimensional distributions of  $X$ ).

Exercise 1.5.4

Show that



1. the Wiener process is not even stochastically differentiable at any  $t \in [0; \infty)$ .
2. the homogeneous Poisson process on  $\mathbb{R}$  is stochastically differentiable on  $\mathbb{R}$ , but not in  $p$ -mean,  $p \geq 1$ .

Let us dwell on the mean-quadratic differentiability of centered random functions  $X = \{X(t), t \in T\}$ .

### Lemma 1.5.3

The random function  $X = \{X(t), t \in T\}$  is differentiable in quadratic mean at  $t \in T$  in direction  $h$  if its covariance function  $C(s, t)$  is twice differentiable at  $(t, t)$  in direction  $h$ , i.e. if there exists

$$C''_{hh}(t, t) = \left. \frac{\partial^2 C(s, t)}{\partial s_h \partial t_h} \right|_{s=t}.$$

Moreover,  $X'_h(t)$  is mean-square continuous at  $t \in T$ , if

$$C''_{hh}(s, t) = \frac{\partial^2 C(s, t)}{\partial s_h \partial t_h}$$

is continuous at  $s = t$ . Here  $C''_{hh}(s, t)$  is the covariance function of  $X'_h = \{X'_h(t), t \in T\}$ .

*Proof* Due to Lemma 1.5.2, it suffices to show the existence of the limit

$$\lim_{l, l' \rightarrow 0} \mathbb{E} \left[ \frac{X(t+lh) - X(t)}{l} \cdot \frac{X(s+l'h) - X(s)}{l'} \right]$$

for  $s = t$ . Indeed, we have

$$\begin{aligned} & \mathbb{E} \left[ \frac{X(t+lh) - X(t)}{l} \cdot \frac{X(s+l'h) - X(s)}{l'} \right] \\ &= \frac{1}{ll'} [C(t+lh, s+l'h) - C(t+lh, s) - C(t, s+l'h) + C(t, s)] \\ &= \frac{1}{l} \left[ \frac{C(t+lh, s+l'h) - C(t+lh, s)}{l'} - \frac{C(t, s+l'h) - C(t, s)}{l'} \right] \rightarrow C''_{hh}(s, t) \end{aligned}$$

as  $l, l' \rightarrow 0$ . All statements of the Lemma immediately follow from this relation.  $\square$

### Corollary 1.5.2

If  $X = \{X(t), t \in T\}$  is a wide sense stationary centered random function with covariance function  $C(\cdot, \cdot)$ , then

1.  $X$  is differentiable in quadratic mean in direction  $h \in T$  iff  $C''_{hh}(0)$  exists and is finite.
2. If  $C(\tau)$  is twice differentiable in direction  $h \in T$  at  $\tau = 0$  then it is twice differentiable in this direction for all  $\tau \in T$ . Then, it holds  $C'_h(0) = 0$ .
3. If  $C''_{hh}(\tau)$  is continuous at  $\tau = 0$ , then it is continuous for any  $\tau \in T$ .
4.  $-C''_{hh}(\tau)$  is the covariance function of  $X'_h$ , i.e. it holds  $-C''_{hh}(\tau) = \mathbb{E}[X'_h(t)X'_h(t+\tau)]$ .
5. If  $X$  is differentiable in quadratic mean in direction  $h$ , then  $X$  and  $X'_h$  are uncorrelated, i.e.  $\mathbb{E}[X(t)X'_h(t)] = 0$ ,  $t \in T$ .

Proof Following the guidelines of the proof of Lemma 1.5.3, we get for  $s, t \in T$

$$\begin{aligned} & \lim_{l, l' \rightarrow 0} \mathbb{E} \left[ \frac{X(t+lh) - X(t)}{l} \cdot \frac{X(s+l'h) - X(s)}{l'} \right] \\ &= \lim_{l, l' \rightarrow 0} \frac{1}{l} \left[ \frac{C(t-s+(l-l')h) - C(t-s+lh)}{l'} - \frac{C(t-s-l'h) - C(t-s)}{l'} \right] \quad (1.5.3) \\ &= -C''_{hh}(t-s). \end{aligned}$$

This proves 1) for  $s = t$  and 2), 4) for  $\tau = t - s$ . The property  $C'_h(0) = 0$  follows from the symmetry property  $C(-\tau) = C(\tau)$ ,  $\tau \in T$ .

3) Since  $-C''_{hh}$  is the covariance function of  $X'_h$  due to 4), the continuity of  $C''_{hh}(\tau)$ ,  $\tau \in T$  is guaranteed by the continuity of  $C''_{hh}(0)$  (see Corollary 1.5.1).

5) Similarly as in (1.5.3), it can be shown that

$$\mathbb{E}[X(t)X'_h(t+\tau)] = C'_h(\tau),$$

for  $t, \tau \in T$ . The rest of the proof follows from 2) ( $C'_h(0) = 0$ ).  $\square$

#### Remark 1.5.2

The properties of  $L^2$ -differentiability and a.s. differentiability are disjoint in the following sense: One can construct examples of stochastic processes that are mean-squared differentiable, but have discontinuous realizations, and vice versa, processes with a.s. differentiable realizations might have discontinuous  $C'_h(\tau)$  at  $\tau = 0$  and hence be not mean-squared differentiable.

#### Exercise 1.5.5

Give the corresponding examples!

#### Remark 1.5.3

If  $C''_{hh}(0)$  exists for a stationary stochastic process, then the condition of Theorem 1.5.1 is fulfilled with  $\alpha = 2$  and  $\delta = 1$ . Hence,  $X$  will have an a.s. continuous modification. Under further regularity conditions, it can be shown that  $X'_h(t)$  exists in a.s. sense for almost all  $t \in [a; b]$  and is a.s. integrable on  $[a; b]$ . See also [11], pp. 125, 171.

## 1.6 Proof of the Theorem of Kolmogorov

Let us prove Theorem 1.1.2. Here we give only an idea of the proof following [9], Appendix 1.

Proof According to page 4 let  $(E_t, \mathcal{E}_t)_{t \in T}$  be a family of Borel spaces, and

$$E_{t_1, \dots, t_n} = E_{t_1} \times \dots \times E_{t_n},$$

$$\mathcal{E}_{t_1, \dots, t_n} = \mathcal{E}_{t_1} \otimes \dots \otimes \mathcal{E}_{t_n},$$

for all  $n \in \mathbb{N}$ ,  $t_1, \dots, t_n \in T$ ,  $t_i \neq t_j$ ,  $i \neq j$ . Let  $\{P_{t_1, \dots, t_n}\}$  be a family of measures on  $(E_{t_1, \dots, t_n}, \mathcal{E}_{t_1, \dots, t_n})$  satisfying the properties of symmetry and consistency as on page 4. We show that there exists a unique probability measure  $\mu(\cdot)$  on  $(S, \mathcal{B}_T)$  such that the  $P_{t_1, \dots, t_n}$  are "projections" of  $\mu$  onto  $(E_{t_1, \dots, t_n}, \mathcal{E}_{t_1, \dots, t_n})$ . These "projections" are understood in the following sense: Let  $\mathcal{F}(T)$  be the family of all finite subsets of  $T$ , consisting of index sets  $J \in \mathcal{F}(T)$ ,  $J = \{t_1, \dots, t_n\}$ . For  $(E_{t_1, \dots, t_n}, \mathcal{E}_{t_1, \dots, t_n})$  we use the notation  $(E_J, \mathcal{E}_J)$ . Analogously,  $P_J$  denotes  $P_{t_1, \dots, t_n}$ . This notation is correct due to the symmetry property of the measures  $P_{t_1, \dots, t_n}$ .

Let  $\pi_{T,J} : S \rightarrow E_J$  be the coordinate projection of a function  $\{y(t), t \in T\} \in S$  onto coordinates with indexes in  $J$ , i.e.  $\pi_{T,J} y = (y(t_1), \dots, y(t_n))$  or  $\pi_{T,J} \{y(t), t \in T\} = \{y(t), t \in J\}$ , if  $J = \{t_1, \dots, t_n\}$ . Then, "projection" of  $\mu$  means that

$$\mu \circ \pi_{T,J}^{-1}(B_{t_1} \times \dots \times B_{t_n}) = P_J(B_{t_1} \times \dots \times B_{t_n})$$

for any  $n \in \mathbb{N}$ ,  $J = \{t_1, \dots, t_n\} \in \mathcal{F}(T)$ ,  $B_{t_i} \in \mathcal{E}_{t_i}$ ,  $i = 1, \dots, n$ .

If such a probability measure  $\mu$  on  $(S, \mathcal{B}_T)$  is found, then the random function  $X$  with this distribution  $\mu$  is given by the coordinate projection on the canonical space: We take  $\Omega = S$ ,  $\mathcal{F} = \mathcal{B}_T$ ,  $P = \mu$  and set  $X(t, \omega) = \omega(t)$  for  $\omega \in S$  and  $t \in T$ . Let us transfer measures  $P_J$  from  $(E_J, \mathcal{E}_J)$  onto the space  $(S, \mathcal{B}_{T,J})$  with  $\sigma$ -Algebra  $\mathcal{B}_{T,J} = \pi_{T,J}^{-1} \mathcal{E}_J \subset \mathcal{B}_T$  in the following way: A new measure  $\mu_J$  is defined on  $(S, \mathcal{B}_{T,J})$  by

$$\mu_J(\tilde{B}) = P_J(B),$$

where  $B = B_{t_1} \times \dots \times B_{t_n} \in \mathcal{E}_J$ ,  $J = \{t_1, \dots, t_n\}$  and  $\tilde{B} = B \times \prod_{t \in T \setminus J} E_t \in \mathcal{B}_{T,J}$ . It is evident that  $B \in \mathcal{E}_J$  iff  $\tilde{B}$  defined as above belongs to  $\mathcal{B}_{T,J}$ .

So, our goal is to find a measure  $\mu$  on  $(S, \mathcal{B}_T)$  such that  $\mu = \mu_J$  on any  $\mathcal{B}_{T,J}$ ,  $J \in \mathcal{F}(T)$ . Equivalently, let us define  $\mu$  on the "cylindrical" algebra  $\mathcal{C}_T = \bigcup_{J \in \mathcal{F}(T)} \mathcal{B}_{T,J}$  by letting  $\mu(B) = \mu_J(B)$ , if there exists a  $J \in \mathcal{F}(T)$  such that  $B \in \mathcal{B}_{T,J}$ . This definition yields a finitely additive function on  $\mathcal{C}_T$ . By Caratheodory's Theorem,  $\mu$  can be uniquely extended to a measure on  $\mathcal{B}_T = \sigma(\mathcal{C}_T)$  if  $\mu$  is  $\sigma$ -additive on  $\mathcal{C}_T$ . So, let us show the countable additivity, which is equivalent to showing finite additivity and continuity in  $\emptyset$ , i.e. for any sequence  $\{C_n\} \subset \mathcal{C}_T$ ,  $C_n \searrow \emptyset$  ( $C_{n+1} \subset C_n$ ,  $\bigcap_{n=1}^{\infty} C_n = \emptyset$ ) it must hold  $\mu(C_n) \rightarrow 0$  as  $n \rightarrow \infty$ . Thus, prove that if  $\mu(C_n) \geq \varepsilon_0$  for some  $\varepsilon_0 > 0$  and all large enough  $n$  then

$$C_n \not\rightarrow \emptyset \text{ as } n \rightarrow \infty. \quad (1.6.1)$$

Since  $C_{n+1} \subset C_n$ , this must hold for all  $n \in \mathbb{N}$ . Since  $C_n \in \mathcal{C}_T$  it means that there exists a  $J_n \in \mathcal{F}(T)$  such that  $C_n \in \mathcal{B}_{T,J_n}$ .

Without loss of generalization we now assume that  $J_n \subset J_{n+1}$ . First prove the statement (1.6.1) for spaces  $E_t = [0; 1]$ ,  $\mathcal{E}_t = \mathcal{B}([0; 1])$  equipped with the Euclidean metric  $d(\cdot, \cdot)$ . After that, generalize this proof for arbitrary Borel spaces. Reduce the consideration to sets  $C_n = \pi_{T,J_n}^{-1} B_n$ , where the  $B_n$  are compact in  $S_{J_n}$ ,  $J_n \in \mathcal{F}(T)$ .

First formulate the following results (without proof), which are helpful in the sequel:

#### Lemma 1.6.1

Let  $E_t$ ,  $t \in T$  be separable metric spaces with metrics  $d_t(\cdot, \cdot)$  and Borel  $\sigma$ -algebras  $\mathcal{B}_t$ . Then, the space  $S_J = \{\text{functions } y \text{ on } J : y(t) \in E_t\}$ ,  $J \in \mathcal{F}(T)$  equipped with the metric  $d_J(x, y) = \max_{t \in J} d_t(x(t), y(t))$ ,  $x, y \in S_J$  is a separable metric space with "cylindrical"  $\sigma$ -algebra  $\mathcal{B}_J$  equal to the Borel  $\sigma$ -algebra  $\mathcal{B}(S_J)$ . If  $E_t$ ,  $t \in T$  are complete (Polish), then  $S_J$  is complete (Polish) as well.

Lemma 1.6.2

Let  $E$  be a metric space with measure  $\mu$  on the Borel  $\sigma$ -algebra  $\mathcal{B}(E)$ . Then it holds

$$\mu(B) = \sup_{\substack{A \subset B \\ A \text{ closed}}} \mu(A) = \inf_{\substack{A \supset B \\ A \text{ open}}} \mu(A), \quad B \in \mathcal{B}(E).$$

By Lemma 1.6.1, it holds  $\mathcal{B}_{J_n} = \mathcal{B}(S_{J_n})$ . By Lemma 1.6.2, for any  $B_n \in \mathcal{B}_{J_n}$  there exists a closed set  $K_n \subset B_n$  in  $(S_{J_n}, d_{J_n})$  such that  $\mu_{J_n}(B_n \setminus K_n) < 2^{-(n+1)}\varepsilon_0$ ,  $n \in \mathbb{N}$ . Since  $S_{J_n}$  is compact, so is  $K_n$ . Then, for  $C_n = \pi_{T, J_n}^{-1} B_n$  and  $\widetilde{K}_n = \pi_{T, J_n}^{-1} K_n$ , it holds

$$\mu(C_n \setminus \widetilde{K}_n) = \mu_{J_n}(B_n \setminus K_n) < 2^{-(n+1)}\varepsilon_0, \quad n \in \mathbb{N}.$$

Introduce the sets  $L_n = \bigcap_{i=1}^n \widetilde{K}_i$ . It holds  $L_n \searrow \emptyset$  since  $L_{n+1} \subset L_n$  and  $L_n \subset \widetilde{K}_i \subset C_n$ . Furthermore,

$$\begin{aligned} \mu(C_n \setminus K_n) &= \mu(C_n \cap (\bigcup_{i=1}^n \widetilde{K}_i)) = \mu(\bigcup_{i=1}^n (C_n \setminus \widetilde{K}_i)) \\ &\leq \sum_{i=1}^n \mu(C_i \setminus \widetilde{K}_i) < \sum_{i=1}^n 2^{-(i+1)}\varepsilon_0 < \varepsilon_0/2 \end{aligned}$$

and thus

$$\varepsilon_0 \leq \mu(C_n) = \mu(L_n) + \mu(C_n \setminus L_n) \leq \mu(L_n) + \varepsilon_0/2.$$

Hence, it follows  $\mu(L_n) \geq \varepsilon_0/2$  for all  $n \in \mathbb{N}$ . Since the basis  $D_n = \bigcap_{i=1}^n \pi_{J_n, J_i}^{-1} K_i$  of the cylinder  $L_n = \pi_{T, J_n}^{-1} D_n$  is compact, we can further consider only  $C_n = \pi_{T, J_n}^{-1} B_n$  for compact sets  $B_n$  in  $S_{J_n}$ . Define  $J = \bigcup_{n=1}^{\infty} J_n$ . On  $S_J$ , introduce the metric

$$d_J(x, y) = \sum_{n=1}^{\infty} 2^{-n} \frac{d_{J_n}(x|_{J_n}, y|_{J_n})}{1 + d_{J_n}(x|_{J_n}, y|_{J_n})}.$$

Similarly to the result of Lemma 1.6.1, one can show that the metric space  $(S_J, d_J)$  is a Polish space with "cylindrical"  $\sigma$ -algebra  $\mathcal{B}_J$  being equal to  $\mathcal{B}(S_J)$ , which is the usual Borel  $\sigma$ -algebra.  $S_J$  is compact. Then, the sets  $\widehat{C}_n = \pi_{J, J_n}^{-1} B_n$ ,  $n \in \mathbb{N}$  are compact in  $S_J$  as closed subsets of a compact set (since  $\pi_{J, J_n}$  is continuous). It holds

$$C_n = \pi_{T, J_n}^{-1} B_n = \pi_{T, J}^{-1} \pi_{J, J_n}^{-1} B_n = \pi_{T, J} \widehat{C}_n.$$

Since  $C_n \subset C_m$ ,  $n \geq m$  it follows  $\widehat{C}_n \subset \widehat{C}_m$ ,  $n \geq m$  and  $\bigcap_{n=1}^{\infty} C_n = \pi_{T, J}^{-1} (\bigcap_{n=1}^{\infty} \widehat{C}_n)$ .

A sequence of contracting compacts has at least one point in its intersection, and is hence non-empty, i.e.  $\bigcap_{n=1}^{\infty} \widehat{C}_n \neq \emptyset$  and  $\bigcap_{n=1}^{\infty} C_n \neq \emptyset$ . This is a contradiction to the assumption  $\bigcap_{n=1}^{\infty} C_n = \emptyset$ .

Now let  $E_t \in \mathcal{B}([0; 1])$ ,  $\mathcal{B}_t = S_t \cap \mathcal{B}([0; 1])$  and  $S_t \neq [0; 1]$  for at least one  $t \in T$ . Set  $L_t = [0; 1]$ ,  $t \in T$ ,  $L_J = \prod_{t \in J} L_t$ ,  $J \in \mathcal{F}(T)$ . Introduce the measures

$$\tilde{\mu}_J(B) = \mu_J(B \cap S_J)$$

on  $\mathcal{B}(L_J)$ . These measures satisfy the conditions of symmetry and consistency for any  $J \in \mathcal{F}(T)$ . As above, there exists a measure  $\tilde{\mu}$  on  $(L_T, \mathcal{L}_T)$ ,  $\mathcal{L}_T = \bigotimes_{t \in T} \mathcal{B}([0; 1])$  with projection  $\tilde{\mu}_J$  onto  $(L_J, \mathcal{B}(L_J))$ ,  $J \in \mathcal{F}(T)$  and a random function  $\tilde{X}$  on  $(\Omega, \mathcal{F}, \mathbb{P})$ , where  $\Omega = L_T$ ,  $\mathcal{F} = \mathcal{L}_T$ ,  $\mathbb{P} = \tilde{\mu}$ , with the following distribution:  $\tilde{X}(t, \omega) = \omega(t)$ ,  $\omega \in L_T$ .

Now let  $E_t \neq [0; 1]$  for at least one  $t \in T$ . We define the random function  $X : T \times \Omega \rightarrow E_t$  as

$$X(t, \omega) = \begin{cases} \tilde{X}(t, \omega) & \text{for } \tilde{X}(t, \omega) \in E_t, \\ a_t & \text{for } \tilde{X}(t, \omega) \notin E_t, \end{cases}$$

where  $a_t \in E_t$  is some point of  $E_t \neq \emptyset$ . For all  $t \in T$  it holds that

$$\{\omega : X(t, \omega) \neq \tilde{X}(t, \omega)\} = \{\omega : \omega(t) \in [0; 1] \setminus E_t\} = C_t.$$

$C_t$  is an elementary cylinder and hence

$$\mathbb{P}(C_t) = \tilde{\mu}(C_t) = \mu_{\{t\}}(\{[0; 1] \setminus E_t\} \cap E_t) = 0.$$

Moreover,

$$\begin{aligned} \mathbb{P}_{t_1, \dots, t_n}(B_{t_1} \times \dots \times B_{t_n}) &= \mathbb{P}(X(t_i) \in B_{t_i}, i = 1, \dots, n) \\ &= \mathbb{P}(\tilde{X}(t_i) \in B_{t_i}, i = 1, \dots, n) = \tilde{\mu}_J(B_J) = \mu_J(B_J), \end{aligned}$$

where  $B_J = B_{t_1} \times \dots \times B_{t_n}$ . Hence,  $\mu = \mathbb{P}_X$  is the measure on  $\mathcal{B}_T$  we looked for.

Now, the extension of the above result to the case of arbitrary spaces  $(E_t, \mathcal{E}_t)$ , which are Borel spaces, follows from the next lemma.

Lemma 1.6.3

Let  $(E_t, \mathcal{E}_t)_{t \in T}$  and  $(G_t, \mathcal{A}_t)_{t \in T}$  be families of isomorphic measurable spaces:  $(E_t, \mathcal{E}_t) \sim (G_t, \mathcal{A}_t)$  for all  $t \in T$ . Then, for all  $J \subset T$ , it holds  $(E_J, \mathcal{B}_J) \sim (G_J, \mathcal{A}_J)$ , where  $\mathcal{B}_J$  and  $\mathcal{A}_J$  are cylindrical  $\sigma$ -algebras on  $E_J = \prod_{t \in J} E_t$ ,  $G_J = \prod_{t \in J} G_t$ .

□

## 1.7 Additional exercises

1. Prove the existence of a random field with the following finite dimensional distributions and specify the measurable spaces  $(E_{t_1 \dots t_n}, \mathcal{E}_{t_1 \dots t_n})$ :
  - a) The finite dimensional distributions are multivariate Gaussian.
  - b) The marginals are Poisson and  $X_t, X_s$  are independent for  $t \neq s$ .
2. Give an example for a family of probability measures  $\{\mathbb{P}_{t_1 \dots t_n}\}$  which do not fulfill the conditions in the theorem of Kolmogorov.
3. Give additional examples of a non-continuous random function which has a continuous modification.
4. A random process  $W$  defined on  $\mathcal{B}(\mathbb{R}^d)$  such that, for all sets  $A, B \in \mathcal{B}(\mathbb{R}^d)$  with  $\lambda_d(A)$  and  $\lambda_d(B)$  finite,

- $W(B) \sim \mathcal{N}(0, |B|)$ ,
- $A \cap B = \emptyset \Rightarrow W(A \cup B) = W(A) + W(B)$  almost surely,
- $A \cap B = \emptyset \Rightarrow W(A)$  and  $W(B)$  are independent,

is called Gaussian white noise indexed by Borel sets. Define the field  $X = \{X_t, t \in [0; \infty)^d\}$  by  $X_t = W([0; t])$  where  $[0; t]$  is the paraxial rectangle with lower left corner 0 and upper right corner  $t$ . Show (for  $d = 2$ ) that  $X$  is a Gaussian random field with  $\mathbb{E}X_t = 0$  and  $\text{cov}(X_s, X_t) = \prod_{j=1}^d \min\{s_j, t_j\}$ .

Note: The process  $X$  is called Brownian sheet or multiparameter Brownian motion. For  $d = 1$  it is the Brownian motion.

5. Let  $\eta_1, \eta_2, \dots$  be non-negative iid random variables and  $X_1, X_2, \dots$  non-negative iid random variables, where  $\eta_j$  and  $X_j$  are independent for all  $j$ . Define the process  $N = \{N_t, t \in [0; \infty)\}$  by

$$N_t(\omega) = \sup \left\{ n \in \mathbb{N} : \sum_{j=1}^n \eta_j(\omega) \leq t \right\}.$$

The process  $Y = \{Y_t, t \in [0, \infty)\}$  is given by

$$Y_t(\omega) = y_0 + ct - \sum_{j=1}^{N_t(\omega)} X_j(\omega), \quad t \geq 0$$

with positive constants  $y_0$  and  $c$ . Draw a sketch of a trajectory of  $Y$ .

Note: The process  $Y_t$  is the classical Cramér-Lundberg model in insurance mathematics. It describes the surplus at time  $t$  of an insurance portfolio, where  $y_0$  is the initial capital,  $c$  is the premium intensity and  $\{X_j\}_{j \geq 1}$  is the sequence of claim sizes.  $N_t$  is called the claim number process, whereas  $\{\eta_j\}_{j \geq 1}$  are claim inter-arrival times.

6. Let  $\Phi$  be a homogeneous Poisson point process in  $\mathbb{R}^d$  with intensity  $\lambda > 0$ .
- a) Write down the finite-dimensional distributions of  $\Phi$  for disjoint bounded Borel sets  $B_1, \dots, B_n$ .
  - b) Compute the expectation  $\mathbb{E}\Phi(B)$  and the variance  $\text{var} \Phi(B)$  for bounded Borel sets  $B$  and interpret why  $\lambda$  is called the intensity of  $\Phi$ .
7. Let  $\Phi$  be a homogeneous Poisson process in  $\mathbb{R}^d$  of intensity  $\lambda > 0$ .
- a) Independent thinning: Each point of  $\Phi$  is retained with probability  $p \in (0; 1)$  and deleted with probability  $1 - p$ , independently of other points. Prove that the thinned process  $\tilde{\Phi}$  is a homogeneous Poisson process of intensity  $\lambda p$ .
  - b) Superposition: The superposition of two independent Poisson processes  $\Phi_1$  with intensity  $\lambda_1$  and  $\Phi_2$  with intensity  $\lambda_2$  is the union  $\tilde{\Phi} = \Phi_1 \cup \Phi_2$ . Prove that  $\tilde{\Phi}$  is a homogeneous Poisson process with intensity  $\lambda_1 + \lambda_2$ .

Hint: The void probabilities of a point process are defined by  $v_B = P(\Phi(B) = 0)$  for all Borel sets  $B$ . A simple point process is characterized by the void probabilities  $v_B$  as  $B$  ranges through the Borel sets.

8. Consider the shot-noise field  $X_t = \sum_{v \in \Phi} g(t - v)$  where  $\Phi$  is a homogeneous Poisson process of intensity  $\lambda$  and  $g : \mathbb{R}^d \rightarrow \mathbb{R}$  is a deterministic function fulfilling the integrability conditions on p. 31. Prove that

- a)  $\mathbb{E}X_t = \lambda \int_{\mathbb{R}^d} g(t - z) dz$   
 b)  $\text{cov}(X_t, X_s) = \lambda \int_{\mathbb{R}^d} g(t - z) g(s - z) dz.$

Hint: Campbell's theorem can be useful: Let  $\Phi$  be a homogeneous Poisson process in  $\mathbb{R}^d$  with intensity  $\lambda$  and  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  a non-negative measurable function. Then it holds that

$$\mathbb{E} \sum_{v \in \Phi} f(v) = \lambda \int_{\mathbb{R}^d} f(z) dz.$$

Further, it holds that

$$\mathbb{E} \sum_{\substack{v, w \in \Phi \\ v \neq w}} f(v) g(w) = \lambda^2 \int_{\mathbb{R}^d} f(z) dz \int_{\mathbb{R}^d} g(z) dz$$

9. Consider the Ising model given in Example 1.2.3.

- a) Prove that the Ising model has the Markov property with respect to the 4-neighborhood relation  $\sim_4$ . Does the Ising model possess the Markov property with respect to the 8-neighborhood relation  $\sim_8$ ?
- b) For any  $\Gamma \subset T_N$  the joint distribution of the system of random variables  $\{X_t, t \in \Gamma\}$  is denoted by  $P_{T_N}^\Gamma$ , i.e. for  $\Gamma = \{t_1, \dots, t_n\}$  and  $x_{t_1}, \dots, x_{t_n} = \pm 1$  it holds that  $P_{T_N}^\Gamma(x_{t_1}, \dots, x_{t_n}) = \mathbb{P}(X_{t_1} = x_{t_1}, \dots, X_{t_n} = x_{t_n})$ . For any such  $\Gamma$  the expectation  $\sigma_\Gamma = \mathbb{E} \prod_{t \in \Gamma} X_t$  is called the mixed moment.

Prove that the probabilities  $P_{T_N}^\Gamma$  can be expressed in terms of the mixed moments  $\sigma_\Gamma$  as follows:

$$P_{T_N}^\Gamma(x_{t_1}, \dots, x_{t_n}) = \frac{(-1)^k}{2^n} \sum_{\Gamma' \subset \Gamma} C_{\Gamma'} \sigma_{\Gamma'},$$

where  $k$  is the number of values  $x_{t_i}$  equal to  $-1$  and  $C_{\Gamma'} = \prod_{t \in \Gamma \setminus \Gamma'} x_t$ .

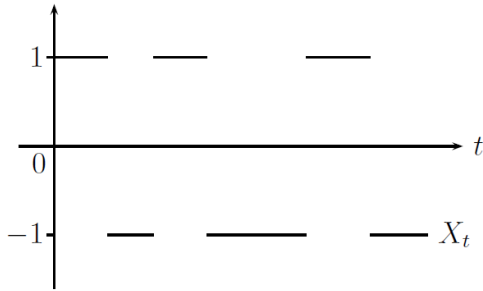
- c) Assume that  $J = 0$ , i.e. there is no interaction between particles. Prove that for any  $\Gamma \subset T_N$  the mixed moment  $\sigma_\Gamma$  is given by

$$\sigma_\Gamma = \left( \frac{\exp\left(\frac{mB}{kt_0}\right) - \exp\left(-\frac{mB}{kt_0}\right)}{\exp\left(\frac{mB}{kt_0}\right) + \exp\left(-\frac{mB}{kt_0}\right)} \right)^{|\Gamma|}.$$

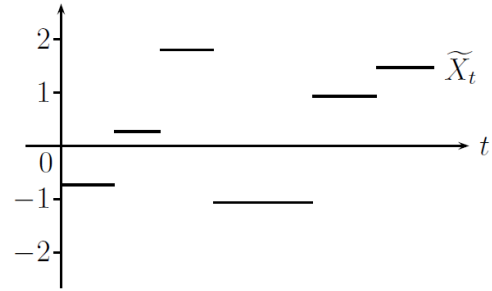
10. The process  $X = \{X_t, t \in [0; \infty)\}$  is defined as follows:  $X_0$  takes values  $+1$  and  $-1$  with probability  $1/2$  each and  $X_t = X_0 \cdot (-1)^{Y([0;t])}$  for  $t > 0$  where  $Y$  is a homogeneous Poisson process on  $[0, \infty)$  with intensity  $\lambda > 0$ , independent of  $X_0$ . See Figure 1.10 (left) for a trajectory of  $X$ .

- a) Compute the expectation function of  $X$  and its covariance function.

- b) Assume that the process  $\tilde{X}$ , if the  $k$ th point of  $Y$  occurs, attains a random value  $V_k$  and retains that value till the next point of  $Y$  occurs, i.e.  $X_0 = V_0$  and  $X_t = V_{Y([0;t])}$  for  $t > 0$  where  $V_0, V_1, \dots$  are iid random variables with  $V_0 \sim \mathcal{N}(0, \sigma^2)$ . Figure 1.10 (right) shows a trajectory of  $\tilde{X}$ . Specify its marginal distribution. Is it a Gaussian process?



(a) Trajectory of the process  $X$  in Exercise 10a.



(b) Trajectory of the process  $\tilde{X}$  in Exercise 10b.

Fig. 1.10: Illustration for Exercise 10a and 10b.

11. One-dimensional random walk:

- a) Let  $Y$  denote a homogeneous Poisson process on  $[0; \infty)$  with intensity  $\lambda$ . Let  $X_1, X_2, \dots$  be i.i.d. random variables, independent of  $Y$  with  $\mathbb{E}X_1 = 0$  and  $\text{var}X_1 = \sigma^2$ . Define the random process  $Z$  on  $[0; \infty)$  by  $Z_t = \sum_{i=1}^{Y_t} X_i$ . Compute the expectation function and the covariance function of  $Z$ .
- b) Consider the process  $\tilde{Z}_t = Y_t - \lambda t$ . Compare the expectation, the covariance and the trajectories of  $Z$  and  $\tilde{Z}$ .

Hint: Wald's identity could be useful: Let  $N$  be a random variable with  $\mathbb{P}(N \in \mathbb{N}) = 1$  and let  $(X_n)_{n \in \mathbb{N}}$  be a sequence of i.i.d. random variables independent of  $N$ . Assume that  $\mathbb{E}N$  and  $\mathbb{E}X_0$  exist. Then  $\mathbb{E} \sum_{n=1}^N X_n$  exists and is given by  $\mathbb{E} \sum_{n=1}^N X_n = \mathbb{E}N \mathbb{E}X_0$ . Further, if  $\text{var}X_1$  and  $\text{var}N$  exist, it holds that  $\text{var} \left( \sum_{n=1}^N X_n \right) = \text{var}X_1 \mathbb{E}N + (\mathbb{E}X_1)^2 \text{var}(N)$ .

12. a) Compute all cumulants of a  $\mathcal{N}(\mu, \sigma^2)$ -distributed random variable.  
 b) Prove that the cumulants  $\langle X^n \rangle$  and the moments  $\mu_n$  of a random variable  $X$  with  $\mathbb{E}|X|^n < \infty$  are related by the following recursive formula:

$$\langle X^n \rangle = \mu_n - \sum_{i=1}^{n-1} \binom{n-1}{i-1} \langle X^i \rangle \mu_{n-i}$$

13. Give an example for a random field which is stationary in the wide sense but not strictly stationary.
14. Consider the Shot-Noise process  $X_t = \sum_{v \in \Phi} g(t-v)$ .



- a) Prove that  $X_t$  is stationary in the wide sense.  
 b) Find conditions on the function  $g$  such that the process  $X_t$  is weakly isotropic.

15. The cosine field  $X$  on  $\mathbb{R}^d$  can be defined by

$$X(t) = \frac{1}{\sqrt{d}} \sum_{k=1}^d (Y_k \cos(a_k t_k) + Z_k \sin(a_k t_k))$$

with i.i.d. centered random variables  $Y_1, \dots, Y_d, Z_1, \dots, Z_d$  and positive constants  $a_1, \dots, a_d$ . Prove that the cosine field  $X$  is weakly stationary.

16. Let  $X = \{X_t, t \in \mathbb{R}^+\}$  be a process with the following properties:

- $X_0 = 0$  almost surely
- $X$  has independent increments
- there is  $\sigma^2 > 0$  such that  $X_t - X_s \sim \mathcal{N}(0, \sigma^2 |t - s|)$ ,  $s, t > 0$ .

This process is called Wiener process. For  $\sigma^2 = 1$  it is called standard Wiener process. Prove that there exists an almost surely continuous version of the Wiener process.

17. Construct a stationary shot-noise process with almost surely discontinuous realizations which is continuous in quadratic mean.
18. Give an example of a random process which is not stochastically continuous.
19. Let  $T = \mathbb{N}_0$  and  $E$  be a countable phase space. The process  $X = \{X_t, t \in T\}$  is called a (discrete-time) Markov chain if it satisfies the Markov property: for any  $n \geq 1$ , any  $t, t_1, \dots, t_n \in T$  with  $t_1 < \dots < t_n < t$ , and any  $i_1, \dots, i_n, j \in E$ ,

$$\mathbb{P}(X_t = j | X_{t_1} = i_1, \dots, X_{t_n} = i_n) = \mathbb{P}(X_t = j | X_{t_n} = i_n).$$

The initial distribution  $\alpha = (\alpha_j, j \in E)$  is given by  $\alpha_j = \mathbb{P}(X_0 = j)$  and the transition probabilities  $p_{ij}(s, t)$  are given by  $p_{ij}(s, t) = \mathbb{P}(X_t = j | X_s = i)$  for  $t \geq s$ , and  $i, j \in E$ . The chain  $X$  is called homogeneous, if  $p_{ij}(s, t)$  depends on  $s$  and  $t$  only through  $t - s$ . Then it is enough to know  $\alpha$  and the 1-step transition matrix  $P = (p_{ij})$  with  $p_{ij} = \mathbb{P}(X_{n+1} = j | X_n = i)$ ,  $n \geq 0$ . The  $n$ -step transition matrix  $P^{(n)}$  is given by  $P^{(n)} = (p_{ij}^{(n)})$  with the  $n$ -step transition probabilities  $p_{ij}^{(n)} = \mathbb{P}(X_n = j | X_0 = i)$ . The Chapman-Kolmogorov equation states that  $P^{(n+m)} = P^{(n)}P^{(m)}$  for any  $n, m \in \mathbb{N}$ .

- a) Prove the Chapman-Kolmogorov equation.  
 b) Give an example for a stochastic process with  $T = \mathbb{N}_0$  and countable phase space  $E$  which satisfies the Chapman-Kolmogorov equation but does not fulfill the Markov property.

## 2 Correlation theory of stationary random fields

In this chapter, properties of the first moments of (mostly stationary) random functions and especially random fields are considered. First, let us dwell on the (characteristic) properties and construction principles of covariance functions of random functions as positive semi-definite functions.

### 2.1 Positive semi-definite functions

Here we give a slightly more general definition of positive semi-definiteness than that of Exercise 1.3.1, which allows for complex-valued functions.

Definition 2.1.1 1. A function  $C : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{C}$  is called positive semi-definite, iff

- $C(x, y) = \overline{C(y, x)}$ ,  $x, y \in \mathbb{R}^d$
  - for any  $n = 2, 3, \dots$  and  $x_1, \dots, x_n \in \mathbb{R}^d, z_1, \dots, z_n \in \mathbb{C}$  it holds  $\sum_{i,j=1}^n C(x_i, x_j) z_i \bar{z}_j \geq 0$ , i.e. this expression is real and non-negative. Here  $\bar{z}_j$  means the complex conjugate of  $z_j \in \mathbb{C}$ .
2. A function  $f : \mathbb{R}^d \rightarrow \mathbb{C}$  is called positive semi-definite if the function  $C : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{C}$  given by  $C(x, y) = f(x - y)$  is positive semi-definite.
3. A function  $f_o : \mathbb{R}_+ \rightarrow \mathbb{C}$  is called positive semi-definite if the function  $C : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{C}$  given by  $C(x, y) = f_o(|x - y|)$ ,  $x, y \in \mathbb{R}^d$  is positive semi-definite.

As it is shown in Exercise 1.3.1, the class of all positive semi-definite functions on  $\mathbb{R}^d$  and the class of covariance functions of (complex-valued) random fields on  $\mathbb{R}^d$  are identical.

The following characterization result was proved for  $d = 1$  in 1932 – 1934 independently by Bochner and Khinchin.

Theorem 2.1.1 (Bochner-Khinchin):

A continuous at the origin  $o \in \mathbb{R}^d$  function  $f : \mathbb{R}^d \rightarrow \mathbb{C}$  is positive semi-definite if and only if it can be represented as a characteristic function of a finite measure  $\mu_f$  on  $(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$  (see Def. 1.1.7):

$$f(x) = \varphi_{\mu_f}(x) = \int_{\mathbb{R}^d} \exp(i \langle x, t \rangle) \mu_f(dt), \quad x \in \mathbb{R}^d. \quad (2.1.1)$$

For simplicity, let us prove this result in the special case ( $d = 1$ ). For the general case, see [5]. First of all, let us mention that a positive semi-definite function is continuous iff it is continuous at the origin.

For the proof of Theorem 2.1.1, we need to introduce the so-called Fourier transform  $F$ : let  $L^p(\mathbb{R})$  be the space of all functions  $h : \mathbb{R} \rightarrow \mathbb{C}$  with  $\int_{\mathbb{R}} |h(x)|^p dx < \infty$ ,  $p \geq 1$ . Define

$$F(h)(s) = \int_{\mathbb{R}} e^{ixs} h(x) dx, \quad h \in L^1(\mathbb{R}), \quad s \in \mathbb{R}.$$

(see, e.g. [32]). If  $g = F(h)$ , then the inverse Fourier transform is defined by

$$F^{-1}(g)(t) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-itx} g(x) dx, \quad t \in \mathbb{R}. \quad (2.1.2)$$

If additionally  $h \in L^2(\mathbb{R})$ , then

$$F^{-1}(F(h))(x) = h(x) \quad (2.1.3)$$

for almost all  $x$  with respect to the Lebesgue measure. Thus,  $F : L^2(\mathbb{R}) \rightarrow L^2(\mathbb{R})$  is a one-to-one mapping satisfying the following Parseval's identity:

$$\langle F(h), F(l) \rangle_{L^2(\mathbb{R})} = 2\pi \langle h, l \rangle_{L^2(\mathbb{R})}, \quad h, l \in L^2(\mathbb{R}), \quad (2.1.4)$$

where  $\langle h, l \rangle_{L^2(\mathbb{R})} = \int_{\mathbb{R}} h(x) \bar{l}(x) dx$  is the scalar product in  $L^2(\mathbb{R})$ . If  $h \in L^1(\mathbb{R})$ , then  $F(h) \in C(\mathbb{R})$  (which follows easily from Lebesgue's Theorem on dominated convergence).

Proof of Theorem 2.1.1. Necessity is trivial, see Exercise 2.6 of §2.6.

Sufficiency: First, we shall assume that a positive semi-definite continuous function  $f : \mathbb{R} \rightarrow \mathbb{C}$  belongs to  $L^1(\mathbb{R})$ . Introduce  $h(x) = F^{-1}(f)(x)$  and prove that  $\mu(dx) = h(x)dx$  is a positive finite measure on  $\mathbb{R}$  from (2.1.1). After that, we shall relax the condition  $f \in L^1(\mathbb{R})$  and prove (2.1.1) for any positive semi-definite continuous  $f$  by using a smoothing argument.

If  $f \in L^1(\mathbb{R})$ , then  $f \in L^2(\mathbb{R})$ , since  $f$  is a covariance function of some centered complex-valued stationary random process  $X : \Omega \times \mathbb{R} \rightarrow \mathbb{C}$ , i.e.  $f(t) = C_X(t) = \mathbb{E} [X(0) \overline{X(t)}]$ , and then  $|f(t)| \leq f(0)$ ,  $t \in \mathbb{R}$ , which follows from  $|C_X(t)| \leq C_X(0) = \text{var}X(0)$ . Hence,  $\int_{\mathbb{R}} |f(x)|^2 dx \leq f(0) \cdot \int_{\mathbb{R}} |f(x)| dx < \infty$  for  $f \in L^1(\mathbb{R})$ .

Take  $h = F^{-1}(f)$  and prove that

a).  $h(x) \geq 0$ ,  $x \in \mathbb{R}$

b). Formula (2.1.3), which reads here  $f(x) = F(h)(x) = \int_{\mathbb{R}} e^{itx} h(t) dt$  holds for all  $x \in \mathbb{R}$ , and not for almost all  $x \in \mathbb{R}$ .

Proof of a). Since  $f$  is a covariance function of the above random process  $X$ , it is easy to see that  $e^{-itx} f(t)$  is a covariance function of  $e^{-itx} X(t)$ , which is again centered and stationary:

$$\begin{aligned} \text{cov} (e^{-itx} X(t), e^{-isx} X(s)) &= \mathbb{E} [e^{-itx} X(t) \overline{e^{-isx} X(s)}] \\ &= e^{-i(t-s)x} f(t-s), \quad s, t \in \mathbb{R}. \end{aligned}$$

Hence, it suffices to show that for any continuous covariance function  $C : \mathbb{R} \rightarrow \mathbb{C}$  (which is positive semi-definite),  $C \in L^1(\mathbb{R})$ , it holds that  $\int_{\mathbb{R}} C(x) dx \geq 0$ ,  $x \in \mathbb{R}$ . If this holds true, then

$$h(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-itx} f(x) dx \geq 0, \quad x \in \mathbb{R}$$

for  $C(x) = e^{-itx}f(x)$ ,  $x \in \mathbb{R}$ . Since  $C$  is continuous and positive semi-definite, it holds

$$\int_{-N}^N \int_{-N}^N C(t-s) dt ds = \lim_{n \rightarrow \infty} \sum_{k=-n}^{n-1} \sum_{l=-n}^{n-1} C(t_k(n) - t_l(n)) \left(\frac{N}{n}\right)^2 \geq 0, \quad N \in \mathbb{N} \quad (2.1.5)$$

as a limit of integral sums on  $[-N; N]^2$ , where  $\frac{N}{n}$  is the side length of the squares  $[k\frac{N}{n}; (k+1)\frac{N}{n}] \times [l\frac{N}{n}; (l+1)\frac{N}{n}]$  building the decomposition of  $[-N; N]^2$  and  $t_j(n) \in [j\frac{N}{n}; (j+1)\frac{N}{n}]$  are arbitrary fixed points.

Transforming the integral on the left-hand side of (2.1.5), we get by substitution

$$\begin{aligned} 0 &\leq \frac{1}{2N} \int_{-N}^N \int_{-N}^N C(t-s) dt ds = \frac{1}{4N} \left( \int_0^{2N} C(u) \int_{-2N+u}^{2N-u} dv du + \int_{-2N}^0 C(u) \int_{-u-2N}^{u+2N} dv du \right) \\ &= \int_{-2N}^{2N} \left(1 - \frac{|u|}{2N}\right) C(u) du = \int_{\mathbb{R}} \left(1 - \frac{|u|}{2N}\right) 1\{u \in [-2N; 2N]\} C(u) du \\ &\xrightarrow{N \rightarrow \infty} \int_{\mathbb{R}} C(u) du \end{aligned}$$

by Lebesgue's Theorem on dominated convergence, since

$$\left(1 - \frac{|u|}{2N}\right) 1\{u \in [-2N; 2N]\} \xrightarrow{N \rightarrow \infty} 1,$$

$$\left| \left(1 - \frac{|u|}{2N}\right) 1\{u \in [-2N; 2N]\} C(u) \right| \leq |C(u)| \in L^1(\mathbb{R}) \text{ for all } N \in \mathbb{N}$$

and the Jacobian  $\frac{\partial(t,s)}{\partial(u,v)} = 1/2$ .

Proof of b). Show that

$$f(x) = \int_{\mathbb{R}} e^{itx} h(t) dt \quad (2.1.6)$$

holds for all  $h \in L^1(\mathbb{R})$ ,  $x \in \mathbb{R}$ . It is known that  $\varphi_Y(s) = e^{-\varepsilon^2 s^2/2}$  for a random variable  $Y \sim \mathcal{N}(0, \varepsilon^2)$ ,  $\varepsilon > 0$ . Since  $\varphi_Y(s) = F(f_Y)(s)$  for the density  $f_Y(x) = \frac{1}{\varepsilon\sqrt{2\pi}} e^{-x^2/2\varepsilon^2}$ ,  $x \in \mathbb{R}$ , use Parseval's identity (2.1.4) for  $f$  and  $f_Y$ :

$$\begin{aligned} f(0) &\xleftarrow{\varepsilon \rightarrow 0} \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi\varepsilon}} e^{-x^2/2\varepsilon^2} f(x) dx = \langle f_Y, f \rangle_{L^2(\mathbb{R})} = 2\pi \langle F^{-1}(f_Y), F^{-1}(f) \rangle_{L^2(\mathbb{R})} \\ &= \int_{\mathbb{R}} e^{-(\varepsilon x)^2/2} h(x) dx \xrightarrow{\varepsilon \rightarrow 0} \int_{\mathbb{R}} h(x) dx, \end{aligned}$$

with  $h = F^{-1}(f)$ , since  $f$  is continuous. By the dominated convergence theorem we get  $\int_{\mathbb{R}} h(x) dx = f(0)$ , i.e.  $h \in L^1(\mathbb{R})$  and formula (2.1.6) holds for  $x = 0$ . Then  $F(h) \in C(\mathbb{R})$ . Since both left- and right-hand sides of (2.1.6) are continuous functions of  $x$  on  $\mathbb{R}$ , formula (2.1.6) holds for any  $x \in \mathbb{R}$ .

Now suppose that  $f \notin L^1(\mathbb{R})$ . Take  $f_\varepsilon(t) = f(t)e^{-(\varepsilon t)^2/2}$ ,  $\varepsilon > 0$ . Then,  $f_\varepsilon$  is continuous positive semi-definite, since  $e^{-(\varepsilon s)^2/2} = F(f_Y)$  for  $Y \sim \mathcal{N}(0, \varepsilon^2)$ , and then the product of  $f$  and  $F(f_Y)$  should inherit the same properties (see Theorem 2.1.5). Moreover,  $f_\varepsilon \in L^1(\mathbb{R})$ . Then,

$f_\varepsilon(t)/f_\varepsilon(0) = f_\varepsilon(t)/f(0) = \varphi_Z(t) = F(h_\varepsilon)$  is a characteristic function of some random vector  $Z$  with density  $h_\varepsilon \geq 0$ , i.e.  $f_\varepsilon(t)/f(0) = \int_{\mathbb{R}} e^{itx} h_\varepsilon(x) dx$ , by the first part of our proof. It holds  $f_\varepsilon(t)/f(0) \rightarrow f(t)/f(0)$ ,  $t \in \mathbb{R}$ , as  $\varepsilon \rightarrow 0$ , where  $\{f_\varepsilon(t)/f(0)\}_{\varepsilon>0}$  is a sequence of characteristic functions and  $f(t)/f(0)$  is continuous at zero. Then, by a very well known fact  $f(t)/f(0)$  is a characteristic function of some probability distribution  $\Psi$ :

$$f(t)/f(0) = \int_{\mathbb{R}} e^{itx} \Psi(dx),$$

hence,  $\mu_f(dx) = f(0) \cdot \Psi(dx)$  is the needed finite measure in (2.1.1).  $\square$

### Definition 2.1.2

The measure  $\mu_f$  from representation (2.1.1) is called a spectral measure of  $f$ . If  $\mu_f$  has a density  $h$  with respect to the Lebesgue measure on  $\mathbb{R}^d$ , i.e.  $\mu_f(dx) = h(x)dx$ , then  $h$  is called spectral density of  $f$ .

### Remark 2.1.1

If  $\mu_f$  is a symmetric measure, i.e.  $\mu(A) = \mu(-A)$ ,  $A \in \mathcal{B}(\mathbb{R}^d)$ , where  $-A = \{-x : x \in A\}$ , then  $f(x)$  is real, since

$$\begin{aligned} f(x) &= \int_{\mathbb{R}^d} e^{i\langle t, x \rangle} \mu_f(dx) = \int_{\mathbb{R}^{d-1} \times \mathbb{R}_+} e^{i\langle t, x \rangle} \mu_f(dx) + \int_{\mathbb{R}^{d-1} \times \mathbb{R}_-} e^{i\langle t, x \rangle} \mu_f(dx) \\ &= \int_{\mathbb{R}^{d-1} \times \mathbb{R}_+} \cos(\langle t, x \rangle) \mu_f(dx) + i \int_{\mathbb{R}^{d-1} \times \mathbb{R}_+} \sin(\langle t, x \rangle) \mu_f(dx) \\ &\quad + \int_{\mathbb{R}^{d-1} \times \mathbb{R}_+} \cos(\langle t, x \rangle) \mu_f(dx) - i \int_{\mathbb{R}^{d-1} \times \mathbb{R}_+} \sin(\langle t, x \rangle) \mu_f(dx) \\ &= 2 \int_{\mathbb{R}^{d-1} \times \mathbb{R}_+} \cos(\langle t, x \rangle) \mu_f(dx) \end{aligned}$$

by substitution  $x \mapsto -x$  in the integral  $\int_{\mathbb{R}^{d-1} \times \mathbb{R}_-}$

The next theorem due to Riesz (1932-1934) will characterize all measurable positive semi-definite functions.

### Theorem 2.1.2 (Sasvári (1994)):

If  $f$  is positive semi-definite and measurable, then  $f = f_c + f_0$ , where  $f_c$  is positive semi-definite and continuous (and hence Bochner's theorem can be applied) and  $f_0$  is positive semi-definite and equals zero almost everywhere on  $\mathbb{R}^d$  with respect to the Lebesgue measure.

Proof See [47].  $\square$

It follows from Theorem 2.1.4 that any function which cannot be turned into a continuous one by changing it in a set of points of Lebesgue measure zero cannot be positive semi-definite. The most popular function  $f_0$  in applications is the so-called nugget effect:

$$f_0(s) = \begin{cases} a & s = 0, \\ 0 & s \neq 0 \end{cases}$$

for  $a > 0$ .

### Exercise 2.1.1

Show that the function  $f_0(x) = a1_{\mathbb{Z}^d}(x)$  is positive semi-definite. Construct the corresponding stationary random field.

### 2.1.1 Isotropic case

In the course of the next sections, we follow [49] and [48]. Consider covariance functions of stationary isotropic random fields in  $\mathbb{R}^d$ : they have the form  $C(x, y) = C_0(|x - y|)$ , where  $|\cdot|$  is the Euclidean norm in  $\mathbb{R}^d$ .

It is worth noting that the function  $C_0 : \mathbb{R}_+ \rightarrow \mathbb{R}$  has the following property:

$|C_0(h)| \leq C_0(0) > 0$ ,  $h \in \mathbb{R}_+$ , which follows directly from the definition of the positive semi-definiteness of  $C_0$ .

Let

$$J_\nu(r) = \sum_{j=0}^{\infty} \frac{(-1)^j}{j! \Gamma(\nu + j + 1)} \left(\frac{r}{2}\right)^{\nu+2j}, \quad r \in \mathbb{R}$$

be the Bessel function of the first kind of order  $\nu \geq -1/2$ .

The following characterization result can be obtained by passing to polar coordinates in Bochner's theorem:

**Theorem 2.1.3** (Schoenberg, 1938):

A continuous rotation-invariant function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  is positive semi-definite iff  $f(x) = f_0(|x|)$ ,  $x \in \mathbb{R}^d$  with  $f_0 : \mathbb{R}_+ \rightarrow \mathbb{R}$  given by:

$$f_0(s) = \int_0^\infty \left(\frac{1}{rs}\right)^\nu J_\nu(rs) \mu(dr), \quad (2.1.7)$$

where  $\mu$  is a finite measure and  $\nu = \frac{(d-2)}{2}$ .

Proof See [50] or [1], p. 116-117. □

It follows from Theorem 2.1.8 that measurable isotropic covariance functions are discontinuous at most in zero.

**Example 2.1.1**

Since  $J_{-1/2}(r) = \sqrt{\frac{2}{\pi r}} \cos(r)$ ,  $J_0(r) = \frac{2}{\pi} \int_0^\infty \sin(r \cosh(t)) dt$ ,  $J_{1/2}(r) = \sqrt{\frac{2}{\pi r}} \sin(r)$ ,  $r \in \mathbb{R}$ , we get e.g. in three dimensions ( $d = 3$ ):

$$C(x, y) = C_0(|x - y|) = \int_0^\infty \frac{\sin(sr)}{sr} \mu(dr) \Big|_{s=|x-y|}$$

from (2.1.7), because

$$\begin{aligned} C_0(s) &= \int_0^\infty \sqrt{\frac{1}{sr}} \sqrt{\frac{2}{\pi sr}} \sin(sr) \mu(dr) \\ &= \frac{\sqrt{2}}{\sqrt{\pi}} \int_0^\infty \frac{\sin(sr)}{sr} \mu(dr), \end{aligned}$$

where the constant factor  $\frac{\sqrt{2}}{\sqrt{\pi}}$  can be included into the measure  $\mu$ .

For isotropic measurable positive semi-definite functions, a stronger version of Riesz theorem is available:

Theorem 2.1.4

If  $f$  is a rotation-invariant, measurable positive semi-definite function  $f : \mathbb{R}^d \rightarrow \mathbb{C}$ ,  $d \geq 2$ , then

$$f(x) = f_c(x) + a \cdot 1\{x = 0\},$$

where  $a \geq 0$  and  $f_c$  is positive semi-definite and continuous.

Proof See [21]. □

### 2.1.2 Construction principles of positive semi-definite functions

Theorem 2.1.5

Let  $C_i : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{C}$ ,  $i = 0, 1, 2, \dots$ ,  $C_\nu : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{C}$ ,  $\nu \in E$  be positive semi-definite functions. A function  $C : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{C}$  is positive semi-definite iff

1. Scaling:  $C(x, y) = C_0(ax, ay)$ ,  $x, y \in \mathbb{R}^d$ ,  $a \in \mathbb{R}$
2. Linear combination:  $C(x, y) = \sum_{i=1}^n a_i C_i(x, y)$ ,  $x, y \in \mathbb{R}^d$
3. Multiplication:  $C(x, y) = C_1(x, y) \cdot C_2(x, y)$ ,  $x, y \in \mathbb{R}^d$
4. Substitution:  $C(x, y) = C_0(g(x), g(y))$ , where  $C_0 : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{C}$  is positive semi-definite and  $g : \mathbb{R}^d \rightarrow \mathbb{R}^d$  is an arbitrary mapping.
5. Kernel approach:  $C(x, y) = \langle g(x), g(y) \rangle_{\mathbb{L}}$ , where  $\mathbb{L}$  is a hilbert space over  $\mathbb{C}$  with scalar product  $\langle \cdot, \cdot \rangle_{\mathbb{L}}$  and  $g : \mathbb{R}^d \rightarrow \mathbb{L}$  is an arbitrary mapping
6. Pointwise limit:  $C(x, y) = \lim_{n \rightarrow \infty} C_n(x, y)$ ,  $x, y \in \mathbb{R}^d$
7. Integration:  $C(x, y) = \int_E C_\nu(x, y) \mu(d\nu)$ , where  $\mu$  is a finite measure over some space  $E$  and  $C_\nu(x, y)$  are positive semi-definite functions. In particular, Series expansions:  $C(x, y) = \sum_{i=0}^{\infty} a_i C_i(x, y)$  for a counting measure  $\mu$
8. Scale mixture:  $C(x, y) = \int_0^{\infty} C_0(sx, sy) \mu(ds)$  for some finite measure  $\mu$  on  $[0; \infty)$  and a positive semi-definite function  $C_0$
9. Convolution:  $C(x, y) = f(x - y)$ ,  $x, y \in \mathbb{R}^d$ , where  $f(h) = \int_{\mathbb{R}^d} f_1(h - s) \bar{f}_2(s) ds$ ,  $h \in \mathbb{R}^d$  and  $f_1, f_2 : \mathbb{R}^d \rightarrow \mathbb{C}$  are positive semi-definite and continuous.

Proof 1. This follows directly from Definition 2.1.1. See also Exercise 2.6.

2., 3. To see this, stationary random fields have to be constructed with covariances  $\sum_{i=1}^n a_i C_i(x, y)$ ,  $C_1(x, y) \cdot C_2(x, y)$ .

4. Use Definition 2.1.1 directly: for any  $n \in \mathbb{N}$ ,  $z_i \in \mathbb{C}$ ,  $i = 1, \dots, n$  and  $x_i \in \mathbb{R}^d$ ,  $i = 1, \dots, n$  one has

$$\sum_{i,j=1}^n C(x_i, x_j) z_i \bar{z}_j = \sum_{i,j=1}^n C_0(g(x_i), g(x_j)) z_i \bar{z}_j \geq 0,$$

since  $C_0$  is positive definite.

5. Use Definition 2.1.1: for any  $n \in \mathbb{N}$ ,  $z_i \in \mathbb{C}$ ,  $x_i \in \mathbb{R}^d$ ,  $i = 1, \dots, n$  one has

$$\begin{aligned} \sum_{i,j=1}^n C(x_i, x_j) z_i \bar{z}_j &= \sum_{i,j=1}^n \langle g(x_i), g(x_j) \rangle_{\mathbb{L}} \\ &= \left\langle \sum_{i=1}^n z_i g(x_i), \sum_{j=1}^n \bar{z}_j g(x_j) \right\rangle_{\mathbb{L}} = \left\| \sum_{i=1}^n z_i g(x_i) \right\|_{\mathbb{L}}^2 \geq 0. \end{aligned}$$

6. This follows directly from Definition 2.1.1.
7. This follows from 6), since  $\int_E C_\nu(x, y)\mu(d\nu)$  is a limit of its integral sums, each of which is a linear combination of positive semi-definite functions  $C_{\nu_i}(x, y)$ ,  $i = 1, \dots, n$ , which is positive semi-definite by 2). The same reasoning works for series expansions.
8. For any  $s \in [0; \infty)$ ,  $C_0(sx, sy)$  is positive semi-definite by 1). Then use 7).
9. See [47]. □

### Examples and Remarks

1. In Theorem 2.1.5, 5) take  $\mathbb{L} = L_\mu^2(\mathbb{R}^d)$ ,  $g : x \in \mathbb{R}^d \mapsto g(x) = e^{i\langle t, x \rangle}$ ,  $t \in \mathbb{R}^d$ , where  $\mu$  is a finite measure on  $\mathbb{R}^d$ . Then

$$\begin{aligned} C(x, y) &= \left\langle e^{i\langle t, x \rangle}, e^{i\langle t, y \rangle} \right\rangle_{\mathbb{L}} = \int_{\mathbb{R}^d} e^{i\langle t, x \rangle} e^{-i\langle t, y \rangle} \mu(dt) \\ &= \int_{\mathbb{R}^d} e^{i\langle t, x-y \rangle} \mu(dt) = \varphi_\mu(x-y), \end{aligned}$$

which is positive semi-definite by Bochner's theorem.

2. By means of property 2) and 3), covariance functions for space-time random fields  $X = \{X(x, t), x \in \mathbb{R}^d, t \in \mathbb{R}\}$  can be constructed by  $C((x, s), (y, t)) = C_x(x, y) + C_t(s, t)$ ,  $x, y \in \mathbb{R}^d$ ,  $s, t \in \mathbb{R}$ , where  $C_x$  is a space covariance and  $C_t$  is a time covariance component. The same holds for  $C((x, s), (y, t)) = C_x(x, y) \cdot C_t(s, t)$ ,  $x, y \in \mathbb{R}^d$ ,  $s, t \in \mathbb{R}$  (the so-called separable space-time models).
3. By means of property 7) functions like  $e^{C(x, y)}$ ,  $\cosh C(x, y)$  etc. of a positive semi-definite function  $C$  are also positive semi-definite as they can be represented as Taylor series with positive coefficients, e.g.  $e^{C(x, y)} = \sum_{n=0}^{\infty} \frac{(C(x, y))^n}{n!}$ ,  $x, y \in \mathbb{R}^d$ .

### 2.1.3 Sufficient conditions for positive semi-definiteness

In Bochner's theorem, necessary and sufficient conditions are not so easy to verify. Here we give a series of sufficient conditions for positive semi-definiteness that are relatively easy to check in many concrete cases.

Theorem 2.1.6 (Pólya-Askey):

If a function  $f : \mathbb{R}_+ \rightarrow \mathbb{R}$  is continuous with  $\lim_{t \rightarrow \infty} f(t) = 0$ ,  $f(0) = 1$ ,  $(-1)^k f^{(k)}(t)$  convex for  $k = [d/2]$  ( $[a]$  is the integral part of  $a$ ), then  $f(\|x\|)$  is positive semi-definite in  $\mathbb{R}^d$ .

Proof See [2]. □

A sharper criterion gives the following result:

Theorem 2.1.7 (Gneiting, 1999):

Let  $f : \mathbb{R}_+ \rightarrow \mathbb{R}$  be continuous with  $f(0) = 1$ ,  $\lim_{t \rightarrow \infty} f(t) = 0$ ,  $(-1)^k \frac{d^k}{dt^k} \left( -f'(\sqrt{t}) \right)$  convex for  $k = \left[ \frac{d-2}{2} \right]$ , then  $f(\|x\|)$  is positive semi-definite in  $\mathbb{R}^d$ ,  $d \geq 2$ .

Proof See [20]. □



## 2.1.4 Examples

In this section some important classes of positive semi-definite functions are introduced. They are all rotation invariant and hence can serve as covariance functions of stationary and isotropic random fields in  $\mathbb{R}^d$ , where  $d$  is indicated in the examples. As the lemma below shows, these models are valid for dimensions  $\leq d$ , but the converse statement is not always true (see example 1.5).

## Lemma 2.1.1

If  $\varphi : \mathbb{R}_+ \rightarrow \mathbb{R}$  is such that  $g_d(t) = \varphi(|t|_d)$ ,  $t \in \mathbb{R}^d$ ,  $d \geq 2$  is positive semi-definite, then  $g_{d-1}(t) = \varphi(|t|_{d-1})$ ,  $t \in \mathbb{R}^{d-1}$  is positive semi-definite as well; here  $|\cdot|_d$  is the Euclidean norm in  $\mathbb{R}^d$ .

Proof Let  $X = \{X(t) : t \in \mathbb{R}^d\}$  be a random field with covariance function  $g_d$ . Then for any hyperplane  $\xi \subset \mathbb{R}^d$  the random field  $X = \{X(t) : t \in \xi\}$  is a random field over  $\xi$  with the same covariance function  $g_d$  restricted on  $\xi$ . Taking  $\xi = \{(x_1, \dots, x_{d-1}, 0) : x_i \in \mathbb{R}, i = 1, \dots, d-1\}$  finishes the proof.  $\square$

The next result of Schoenberg shows when the converse statement holds:

## Theorem 2.1.8 (Schoenberg):

Let  $\varphi : \mathbb{R}_+ \rightarrow \mathbb{R}$  be a continuous function. Then  $\varphi(|\cdot|_d)$  is positive semi-definite for all  $d$  iff  $\varphi(h) = \int_0^\infty e^{-rh^2} \mu(dr)$  for some finite measure  $\mu$  on  $[0, \infty)$ , i.e.,  $\varphi$  is scale mixture of the normal density.

Proof See [50]  $\square$

In the following examples only the function  $\varphi : \mathbb{R}_+ \rightarrow \mathbb{R}$  of  $\varphi(|\cdot|_d)$  is given.

## 1. Bessel family:

$$\varphi(h) = b(ah)^{-\nu} J_\nu(ah), \nu \geq \frac{d-2}{2}, a, b > 0$$

here  $J_\nu$  is the Bessel function of the 1st kind of order  $\nu$ . For  $\nu = \frac{d-2}{2}$ , this function (up to scaling factors, cf. Theorem 2.1.4, 1), 2)) is clearly positive semi-definite as  $\varphi(h) = 2^\nu \Gamma(\nu + 1) h^{-\nu} J_\nu(h)$  is a special case of Theorem 2.1.3, where  $\mu(\cdot) = \delta_{\{1\}}(\cdot)$ . For  $\nu > \frac{d-2}{2}$  this statement is less trivial (cf. [57], p. 367). The spectral density of  $\varphi(h)$  is given by

$$f(h) = \frac{b(a^2 - h^2)^{\nu - \frac{d}{2}}}{2^\nu \pi^{\frac{d}{2}} a^{2\nu} \Gamma(\nu + 1 - \frac{d}{2})} I(h \in [0, a])$$

A special case (for  $\nu = \frac{1}{2}$ , i.e.  $d = 3$ ) yields the so-called hole effect model  $\varphi(h) = b \frac{\sin(ah)}{ah}$ . This model is valid only in  $\mathbb{R}^d$ ,  $d \leq 3$ ; whereas models of Bessel family are valid in  $\mathbb{R}^d$  (iff  $\nu = \frac{d-2}{2}$ ).

## 2. Cauchy family:

$$\varphi(h) = \frac{b}{(1 + (ah)^2)^\nu}, \quad a, b, \nu > 0.$$

Up to scaling, this function is positive semi-definite by Theorem 2.1.7 with  $\mu(dr) = cr^{\nu-1}e^{-r}dr$  for some constant  $c$ .

3. Stable family:

$$\varphi(h) = be^{-(ah)^\nu}, \quad \nu \in (0, 2]$$

This function is positive semi-definite since it is equal to the characteristic function of a symmetric  $\nu$ -stable random variable cf. e. g. [46], p. 20. It is valid in  $\mathbb{R}^d$  for all  $d \geq 1$ . Moreover it can be shown that for  $\nu > 2$   $\varphi$  is not positive semi-definite in any dimension  $d$  (cf. [49], p.19).

A special case ( $\nu = 2$ ) of the stable family is a Gaussian model:  $\varphi(h) = be^{-ah^2}$ . Its spectral density is equal to  $f(h) = \frac{b\sqrt{a}}{2}he^{-\frac{ah^2}{4}}$ .

4. Whittle-Matérn family:

$$\varphi(h) = b(ah)^\nu K_\nu(h), \quad \nu, a, b > 0$$

It is valid in any dimension  $d$ . Here  $K_\nu$  is a modified Bessel function of third kind:

$$K_\nu(z) = \frac{\pi}{2\sin(\pi\nu)}(e^{i\frac{\pi}{2}\nu}J_{-\nu}(ze^{i\frac{\pi}{2}}) - e^{-i\frac{\pi}{2}\nu}J_\nu(ze^{-i\frac{\pi}{2}})), \quad z \in \mathbb{R}, \nu \notin \mathbb{N}.$$

For  $\nu = n \in \mathbb{N}$  it should be understood in the sense of a limit as  $\nu \rightarrow n$  (see [38], p. 69).

The spectral density of  $\varphi$  is given by

$$f(h) = b \frac{2\Gamma(\nu + \frac{d}{2})}{\Gamma(\frac{d}{2})\Gamma(\nu)} \frac{(ah)^{d-1}}{(1 + (ah)^2)^{\nu + \frac{d}{2}}} I(h > 0).$$

If  $\nu = \frac{2d+1}{2}$  then  $\varphi \in C^{2d}(\mathbb{R}_+)$  and hence a random field with covariance function  $\varphi$  is  $d$  times differentiable in mean-square sense.

If  $\nu = \frac{1}{2}$  then the exponential model  $\varphi(h) = be^{-ah}$  is an important special case. The same exponential covariance belongs to the stable family for  $\nu = 1$ .

5. Spherical model is valid in  $\mathbb{R}^d$ ,  $d \leq 3$ .

It is given by  $\varphi(h) = b(1 - \frac{3}{2}\frac{h}{a} + \frac{1}{2}\frac{h^3}{a^3}) I(h \in [0, a])$ ,  $a, b > 0$ , which is the volume of  $B_{\frac{a}{2}}(0) \cap B_{\frac{a}{2}}(x_0)$ , where  $x_0 \in \mathbb{R}^3$ ,  $|x_0| = h$ . This is exactly the way how it can be generalized to higher dimensions:

$$\varphi(x) = V_d(B_{\frac{a}{2}}(0) \cap B_{\frac{a}{2}}(x)), \quad x \in \mathbb{R}^d.$$

The advantage of spherical models is that they have a compact support.

Some more covariance models are given in exercises: see Section 2.3.

## 2.2 Variograms

In this section we consider variograms of (intrinsically) stationary real-valued random fields of order two: they can be written as  $\gamma(h) = \frac{1}{2}E(X(t) - X(t+h))^2$  for any  $t \in \mathbb{R}^d$ .

**Definition 2.2.1**

A function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  is conditionally negative definite, if it holds  $\sum_{i,j=1}^n z_i \bar{z}_j f(x_i - x_j) \leq 0$  for any  $n \in \mathbb{N}$ , points  $\{x_i\}_{i=1}^n \subset \mathbb{R}^d$  and weights  $\{z_i\}_{i=1}^n \subset \mathbb{C}$  such that  $\sum_{i=1}^n z_i = 0$ .

**Proposition 2.2.1 (Properties of variograms):**

Let  $\gamma$  be a variogram an (intrinsically) stationary random field  $X$ . Then

1.  $\gamma(0) = 0$ ,  $\gamma(h) \geq 0$ ,  $h \in \mathbb{R}^d$
2.  $\gamma(h) = \gamma(-h)$ ,  $h \in \mathbb{R}^d$  ( $\gamma$  is an even function)
3. If  $X$  is wide sense stationary then

$$\gamma(h) = C(0) - C(h), \quad h \in \mathbb{R}^d \quad (2.2.1)$$

where  $C(\cdot)$  is the covariance function of  $X$  and thus  $\gamma(h)$  is bounded:  $|\gamma(h)| < 2C(0)$ ,  $h \in \mathbb{R}^d$ .

4.  $\gamma$  is conditionally negative definite.
5. If  $X$  is wide sense stationary and  $C(\infty) = \lim_{|h| \rightarrow \infty} C(h) = 0$ , then there exists  $\gamma(\infty) = \lim_{|h| \rightarrow \infty} \gamma(h) = C(0)$  and  $C(h) = \gamma(\infty) - \gamma(h)$ ,  $h \in \mathbb{R}^d$ .
6. A function  $\gamma : \mathbb{R}^d \rightarrow \mathbb{R}$  with  $\gamma(0) = 0$  is a variogram if  $e^{-\lambda\gamma(\cdot)}$  is a positive semi-definite function for all  $\lambda > 0$ .
7.  $\gamma(h) \leq c|h|^2$ , if  $X$  is mean square continuous,  $\lim_{|h| \rightarrow \infty} \frac{\gamma(h)}{|h|^2} = 0$ , if  $X$  is mean square differentiable.

**Proof** Apart from obvious properties 1), 2), 3) (3) follows from 1.3.3 on page 16), let us show:

4) Take any  $n \in \mathbb{N}$ ,  $\{t_i\}_{i=1}^n \in \mathbb{R}^d$ ,  $\{z_i\}_{i=1}^n \subset \mathbb{C} : \sum_{i=1}^n z_i = 0$ . Let us show that

$$0 \leq \text{Var} \left( \sum_{i=1}^n z_i X(t_i) \right) = - \sum_{i,j=1}^n z_i \bar{z}_j \gamma(t_i - t_j)$$

Then  $\gamma$  will be conditionally negative definite. First  $\text{Var}(\sum_{i=1}^n z_i X(t_i))$  exists since

$$\sum_{i=1}^n z_i X(t_i) = \sum_{i=1}^n z_i (X(t_i) - X(t_0))$$

as  $\sum_{i=1}^n z_i = 0$  for any  $t_0 \in \mathbb{R}^d$  and the variance of increments exists. Then

$$\begin{aligned} \text{Var} \left( \sum_{i=1}^n z_i X(t_i) \right) &= \text{Var} \left( \sum_{i=1}^n (X(t_i) - X(t_0)) \right) \stackrel{1)}{=} \mathbb{E} \left| \sum_{i=1}^n z_i (X(t_i) - X(t_0)) \right|^2 \\ &\stackrel{2)}{=} \sum_{i,j=1}^n z_i \bar{z}_j (\gamma(t_i - t_0) + \gamma(t_j - t_0) - \gamma(t_i - t_j)) = \sum_{i=1}^n z_i \gamma(t_i - t_0) \underbrace{\left( \sum_{j=1}^n z_j \right)}_0 \\ &+ \underbrace{\sum_{i=1}^n z_i \sum_{j=1}^n \bar{z}_j \gamma(t_j - t_0)}_0 - \sum_{i,j=1}^n z_i \bar{z}_j \gamma(t_i - t_j) = - \sum_{i,j=1}^n z_i \bar{z}_j \gamma(t_i - t_j). \end{aligned}$$

1) since  $\mathbb{E}[X(t_i) - X(t_0)] = 0, \quad \forall i$

2) since  $\gamma(t_i - t_j) = \frac{1}{2} \mathbb{E} (X(t_i) - X(t_0) - X(t_j) + X(t_0))^2 = \frac{1}{2} (2\gamma(t_i - t_0) + 2\gamma(t_j - t_0) - 2\text{Cov}(X(t_i) - X(t_0), X(t_j) - X(t_0))) = \gamma(t_i - t_0) + \gamma(t_j - t_0) - \text{Cov}(X(t_i) - X(t_0), X(t_j) - X(t_0))$  and hence  $\text{Cov}(X(t_i) - X(t_0), X(t_j) - X(t_0)) = \gamma(t_i - t_0) + \gamma(t_j - t_0) - \gamma(t_i - t_j)$ .

5) Follows easily from 3). Exercise!

6) This characterization result is due to Schoenberg (1938): See the proof there [50].

7) See the proof in [57], p. 397-400.

Let us show here only the relation  $\gamma(h) \leq C \cdot |h|^2$ .

If  $X$  is mean square continuous, then  $\gamma(h)$  is a continuous function on  $\mathbb{R}^d$ . By Minkowski inequality, it holds

$$\sqrt{\gamma(h_1 + h_2)} \leq \sqrt{\gamma(h_1) + \gamma(h_2)}, \quad h_1, h_2 \in \mathbb{R}^d,$$

since

$$\begin{aligned} &\sqrt{2\gamma(h_1 + h_2)} \\ &= \sqrt{\mathbb{E} [X(t + h_1 + h_2) - X(t + h_1) + X(t + h_1) - X(t)]^2} \\ &\leq \sqrt{\mathbb{E} [X(t + h_1 + h_2) - X(t + h_1)]^2} \\ &+ \sqrt{\mathbb{E} [X(t + h_1) - X(t)]^2} = \sqrt{2\gamma(h_1)} + \sqrt{2\gamma(h_2)}. \end{aligned}$$

Then we can easily show by induction that  $\gamma(nh) \leq n^2\gamma(h)$  for any  $n \in \mathbb{N}$  and  $h \in \mathbb{R}^d$ , or, in other words,

$$\frac{\gamma(h)}{|h|^2} \leq \frac{\gamma(\frac{h}{n})}{|\frac{h}{n}|^2} \quad (2.2.2)$$

(replacing  $h$  by  $\frac{h}{n}$ ).

Fix any  $0 \neq h_0 \in \mathbb{R}^d$ . Let  $c = \max_{h: |h_0| \leq |h| \leq 2|h_0|} \left( \frac{\gamma(h)}{|h|^2} \right)$ , which is finite, since  $\frac{\gamma(h)}{|h|^2}$  is continuous. For any  $h \in \mathbb{R}^d : |h| > |h_0|$  there exists such  $n \in \mathbb{N} : n|h_0| \leq |h| \leq 2n|h_0|$ , or  $|h_0| \leq \frac{|h|}{n} \leq 2|h_0|$ . Hence,  $\frac{\gamma(h)}{|h|^2} \leq c$ . From 2.2.2, i.e.,  $\gamma(h) \leq c|h|^2$  for  $h : |h| > |h_0|$ .  $\square$

## Remark 2.2.1

It is known that Laplace-Stiltjes transforms of finite measures  $\varphi(h) = \int_0^\infty e^{-hr} \mu(dr)$ ,  $h \in \mathbb{R}_+$  are completely monotone, i.e.,  $(-1)^n \varphi^{(n)}(h) \geq 0$  for all  $h > 0$  and  $n \in \mathbb{N}_0 = \{0, 1, 2, 3, \dots\}$  (see e.g. [55]). Hence, under assumptions of Theorem 2.1.8,  $\varphi(h)$  is a Laplace-Stiltjes transform of a measure  $\mu$  evaluated at  $h^2$ , which means that  $\varphi(\sqrt{h})$  should be completely monotone.

This implies, in particular, that  $\varphi(h) \geq 0$ ,  $h \in \mathbb{R}_+$ . It follows from this property that for any function  $\varphi$  which is not non-negative  $\varphi(\|x\|)$  can not be positive semi-definite for all dimensions  $d \in \mathbb{N}$ .

Remark 2.2.2 1. It follows from Proposition 2.2.1, 3), 5) that if the variogram  $\gamma$  of an intrinsically stationary random field  $X$  is unbounded,  $\gamma(h) \rightarrow \infty$  as  $|h| \rightarrow \infty$ , then  $X$  can not be wide sense stationary.

See the corresponding examples which follow.

2. Since  $X$  is real-valued, Bochner's theorem together with formula (2.2.1) yields

$$\begin{aligned} \gamma(h) &= C(0) - C(h) = \int_{\mathbb{R}^d} (1 - e^{i\langle h, x \rangle}) \mu(dx) = \operatorname{Re} \left( \int_{\mathbb{R}^d} (1 - e^{i\langle h, x \rangle}) \mu(dx) \right) \\ &= \int_{\mathbb{R}^d} (1 - \cos \langle h, x \rangle) \mu(dx), \quad h \in \mathbb{R}^d \end{aligned}$$

Example 2.2.1 1. Consider the case  $d \equiv 1$ ,  $X(t) = X_0 + tX_1$ , where  $t \in \mathbb{R}$ ,  $X_0$  and  $X_1$  are random variables,  $\operatorname{E}X_1 = 0$ ,  $\operatorname{E}X_1^2 = \sigma_1^2 \in (0, \infty)$ . The process  $X = \{X(t), t \in \mathbb{R}\}$  is intrinsic stationary of order two since  $X(t) - X(s) = (t - s)X_1$ ,  $s, t \in \mathbb{R}$  and hence  $\operatorname{E}(X(t) - X(s)) = 0$ ,  $\operatorname{E}(X(t) - X(s))^2 = (t - s)^2 \sigma_1^2$ ,  $t, s \in \mathbb{R}$ .

Then  $\gamma(h) = \frac{1}{2} \operatorname{E}(X(t+h) - X(t))^2 = \frac{\sigma_1^2}{2} h^2 \rightarrow \infty$ , as  $h \rightarrow \infty$ .  $X$  is obviously not wide sense stationary, since  $X_0$  may not be integrable. But even for  $X_0$  such that  $\operatorname{E}X_0 = 0$ ,  $\operatorname{E}X_0^2 = \sigma_0^2 \in (0, \infty)$  and  $X_0, X_1$  are independent, it holds  $\operatorname{Cov}(X(s), X(t)) = \operatorname{E}[X(s)X(t)] = \operatorname{E}[(X_0 + sX_1)(X_0 + tX_1)] = \operatorname{E}X_0^2 + (s+t)\operatorname{E}[X_0X_1] + st\operatorname{E}X_1^2 = \sigma_0^2 + st\sigma_1^2$ , which contradicts the stationarity in wide sense.

2. Let  $X = \{X(t), t \in \mathbb{R}^d\}$  with  $X(t) = \langle \varphi, t \rangle$ ,  $t \in \mathbb{R}^d$ , where  $\varphi \sim N(0, I_d)$  is a multivariate standard distributed random vector. Then  $X$  is intrinsic stationary of order two, but not wide sense stationary, since  $X(t) \sim N(0, |t|^2)$ ,  $X(t) - X(s) = X(t - s)$ ,  $t, s \in \mathbb{R}^d$  and hence

$$\begin{aligned} c(s, t) &= \operatorname{Cov}(X(s), X(t)) = \operatorname{E} \left[ \sum_{i,j=1}^d \varphi_i \varphi_j s_i t_j \right] = \sum_{i,j=1}^d \operatorname{E}[\varphi_i \varphi_j] s_i t_j \\ &= \sum_{i,j=1}^d s_i t_j \delta_{ij} = \langle s, t \rangle, \quad s, t \in \mathbb{R}^d \end{aligned}$$

with  $\varphi_i$ -iid  $\sim N(0, 1)$ ;  $\gamma(h) = \frac{1}{2} \operatorname{E}[X(t+h) - X(t)]^2 = \frac{1}{2} \operatorname{E}[X(h)]^2 = \frac{|h|^2}{2}$ ,  $h \in \mathbb{R}^d$ . Here we have  $\gamma(h) \rightarrow \infty$  as  $|h| \rightarrow \infty$  as well.

This example can be extended to the case of a field  $X = \{X(t), t \in \mathbb{E}\}$  over a Hilbert space  $\mathbb{E}$  with a scalar product  $\langle \cdot, \cdot \rangle$  and orthonormal basis

$$\{e_i\}_{i=1}^\infty : X(t) = \langle \sum_{i=1}^\infty N_i e_i, t \rangle = \sum_{i=1}^\infty N_i t_i,$$

$t \in \mathbf{E}$  where  $\{N_i\}_{i=1}^\infty$  is an iid sequence of  $N(0, 1)$ -random variables, and  $\sum_{i=1}^\infty N_i t_i$  converges in the mean square sense  $\mathbb{E}|\sum_{i=n}^m N_i t_i|^2 = \sum_{i=n}^m t_i^2 \rightarrow 0$  as  $n, m \rightarrow \infty$  and since  $\sum_{i=1}^\infty t_i^2 < \infty$  as  $t \in \mathbf{E}$ .

### 3. Fractional Brownian Lévy field

Let  $X = \{X(t), t \in \mathbb{R}^d\}$  be a centered Gaussian Random field with covariance function

$$C(s, t) = \frac{1}{2}(|s|^{2H} + |t|^{2H} - |s - t|^{2H}), \quad s, t \in \mathbb{R}^d, \quad H \in (0, 1].$$

It is called a fractional Brownian (Lévy) field with Hurst index  $H$ . For  $H = \frac{1}{2}$ , we get the usual Brownian field. It is easy to see that  $X$  is intrinsic stationary of order two, since in this case  $\gamma(h) = \frac{1}{2}|h|^{2H}$ ,  $h \in \mathbb{R}^d$ . The dependence of increments of  $X$  Hurst index  $H$  is also a parameter contracting the roughness of the functions  $X$ : the smaller  $H$ , the more rough cover its realisations. In particular, for  $d = 1$  and  $H = 1$   $X$  is a random line:

$$X(t) = X_1 t, \quad X_1 \sim N(0, 1),$$

(cf. Examples 1), 2)).

## 2.3 Stochastic integration

In this section we introduce stochastic integrands of non-random functions with respect to an independently scattered random measure on an abstract space  $\mathbf{E}$ . We shall need these integrands to prove spectral representations of (wide sense) stationary random fields in 2.4 (Theorems of Karhunen and Cramér).

### 2.3.1 Independently scattered random measures

Let us introduce the notion of a random measure on a semiring  $K(\mathbf{E})$  of subsets of a space  $\mathbf{E}$ .

**Definition 2.3.1**

A family  $K(\mathbf{E})$  of subsets of a space  $\mathbf{E}$  is called a semiring if for all  $A, B \in K(\mathbf{E})$

- a)  $\emptyset \in K(\mathbf{E})$
- b)  $A \cap B \in K(\mathbf{E})$
- c) If additionally  $A \subset B$ , then  $B \setminus A = \cup_{i=1}^n B_i$ , where  $n \in \mathbb{N}$  and  $B_j \in K(\mathbf{E})$ ,  $j = 1 \dots n$  pairwise disjoint.

Let  $(\Omega, \mathcal{F}, \mathcal{P})$  be a probability space.

**Definition 2.3.2** 1. Let  $\nu$  be a  $\sigma$ -finite measure on  $K(\mathbf{E})$ .  $W = \{W(A) : A \in K(\mathbf{E})\}$  is called an (independently scattered signed) random measure if

- a)  $W(A)$ ,  $A \in K(\mathbf{E})$  is a (complex-valued) random variable on  $(\Omega, \mathcal{F}, \mathcal{P})$ , which is square integrable:  $\mathbb{E}|W(A)|^2 < \infty$ . Later on we write  $W(A) \in L^2(\Omega, \mathcal{F}, \mathcal{P})$ .
- b)  $\mathbb{E} \left[ W(A) \overline{W(B)} \right] = \nu(A \cap B)$ ,  $A, B \in K(\mathbf{E})$ .

2.  $\nu$  is called the structure measure (deriving, control measure) of  $W$ . It is given by  $\nu(A) = \mathbb{E}|W(A)|^2$ ,  $A \in K(\mathbb{E})$ .

3. If  $\mathbb{E}W(A) = 0$ ,  $A \in K(\mathbb{E})$ , then  $W$  is called centered.

Later on we consider only centered random measures for simplicity.

Proposition 2.3.1 (Properties of random measures):

A family of complex-valued random variables  $W = \{W(A), A \in K(\mathbb{E})\}$  is a random measure iff

- a)  $W(A) \in L^2(\Omega, \mathcal{F}, \mathcal{P})$ ,  $A \in K(\mathbb{E})$
- b)  $\mathbb{E}(W(A)\overline{W(B)}) = 0$ ,  $A, B \in K(\mathbb{E})$ ,  $A \cap B = \emptyset$   
(property of orthogonality (uncorrelatedness) of increments, independent scattering property).
- c)  $W(A) \stackrel{a.s.}{=} \sum_{i=1}^{\infty} W(A_i)$ , for  $A, \{A_i\} \subset K(\mathbb{E})$ ,  $A = \cup_{i=1}^{\infty} A_i$ ,  $A_i \cap A_j = \emptyset$ ,  $i \neq j$ . The series

$$\sum_{i=1}^{\infty} W(A_i)$$

converges in  $L^2(\Omega, \mathcal{F}, \mathcal{P})$ -sense (mean square convergence, property of  $\sigma$ -additivity).

Proof: Necessity: Property b) of Proposition 2.3.1 is a special case of property b), Definition 2.3.2 for disjoint sets  $A, B$ . Let us show that c) holds. First let us show finite additivity of  $W$ :  $W(A \cup B) \stackrel{a.s.}{=} W(A) + W(B)$ ,  $A, B \in K(\mathbb{E})$ ,  $A \cap B = \emptyset$ . For this, it suffices to prove  $\mathbb{E}|W(A \cup B) - W(A) - W(B)|^2 = 0$ .

We have

$$\begin{aligned} & \mathbb{E}|W(A \cup B) - W(A) - W(B)|^2 \\ &= \mathbb{E} \left[ (W(A \cup B) - W(A) - W(B))(\overline{W(A \cup B)} - \overline{W(A)} - \overline{W(B)}) \right] = \underbrace{\mathbb{E}|W(A \cup B)|^2}_{\nu(A \cup B)} + \underbrace{\mathbb{E}|W(A)|^2}_{\nu(A)} + \underbrace{\mathbb{E}|W(B)|^2}_{\nu(B)} \\ & - \underbrace{\mathbb{E}[W(A \cup B)\overline{W(A)}]}_{\nu(A)} - \underbrace{\mathbb{E}[W(A \cup B)\overline{W(B)}]}_{\nu(B)} - \underbrace{\mathbb{E}(W(A)\overline{W(A \cup B)})}_{\nu(A)} - \underbrace{\mathbb{E}(W(A)\overline{W(B)})}_{\nu(\emptyset)=0} \\ & - \underbrace{\mathbb{E}(W(B)\overline{W(A \cup B)})}_{\nu(B)} - \underbrace{\mathbb{E}(W(B)\overline{W(A)})}_{\nu(\emptyset)=0} = \nu(A \cup B) - \nu(A) - \nu(B) = 0 \\ & \Rightarrow W(A \cup B) \stackrel{a.s.}{=} W(A) + W(B). \end{aligned}$$

By induction we can show the finite additivity:

$$\mathbb{E}|W(A) - \sum_{i=1}^n W(A_i)|^2 \stackrel{2.3.1}{=} \nu(A) - \sum_{i=1}^n \nu(A_i)$$

for  $A_1, \dots, A_n \in K(\mathbb{E})$ ,  $A_i \cap A_j = \emptyset$ ,  $i \neq j$ . Hence for  $A = \bigcup_{i=1}^n A_i$ , it holds  $W(A) \stackrel{a.s.}{=} \sum_{i=1}^n W(A_i)$ . Now if

$$A = \bigcup_{i=1}^{\infty} A_i, \quad A_i \cap A_j = \emptyset, \quad i \neq j,$$

then the convergence of

$$\sum_{i=1}^{\infty} W(A_i) = W(A)$$

in the  $L^2(\Omega, \mathcal{F}, \mathcal{P})$ -sense follows from (2.3.1) as

$$\nu(A) = \sum_{i=1}^{\infty} \nu(A_i).$$

Sufficiency: Take any  $A, B \in K(\mathbb{E})$  and prove b) of Definition 2.3.2. First we notice that  $A = \underbrace{(A \setminus B)}_{c_1} \cup \underbrace{(A \cap B)}_{c_2}$ ,  $B = \underbrace{(B \setminus A)}_{c_3} \cup (A \cap B)$ , when

$$c_2 \in K(\mathbb{E}), \quad c_1 = \cup_{i=1}^m c_{1i}, \quad c_3 = \cup_{j=1}^n c_{3j}, \quad c_{1i}, c_{3j} \in K(\mathbb{E}),$$

and are disjoint. Then

$$\begin{aligned} \mathbb{E}(W(A)\overline{W(B)}) &= \mathbb{E}(W(c_1 \cup c_2)\overline{W(c_3 \cup c_2)}) = \mathbb{E} \left[ (W(c_2) + \sum_{i=1}^m W(c_{1i}))(\overline{W(c_2)} + \sum_{j=1}^n \overline{W(c_{3j})}) \right] \\ &\stackrel{c) \text{ of Prop. 2.3.1}}{=} \mathbb{E}|W(c_2)|^2 \stackrel{c) \text{ of Def. 2.3.2,2)}}{=} \nu(c_2) = \nu(A \cap B), \end{aligned}$$

since all  $c_{1i}, c_{3j}$  are disjoint. □

Let us give examples for random measures.

Example 2.3.1

Here we set  $W(A) \sim N(0, \nu(A))$ ,  $A \in K(\mathbb{E})$  (cf. Example 1.2.1 for a special case).

In Definition 2.3.2, we postulated the existence of  $W$  with stated properties. Now we have to prove its existence by giving an explicit construction of a random measure  $W$  on some probability space  $(\Omega, \mathcal{F}, \mathcal{P})$  with properties a), b) of Definition 2.3.2.

Theorem 2.3.1

Let  $\nu$  be a  $\sigma$ -finite measure on  $K(\mathbb{E})$ . Then there exists a probability space  $(\Omega, \mathcal{F}, \mathcal{P})$  and a centered (independently scattered) random measure  $\{W = W(A), A \in K(\mathbb{E})\}$  defined on  $(\Omega, \mathcal{F}, \mathcal{P})$  and  $\{A \in \sigma(K(\mathbb{E})) : \nu(A) < \infty\}$  such that  $\nu$  is the control measure of  $W$ .

Proof Let  $\mathcal{A} = \sigma(K(\mathbb{E}))$ . By Carathéodory's theorem, we can extend the measure  $\nu$  to a  $\sigma$ -finite measure on  $\mathcal{A}$ . Let us construct the required probability space  $(\Omega, \mathcal{F}, \mathcal{P})$  by setting  $\Omega = \mathbb{E}$ ,  $\mathcal{F} = \mathcal{A}$ . For the construction of  $P$ , we have to distinguish two non-trivial cases:

1.  $\nu(\mathbb{E}) \in (0, \infty)$ : set  $P(B) = \frac{\nu(B)}{\nu(\mathbb{E})}$ ,  $B \in \mathcal{F}$ . And let

$$W(A, \omega) = \sqrt{\nu(\mathbb{E})} I_A(\omega), \quad \omega \in \Omega, \quad A \in \mathcal{A}.$$

We have

$$\begin{aligned} W(A, \cdot) &\in L^2(\Omega, \mathcal{F}, \mathcal{P}), \quad \mathbb{E}(W(A)\overline{W(B)}) \\ &= (\sqrt{\nu(\mathbb{E})})^2 \int_{\Omega} I_A(\omega) I_B(\omega) P(d\omega) = \nu(\mathbb{E}) P(A \cap B) = \nu(A \cap B), \quad A, B \in \mathcal{A}. \end{aligned}$$

Hence  $W$  is a (non-centered) random measure.



2.  $\nu(\mathbf{E}) = \infty$  (the case  $\nu(\mathbf{E}) = 0$  is trivial). Since  $\nu$  is  $\sigma$ -additive, there exists a tiling

$$\mathbf{E} = \bigcup_{i=1}^{\infty} \mathbf{E}_i, \quad \mathbf{E}_i \cap \mathbf{E}_j = \emptyset, \quad i \neq j,$$

with  $\nu(\mathbf{E}_j) < \infty$ . Let

$$P(A) = \sum_{n=1}^{\infty} \frac{\nu(A \cap \mathbf{E}_n)}{\nu(\mathbf{E}_n)2^n}, \quad A \in \mathcal{F}.$$

It is clear that  $P(\cdot)$  is a probability measure on  $\mathcal{F}$ , since

$$P(\mathbf{E}) = \sum_{n=1}^{\infty} \frac{1}{2^n} = 1.$$

For any  $B \in \{A \in \mathcal{A} : \nu(A) < \infty\}$  define

$$W(B, \omega) = \sum_{n=1}^{\infty} \sqrt{2^n \nu(\mathbf{E}_n)} I_{B_n}(\omega),$$

where  $B_n = B \cap \mathbf{E}_n$ ,  $n \in \mathbb{N}$ . This series converges in  $L^2(\Omega, \mathcal{F}, \mathcal{P})$ : since  $\{B_n\}$  are disjunct, it holds

$$\mathbb{E} \left| \sum_{n=m}^{\infty} \sqrt{2^n \nu(\mathbf{E}_n)} I_{B_n}(\omega) \right|^2 = \sum_{n=m}^{\infty} 2^n \nu(\mathbf{E}_n).$$

$$\mathbb{E} I_{B_n}^2(\omega) = \sum_{n=m}^{\infty} 2^n \nu(\mathbf{E}_n) P(B_n) = \sum_{n=m}^{\infty} 2^n \nu(\mathbf{E}_n) \frac{\nu(B_n)}{\nu(\mathbf{E}_n)2^n} = \sum_{n=m}^{\infty} \nu(B_n) \xrightarrow{m \rightarrow 0} 0,$$

because  $\nu(B) = \sum_{n=1}^{\infty} \nu(B_n) < \infty$ . Since the scalar product  $\langle \cdot, \cdot \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})}$  is continuous in their arguments, it holds

$$\begin{aligned} \langle W(A), W(B) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} &= \mathbb{E} \left[ W(A), \overline{W(B)} \right] \\ &= \sum_{n=1}^{\infty} 2^n \nu(\mathbf{E}_n) \mathbb{E}(I_{A_n} I_{B_n}) = \sum_{n=1}^{\infty} 2^n \nu(\mathbf{E}_n) P(A_n \cap B_n) \\ &= \sum_{n=1}^{\infty} \nu(A_n \cap B_n) = \nu(A \cap B), \end{aligned}$$

where  $A_n = A \cap \mathbf{E}_n$ ,  $B_n = B \cap \mathbf{E}_n$ ,  $n \in \mathbb{N}$ . Hence  $W$  is a non-centered random measure. In order to get a centered random measure  $W$ , it does not suffice to subtract  $\mathbb{E}W(A)$  from  $W(A)$ , since this will destroy the property b) of Definition 2.3.2. The right way is to enlarge the probability space  $(\Omega, \mathcal{F}, \mathcal{P})$  in the following way:

Let  $Z$  be a random variable on a new probability space  $(\Omega', \mathcal{F}', \mathcal{P}')$  such that  $\mathbb{E}_{P'} Z = 0$ ,  $\text{var}_{P'} Z = 1$ , where  $\mathbb{E}_{P'}$  and  $\text{var}_{P'}$  are calculated w.r.t. measure  $P'$ . Let  $W$  be the random

measure constructed above on  $(\Omega, \mathcal{F}, \mathcal{P})$ . Take  $(\tilde{\Omega}, \tilde{\mathcal{F}}, \tilde{\mathcal{P}}) = (\Omega, \mathcal{F}, \mathcal{P}) \otimes (\Omega', \mathcal{F}', \mathcal{P}')$  and define  $\tilde{W}$  on it by  $\tilde{W}(A, \tilde{\omega}) = W(A, \omega)Z(\omega')$  for  $A \in \{\mathcal{A} : \nu(A) < \infty\}$ ,  $\tilde{\omega} = (\omega, \omega') \in \Omega \times \Omega'$ . It can be easily seen that  $\tilde{\omega}$  is a centered independently scattered random measure on  $(\tilde{\Omega}, \tilde{\mathcal{F}}, \tilde{\mathcal{P}})$ . □

### 2.3.2 Stochastic integral

Let us introduce a stochastic integral

$$\int_{\mathbf{E}} f(t)W(dt),$$

where  $W$  is a centered independently scattered random measure on  $K(\mathbf{E})$  with control measure  $\nu$  and  $f : \mathbf{E} \rightarrow \mathbb{C}$  is a deterministic function. For this,  $W$  should be continued to the algebra generated by  $K(\mathbf{E})$  and then to  $\mathcal{A} = \sigma(K(\mathbf{E}))$ .

Let  $\nu$  be finite, i.e.  $\nu(\mathbf{E}) < \infty$ . Consider the algebra  $\tilde{\mathcal{A}} = \{\bigcup_{i=1}^m B_i \text{ for some } m \in \mathbb{N}, B_i \in K(\mathbf{E}), i = 1, \dots, m\}$ .

$W$  can be continued to  $\tilde{\mathcal{A}}$  from  $K(\mathbf{E})$  by posting  $W(A) \stackrel{a.s.}{=} \sum_{i=1}^m W(A_i)$ , if  $A = \bigcup_{i=1}^m A_i \in \tilde{\mathcal{A}}$ ,  $A_i \in K(\mathbf{E})$ ,  $A_i \cap A_j = \emptyset$ ,  $i \neq j$ . This definition is correct, since for any other representation of  $A$  by  $A = \bigcup_{j=1}^n B_j$ ,  $B_i \cap B_j = \emptyset$ ,  $i \neq j$ ,  $B_j \in K(\mathbf{E})$ , it holds

$$\sum_{i=1}^m W(A_i) = \sum_{i=1}^m \sum_{j=1}^n W(A_i \cap B_j) = \sum_{j=1}^n \sum_{i=1}^m W(B_j \cap A_i) = \sum_{j=1}^n W(B_j), \quad \text{a.s.}$$

#### Definition 2.3.3

A function  $f : \mathbf{E} \rightarrow \mathbb{C}$  is simple if

$$f(x) = \sum_{i=1}^n a_i I_{A_i}(x) \tag{2.3.1}$$

for any  $n \in \mathbb{N}$ ,  $a_i \in \mathbb{C}$ ,  $A_i \cap A_j = \emptyset$ ,  $i \neq j$ ,  $\bigcup_{i=1}^n A_i = \mathbf{E}$ ,  $i = 1, \dots, n$ .

#### Definition 2.3.4

The integral of a simple function  $f$  from 2.3.1 w.r.t. the (orthogonal) measure  $W$  is given by

$$I(f) = \sum_{i=1}^n a_i W(A_i) = \int_{\mathbf{E}} f(x)W(dx)$$

#### Lemma 2.3.1

The above definition of  $I(f)$  is correct, i.e. does not depend on the representation 2.3.1 of  $f$ .

**Proof** Let

$$\begin{aligned} f(x) &= \sum_{i=1}^n a_i I_{A_i}(x) = \sum_{j=1}^m b_j I_{B_j}(x) \quad a_i, b_j \in \mathbb{C}, \\ A_i \cap A_k &= \emptyset, \quad i \neq k, \quad B_j \cap B_l = \emptyset, \quad j \neq l, \\ \bigcup_{i=1}^n A_i &= \mathbf{E}, \quad \bigcup_{j=1}^m B_j = \mathbf{E}, \quad \text{if } A_i \cap B_j \neq \emptyset. \end{aligned}$$

Then it follows that  $a_i = b_j$ . Hence,

$$\begin{aligned} \sum_{i=1}^n a_i W(A_i) &= \sum_{i=1}^n a_i \sum_{j=1}^m W(A_i \cap B_j) = \sum_{j=1}^m \sum_{i: A_i \cap B_j \neq \emptyset} a_i W(A_i \cap B_j) \\ &= \sum_{j=1}^m \sum_{i: A_i \cap B_j \neq \emptyset} b_j W(B_j \cap A_i) = \sum_{j=1}^m \sum_{i=1}^n b_j W(B_j \cap A_i) = \sum_{j=1}^m b_j W(B_j), \quad \text{since } W(\emptyset) = 0. \end{aligned}$$

Hence,  $I(f)$  does not depend on the representation of  $f$  as a simple function.  $\square$

Lemma 2.3.2 (Properties of  $J$ ):

Let  $f$  and  $g$  be two simple functions. Then,

1. Isometry:

$$\langle J(f), J(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \stackrel{\text{def}}{=} \mathbb{E}(J(f)\overline{J(g)}) = \langle f, g \rangle_{L^2(\mathbb{E}, \nu)} = \int_{\mathbb{E}} f(x)\overline{g(x)}\nu(dx)$$

2. Linearity:  $J(af + bg) \stackrel{\text{a.s.}}{=} aJ(f) + bJ(g)$ ,  $a, b \in \mathbb{C}$

Proof 1. Let

$$f = \sum_{i=1}^n a_i I(A_i), \quad g = \sum_{j=1}^m b_j I(B_j), \quad a_i, b_j \in \mathbb{C},$$

$$A_i \cap A_k = \emptyset, \quad i \neq k \quad B_j \cap B_l = \emptyset, \quad j \neq l, \quad \bigcup_{i=1}^n A_i = \bigcup_{j=1}^m B_j = \mathbb{E}. \quad \text{Consider}$$

$$\begin{aligned} \langle J(f), J(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} &= \mathbb{E}(J(f)\overline{J(g)}) = \mathbb{E}\left(\sum_{i=1}^n \sum_{j=1}^m a_i \overline{b_j} W(A_i) \overline{W(B_j)}\right) \\ &= \sum_{i=1}^n \sum_{j=1}^m a_i \overline{b_j} \nu(A_i \cap B_j) = \sum_{i=1}^n \sum_{j=1}^m a_i \overline{b_j} \int_{\mathbb{E}} \underbrace{I_{A_i \cap B_j}(x)}_{I_{A_i}(x)I_{B_j}(x)} \nu(dx) = \int_{\mathbb{E}} \sum_{i=1}^n a_i I_{A_i}(x) \overline{\sum_{j=1}^m b_j I_{B_j}(x)} \nu(dx) \\ &= \int_{\mathbb{E}} f(x)\overline{g(x)}\nu(dx) = \langle f, g \rangle_{L^2(\mathbb{E}, \nu)}. \end{aligned}$$

2. By 1) we get

$$\begin{aligned}
& \|J(af + bg) - aJ(f) - bJ(g)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})}^2 \\
& = \langle J(af + bg) - aJ(f) - bJ(g), J(af + bg) - aJ(f) - bJ(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \\
& = \langle J(af + bg), J(af + bg) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} - a \langle J(f), J(af + bg) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \\
& \quad - b \langle J(g), J(af + bg) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \\
& = \bar{a} \langle J(af + bg), J(f) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} - \bar{b} \langle J(af + bg), J(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \\
& \quad + a\bar{a} \langle J(f), J(f) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} + b\bar{b} \langle J(g), J(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} - \bar{b} \langle J(af + bg), g \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \\
& \quad + a\bar{b} \langle J(f), J(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} + b\bar{b} \langle J(g), J(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \\
& \stackrel{1)}{=} \langle af + bg, af + bg \rangle_{L^2(\mathbb{E}, \nu)} - \bar{a} \langle af + bg, f \rangle_{L^2(\mathbb{E}, \nu)} - \bar{b} \langle af + bg, g \rangle_{L^2(\mathbb{E}, \nu)} \\
& \quad - a \langle f, af + bg \rangle_{L^2(\mathbb{E}, \nu)} + a\bar{a} \langle f, f \rangle_{L^2(\mathbb{E}, \nu)} + a\bar{b} \langle f, g \rangle_{L^2(\mathbb{E}, \nu)} - b \langle g, af + bg \rangle_{L^2(\mathbb{E}, \nu)} \\
& \quad + b\bar{a} \langle g, f \rangle_{L^2(\mathbb{E}, \nu)} + b\bar{b} \langle g, g \rangle_{L^2(\mathbb{E}, \nu)} = 0
\end{aligned}$$

by linearity of the scalar product  $\langle \cdot, \cdot \rangle_{L^2(\mathbb{E}, \nu)}$ . Hence,  $J(af + bg) - aJ(f) - bJ(g) \stackrel{a.s.}{=} 0$   $\square$

#### Definition 2.3.5

The integral of a function  $f \in L^2(\mathbb{E}, \nu)$  with respect to the random measure  $W$  is given by  $J(f) = \lim_{n \rightarrow \infty} J(f_n)$ , where  $\{f_n\}_{n \in \mathbb{N}}$  is a sequence of simple functions s.t.

$$f_n \xrightarrow[n \rightarrow \infty]{L^2(\mathbb{E}, \nu)} f,$$

and the limit  $\lim J(f_n)$  is understood in the mean quadratic sense, i.e., in  $L^2(\Omega, \mathcal{F}, \mathcal{P})$ :

$$\mathbb{E}|J(f_n) - J(f)|^2 = \|J(f_n) - J(f)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})}^2 \rightarrow 0 \quad \text{as } n \rightarrow \infty.$$

Since the set of simple functions is dense in  $L^2(\mathbb{E}, \nu)$ , such a sequence  $\{f_n\}_{n \in \mathbb{N}}$  always exists.

**Lemma 2.3.3** 1. Definition 2.3.5 is correct, i.e.,  $J(f)$  exists and does not depend on the choice of the approximating sequence  $\{f_n\}_{n \in \mathbb{N}}$  of  $f$ .

2. For any  $f, g \in L^2(\mathbb{E}, \nu)$  it holds

a)  $\langle J(f), J(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \langle f, g \rangle_{L^2(\mathbb{E}, \nu)}$

b)  $J(af + bg) = aJ(f) + bJ(g), \quad a, b \in \mathbb{C}$

c) If  $g_n \xrightarrow[n \rightarrow \infty]{L^2(\mathbb{E}, \nu)} g$  as  $n \rightarrow \infty$ , then  $J(g_n) \xrightarrow[n \rightarrow \infty]{L^2(\Omega, \mathcal{F}, \mathcal{P})} J(g)$  as  $n \rightarrow \infty$ , where  $\{g_n\}_{n \in \mathbb{N}}$ ,  $g_n \in L^2(\mathbb{E}, \nu)$  are not necessarily simple.

**Proof** 1. Let  $\{f_n\}_{n \in \mathbb{N}}, \{g_n\}_{n \in \mathbb{N}}$  be simple functions s.t.  $f_n \xrightarrow[n \rightarrow \infty]{L^2(\mathbb{E}, \nu)} f$  as  $n \rightarrow \infty$ ,  $g_n \xrightarrow[n \rightarrow \infty]{L^2(\mathbb{E}, \nu)} g$  as  $n \rightarrow \infty$ . First let us prove that  $J(f)$  exists. By Lemma 2.3.2, it holds

$$\|J(f_n) - J(f_m)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \|J(f_n - f_m)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \|f_n - f_m\|_{L^2(\mathbb{E}, \nu)} \xrightarrow[n, m \rightarrow \infty]{} 0,$$

because  $\{f_n\}$  is a fundamental sequence in  $L^2(\mathbf{E}, \nu)$  due to

$$f_n \xrightarrow[n \rightarrow \infty]{L^2(\mathbf{E}, \nu)} f.$$

Then  $\{J(f_n)\}_{n \in \mathbb{N}}$  is a fundamental sequence in  $L^2(\Omega, \mathcal{F}, \mathcal{P})$ , and since  $L^2(\Omega, \mathcal{F}, \mathcal{P})$  is a full space,  $\exists$  a limit  $\lim_{n \rightarrow \infty} J(f_n) \stackrel{\text{def}}{=} J(f)$ .

Now let us show that

$$\lim_{n \rightarrow \infty} J(f_n) = \lim_{n \rightarrow \infty} J(g_n) = J(f).$$

Suppose that

$$\lim_{n \rightarrow \infty} J(f_n) = \xi, \quad \lim_{n \rightarrow \infty} J(g_n) = \eta,$$

and show that  $\xi \stackrel{\text{a.s.}}{=} \eta$ . It holds

$$\begin{aligned} \|J(f_n) - J(g_n)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} &= \|J(f_n - g_n)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \\ &\stackrel{\text{lemma 2.3.2}}{=} \|f_n - g_n\|_{L^2(\mathbf{E}, \nu)} \leq \|f_n - f\|_{L^2(\mathbf{E}, \nu)} + \|g_n - f\|_{L^2(\mathbf{E}, \nu)} \xrightarrow[n \rightarrow \infty]{} 0, \end{aligned}$$

hence  $J(f_n) - J(g_n) \xrightarrow{L^2(\Omega, \mathcal{F}, \mathcal{P})} 0$  as  $n \rightarrow \infty$ , otherwise  $J(f_n) - J(g_n) \xrightarrow{L^2(\Omega, \mathcal{F}, \mathcal{P})} \xi - \eta$  as  $n \rightarrow \infty$ , hence  $\xi \stackrel{\text{a.s.}}{=} \eta$ .

2. a) Let  $f_n \xrightarrow{L^2(\mathbf{E}, \nu)} f$  as  $n \rightarrow \infty$ ,  $g_n \xrightarrow{L^2(\mathbf{E}, \nu)} g$  as  $n \rightarrow \infty$ . By Lemma 2.3.2, 1) and since the scalar product is continuous we have  $\langle J(f), J(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \lim_{n, m \rightarrow \infty} \langle J(f_n), J(g_m) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \lim_{n, m \rightarrow \infty} \langle f_n, g_m \rangle_{L^2(\mathbf{E}, \nu)} = \langle f, g \rangle_{L^2(\mathbf{E}, \nu)}$ .

b) Is proven exactly as 2), Lemma 2.3.2.

- c) It holds  $\|J(g) - J(g_n)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \|J(g - g_n)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \stackrel{1)}{=} \|g - g_n\|_{L^2(\mathbf{E}, \nu)} \rightarrow 0$  as  $n \rightarrow \infty$ , since  $g_n \xrightarrow{L^2(\Omega, \mathcal{F}, \mathcal{P})} g$  as  $n \rightarrow \infty$ . Then  $J(g_n) \xrightarrow{L^2(\Omega, \mathcal{F}, \mathcal{P})} J(g)$  as  $n \rightarrow \infty$ .  $\square$

Now let us consider the case of a  $\sigma$ -finite  $\nu$ , i.e., there exists a family of pairwise disjoint sets

$$\{\mathbf{E}_n\} \subset \mathbf{E} : \bigcup_{n=1}^{\infty} \mathbf{E}_n = \mathbf{E}, \quad \mathbf{E}_n \in K(\mathbf{E}), \nu(\mathbf{E}_n) < \infty, n \in \mathbb{N}.$$

Then, it follows from general measure theory that  $f \in L^2(\mathbf{E}, \mathcal{A}, \nu)$  iff  $f_n = f|_{\mathbf{E}_n} \in L^2(\mathbf{E}_n, \mathcal{A}_n, \nu_n)$  (where  $\mathcal{A}_n = \sigma(K(\mathbf{E}_n))$  and  $\nu_n$  is a (Lebesgue) continuation of  $\nu|_{K(\mathbf{E}_n)}$  from  $K(\mathbf{E}_n) = K(\mathbf{E}) \cap \mathbf{E}_n$  onto  $\mathcal{A}_n$ ) and

$$\int_{\mathbf{E}} |f(x)|^2 \nu(dx) = \sum_{n=1}^{\infty} \int_{\mathbf{E}_n} |f_n(x)|^2 \nu_n(dx) < \infty, \quad (2.3.1)$$

where the value of  $\int_{\mathbf{E}} |f(x)|^2 \nu(dx)$  does not depend on the choice of  $\{\mathbf{E}_n\}_{n \in \mathbb{N}}$ .

Definition 2.3.6

For  $f \in L^2(\mathbf{E}, \nu)$ , set the integral  $J(f)$  w.r.t. the random measure  $W$  to be

$$J(f) = \sum_{n=1}^{\infty} J_n(f_n), \text{ where } f_n = f|_{\mathbf{E}_n} \text{ and } J_n(f_n) = \int_{\mathbf{E}_n} f_n(x)W(dx)$$

is the integral introduced in Definition 2.3.5.

Lemma 2.3.4 1. Definition 2.3.6 is correct i.e.  $J(f)$  exists and does not depend on the choice of the sets  $\{\mathbf{E}_n\}_{n \in \mathbb{N}}$ .

2. Stochastic integral  $J$  preserves the scalar product (isometry):

$$\text{for any } f, g \in L^2(\mathbf{E}, \nu) \text{ it holds } \langle J(f), J(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \langle f, g \rangle_{L^2(\mathbf{E}, \nu)}$$

3. The random measure  $W$  can be continued from  $\tilde{\mathcal{A}}$  to  $\{A \in \mathcal{A} : \nu(A) < \infty\}$  by the formula  $W(A) = J(I_A)$ .

4. If  $W$  is a centered random measure, then  $E(J(f)) = 0$  for all  $f \in L^2(\mathbf{E}, \nu)$ .

Proof 1. Let us show that the series  $\sum_{n=1}^{\infty} J_n(f_n)$  converges. First, it holds

$$\langle J_n(f_n), J_m(f_m) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = 0, \quad m \neq n.$$

Indeed, this statement is trivial for simple  $f_n$  and  $f_m$ , because

$$\langle W(A), W(B) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = 0 \text{ for } A \in \sigma(K(\mathbf{E}_n)), \quad B \in \sigma(K(\mathbf{E}_m)).$$

For general  $f_n \in L^2(\mathbf{E}_n, \nu_n)$  and  $f_m \in L^2(\mathbf{E}_m, \nu_m)$  it suffices to approximate them. By a sequence of simple functions and use the continuity of  $\langle \cdot, \cdot \rangle$ . Hence,

$$\begin{aligned} & \left\| \sum_{i=1}^n J_i(f_i) - \sum_{i=1}^m J_i(f_i) \right\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})}^2 = \sum_{i=\min\{m,n\}+1}^{\max\{m,n\}} \|J_i(f_i)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})}^2 \\ & = \sum_{i=\min\{m,n\}+1}^{\max\{m,n\}} \|f_i\|_{L^2(\mathbf{E}_i, \nu_i)}^2 = \sum_{i=\min\{m,n\}+1}^{\max\{m,n\}} \int_{\mathbf{E}_i} |f_i(x)|^2 \nu_i(dx) \rightarrow 0 \text{ as } n, m \rightarrow \infty, \end{aligned}$$

since the series (2.3.1) converges. Then,  $\sum_{n=1}^{\infty} J_n(f_n)$  converges as well.

Now let us show that  $J(f)$  does not depend on  $\{\mathbf{E}_i\}_{i \in \mathbb{N}}$ . Let

$$\mathbf{E} = \bigcup_{i=1}^{\infty} \mathbf{E}'_i, \quad \mathbf{E}'_i \subset K(\mathbf{E}), \quad \mathbf{E}'_i \cap \mathbf{E}'_j = \emptyset, \quad i \neq j, \quad \nu(\mathbf{E}'_i) < \infty, \quad i \in \mathbb{N}$$

Denote  $f_{i,j} = f|_{\mathbf{E}_i \cap \mathbf{E}'_j}$ ,  $i, j \in \mathbb{N}$ . Then  $f_i = f|_{\mathbf{E}_i} = \sum_{j=1}^{\infty} f_{i,j}$ ,  $i \in \mathbb{N}$ .

Since  $\sum_{j=1}^n f_{i,j} \xrightarrow{L^2(\mathbf{E}_i)} f_i$  as  $n \rightarrow \infty$ , it holds

$$J_i(f_i) = \sum_{j=1}^{\infty} J_i(f_{i,j})$$

by Lemma 2.3.3, 2c). Consider the integral  $J_{ij}$  on

$$L^2(\mathbf{E}_i \cap \mathbf{E}'_j, \nu) : J_{ij}(g) = \int_{\mathbf{E}_i \cap \mathbf{E}'_j} g(x) \nu(x), \quad g \in L^2(\mathbf{E}_i \cap \mathbf{E}'_j, \nu)$$

Evidently, it holds  $J_{ij}(g) = J_i(g) = J'_j(g)$  for  $g \in L^2(\mathbf{E}_i \cap \mathbf{E}'_j, \nu)$ , where  $J'_j$  is the integral on  $L^2(\mathbf{E}'_j, \nu)$ . Then, we get

$$\sum_{i=1}^{\infty} J_i(f_i) = \sum_{i,j=1}^{\infty} J_{ij}(f_{ij}), \quad \sum_{j=1}^{\infty} J'_j(f_j) = \sum_{j,i=1}^{\infty} J'_{ij}(f_{ij}),$$

where  $J_{ij} = J'_{ij}$  on  $L^2(\mathbf{E}_i \cap \mathbf{E}'_j, \nu)$ . Since  $\langle J_{ij}(f_{ij}), J_{kl}(f_{kl}) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = 0$  for  $(i, j) \neq (k, l)$ , we get

$$\begin{aligned} J(f) &= \sum_{i=1}^{\infty} J_i(f_i) = \sum_{i,j=1}^{\infty} J_{ij}(f_{ij}) = \sum_{j,i=1}^{\infty} J_{ij}(f_{ij}) = \sum_{j,i=1}^{\infty} J'_{ij}(f_{ij}) \\ &= \sum_{j=1}^{\infty} J'_j(f_j) = J'(f), \quad \text{because} \\ \sum_{i,j=1}^{\infty} \|J_{ij}(f_{ij})\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})}^2 &= \sum_{i,j=1}^{\infty} \|f_{ij}\|_{L^2(\mathbf{E}_i \cap \mathbf{E}'_j, \nu)}^2 = \int_{\mathbf{E}} |f(x)|^2 \nu(dx) < \infty, \end{aligned}$$

here  $J'(f)$  is the stochastic integral of  $f$  constructed with the help of tiling  $\{\mathbf{E}'_j\}_{j \in \mathbb{N}}$  of  $\mathbf{E}$ .

2. Since  $\mathbf{E} = \bigcup_{i=1}^{\infty} \mathbf{E}_i$  with  $\nu(\mathbf{E}_i) < \infty$ ,  $i \in \mathbb{N}$ , for any  $f, g \in L^2(\mathbf{E}, \nu)$  it holds

$$f = \sum_{i=1}^{\infty} f_i, \quad g = \sum_{i=1}^{\infty} g_i, \quad \text{where } f_i = f|_{\mathbf{E}_i}, \quad g_i = g|_{\mathbf{E}_i}, \quad i \in \mathbb{N}.$$

The above series converge in  $L^2(\mathbf{E}, \nu)$ -sense. By the continuity of the scalar product and Lemma 2.3.3, 2) we have

$$\begin{aligned} \langle J(f), J(g) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} &= \langle \sum_{i=1}^{\infty} J_i(f_i), \sum_{j=1}^{\infty} J_j(g_j) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \lim_{n, m \rightarrow \infty} \langle \sum_{i=1}^n J_i(f_i), \sum_{j=1}^m J_j(g_j) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \\ &= \lim_{n, m \rightarrow \infty} \sum_{i=1}^n \sum_{j=1}^m \langle J_i(f_i), J_j(g_j) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \stackrel{\text{Lemma 2.3.3}}{=} \lim_{n, m \rightarrow \infty} \sum_{i=1}^n \sum_{j=1}^m \langle f_i, g_j \rangle_{L^2(\mathbf{E}, \nu)} \\ &= \lim_{n, m \rightarrow \infty} \langle \sum_{i=1}^n f_i, \sum_{j=1}^m g_j \rangle_{L^2(\mathbf{E}, \nu)} = \langle f, g \rangle_{L^2(\mathbf{E}, \nu)}, \end{aligned}$$

where  $\langle J_i(f_i), J_j(g_j) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \langle f_i, g_j \rangle_{L^2(\mathbf{E}, \nu)} \delta_{ij}$ , since  $\mathbf{E}_i \cap \mathbf{E}_j = \emptyset$ ,  $i \neq j$ .

3. Take a random measure  $\widetilde{W}$  on  $\mathcal{A}$  defined by  $\widetilde{W}(A) = J(I_A)$ ,  $A \in \mathcal{A} : \nu(A) < \infty$ . It is an independently scattered random measure by linearity of the integral and isometry property, since for any  $B, C \in \{A \in \mathcal{A} : W(A) < \infty\}$  it holds

$$\langle W(B), W(C) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \langle J(I_B), J(I_C) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \langle I_B, I_C \rangle_{L^2(\mathbf{E}, \nu)} = \nu(B \cap C).$$

Show that  $\widetilde{W}$  is continuation of  $W$  from  $K(\mathbf{E})$  onto  $\{A \in \mathcal{A} : \nu(A) < \infty\}$ . For any  $B \in K(\mathbf{E})$  we have  $\nu(B) < \infty$ ,  $B = \bigcup_{i=1}^{\infty} B_i$ , where  $B_i = B \cap \mathbf{E}_i$ ,  $i \in \mathbb{N}$ ,  $\nu(B) = \sum_{i=1}^{\infty} \nu(B_i)$ . Furthermore, we have

$$I_B = \sum_{i=1}^{\infty} I_{B_i} \in L^2(\mathbf{E}, \nu) \text{ and thus } J(I_B) = \sum_{i=1}^{\infty} J_i(I_{B_i}).$$

Since  $J_i(I_{B_i}) = W(B_i)$ ,  $i \in \mathbb{N}$ , (because  $B_i \in K(\mathbf{E}_i)$ ), we get

$$\widetilde{W}(B) = J(I_B) = \sum_{i=1}^{\infty} W(B_i) = W(B), \quad B \in K(\mathbf{E}),$$

(all series in  $L^2$ -sense).

4. Follows for  $\nu(\mathbf{E}) < \infty$  from the fact, that for centered  $W$  it holds  $\mathbf{E}J(f_n) = 0$  obviously for any simple  $f_n$ ,  $n \in \mathbb{N}$ . Suppose that  $f_n \xrightarrow{L^2(\mathbf{E}, \nu)} f$  as  $n \rightarrow \infty$ , hence, by Lemma 2.3.3, we get  $J(f_n) \xrightarrow{L^2(\Omega, \mathcal{F}, \mathcal{P})} J(f)$  as  $n \rightarrow \infty$ , and hence

$$\begin{aligned} |\mathbf{E}J(f)| &= |\mathbf{E}J(f) - \mathbf{E}J(f_n)| \leq \mathbf{E}|J(f) - J(f_n)| \leq \sqrt{\mathbf{E}|J(f) - J(f_n)|^2} \\ &= \|J(f) - J(f_n)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \longrightarrow 0 \quad \text{as } n \rightarrow \infty \end{aligned}$$

by the Lyapunow inequality. Then,  $\mathbf{E}J(f) = 0$  in case  $\nu(\mathbf{E}) < \infty$ .

If  $\nu$  is  $\sigma$ -finite, the usual reasoning with

$$f = \sum_{i=1}^{\infty} f_i, \quad f_i = f|_{\mathbf{E}_i}, \quad i \in \mathbb{N}, \quad \mathbf{E}J_i(f_i) = 0, \quad i \in \mathbb{N}$$

proves the general cases since

$$\mathbf{E}J(f) = \sum_{i=1}^{\infty} \mathbf{E}J_i(f_i) = 0.$$

□

## 2.4 Spectral representation for stationary random functions

Let  $X = \{X(t), t \in T\}$  be a (centered) complex-valued random function defined on  $(\Omega, \mathcal{F}, \mathcal{P})$  with  $\mathbf{E}X^2(t) < \infty$ ,  $t \in T$  and covariance function  $C(s, t) = \mathbf{E}[X(s)\overline{X(t)}]$ ,  $s, t \in T$ . Let us discuss necessary and sufficient conditions, under which  $X$  has the following spectral representation:

Definition 2.4.1

$$X(t) = \int_{\mathbf{E}} f(t, x)W(dx), \quad t \in T \tag{2.4.1}$$

for some  $f(t, \cdot) \in L^2(\mathbf{E}, \mathcal{A}, \nu)$ ,  $t \in T$ , where  $W$  is a independently scattered centered random measure on  $(\Omega, \mathcal{F}, \mathcal{P})$  with control measure  $\nu$  ( $\nu$  is  $\sigma$ -finite on  $(\mathbf{E}, \mathcal{A})$ ) on  $\{A \in \mathcal{A} : \nu(A) < \infty\}$ . Here spaces  $T$  and  $\mathbf{E}$  can be any abstract spaces, and equality (2.4.1) is understood in  $L^2$ -sense, i.e. a.s..



Theorem 2.4.1 (Karhunen):

The random function  $X$  introduced above has spectral representation (2.4.1) iff its covariance function  $C(s, t)$  admits the factorization

$$C(s, t) = \int_{\mathbf{E}} f(s, x) \overline{f(t, x)} \nu(dx), \quad s, t \in T \quad (2.4.2)$$

Here, the spectral measure  $W$  in (2.4.1) is given on an extension  $(\tilde{\Omega}, \tilde{\mathcal{F}}, \tilde{\mathcal{P}})$  of the original probability space  $(\Omega, \mathcal{F}, \mathcal{P})$ . It can be put  $(\tilde{\Omega}, \tilde{\mathcal{F}}, \tilde{\mathcal{P}})$  if the system of functions  $\{f(\cdot, t) : t \in T\}$  is complete in  $L^2(\mathbf{E}, \mathcal{A}, \nu)$ , i.e., for  $g \in L^2(\mathbf{E}, \mathcal{A}, \nu)$  it follows from  $\langle f(t, \cdot), g \rangle_{L^2(\mathbf{E}, \mathcal{A}, \nu)} = 0$ ,  $t \in T$  that  $g = 0$   $\nu$ -a.e..

Proof

1. Necessity: If  $X$  has representation (2.4.1) then by isometry property (cf. Lemma 2.3.4, 2)) we get

$$\begin{aligned} C(s, t) &= \mathbb{E}[X(s), \overline{X(t)}] = \langle X(s), X(t) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \langle f(s, \cdot), f(t, \cdot) \rangle_{L^2(\mathbf{E}, \nu)} \\ &= \int_{\mathbf{E}} f(s, x) \overline{f(t, x)} \nu(dx), \quad s, t \in T. \end{aligned}$$

2. Sufficiency: First let us consider the easier case of  $(\tilde{\Omega}, \tilde{\mathcal{F}}, \tilde{\mathcal{P}}) = (\Omega, \mathcal{F}, \mathcal{P})$ , i.e. the system  $\{f(t, \cdot) : t \in T\}$  is full. Consider the mapping  $\psi$  from the space of functions onto  $(\mathbf{E}, \nu)$  into  $L^2(\Omega, \mathcal{F}, \mathcal{P})$  given by  $\psi : f(t, \cdot) \mapsto X(t, \cdot)$ . Let us show that we can extend  $\psi$  onto  $L^2(\mathbf{E}, \mathcal{A}, \nu)$ . First, set

$$\psi \left( \sum_{i=1}^n a_i f(t_i, \cdot) \right) = \sum_{i=1}^n a_i X(t_i, \cdot)$$

by linearity for any  $n \in \mathbb{N}$ ,  $a_i \in \mathbb{C}$ ,  $t_i \in T$ ,  $i = 1, \dots, n$ .

Let us show that  $\psi$  does not depend on the concrete representation of

$$\sum_{i=1}^n a_i f(t_i, \cdot).$$

Namely, prove that

$$\sum_{i=1}^n a_i X(t_i, \cdot) \stackrel{a.s.}{=} \sum_{j=1}^m b_j X(s_j, \cdot) \quad (2.4.3)$$

for any  $m \in \mathbb{N}$ ,  $b_j \in \mathbb{C}$ ,  $s_j \in T$ ,  $j = 1, \dots, m$  such that

$$\sum_{i=1}^n a_i f(t_i, \cdot) = \sum_{j=1}^m b_j f(s_j, \cdot).$$

$\psi$  is an isometry between the space of all linear combinations

$$L(f) = \left\{ \sum_{i=1}^k c_i f(y_i, \cdot) : k \in \mathbb{N}, \quad c_i \in \mathbb{C}, \quad y_i \in T, \quad i = 1, \dots, k \right\}$$

and

$$L(X) = \left\{ \sum_{i=1}^k c_i X(y_i, \cdot) : k \in \mathbb{N}, \quad c_i \in \mathbb{C}, \quad y_i \in T, \quad i = 1, \dots, k \right\}.$$

because

$$\begin{aligned} & \left\langle \sum_{i=1}^n a_i f(t_i, \cdot), \sum_{j=1}^m b_j f(s_j, \cdot) \right\rangle_{L^2(\mathbb{E}, \nu)} = \sum_{i=1}^n \sum_{j=1}^m a_i \bar{b}_j \int_{\mathbb{E}} f(t_i, x) \overline{f(s_j, x)} \nu(dx) \\ & \stackrel{\text{by (2.4.2)}}{=} \sum_{i=1}^n \sum_{j=1}^m a_i \bar{b}_j C(t_i, s_j) = \mathbb{E} \left[ \sum_{i=1}^n \sum_{j=1}^m a_i \bar{b}_j X(t_i, \cdot) \overline{X(s_j, \cdot)} \right] \\ & = \left\langle \sum_{i=1}^n a_i X(t_i, \cdot), \sum_{j=1}^m b_j X(s_j, \cdot) \right\rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})}. \end{aligned}$$

Hence,

$$\left\| \sum_{i=1}^n a_i X(t_i, \cdot) - \sum_{j=1}^m b_j X(s_j, \cdot) \right\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \left\| \sum_{i=1}^n a_i f(t_i, \cdot) - \sum_{j=1}^m b_j f(s_j, \cdot) \right\|_{L^2(\mathbb{E}, \nu)} = 0$$

and (2.4.3) is proved. Since  $\{f(t, \cdot) : t \in T\}$  is full, we have that closure  $\overline{L(f)}$  of  $L(f)$  in  $L^2(\mathbb{E}, \nu)$  is equal to the whole  $L^2(\mathbb{E}, \nu)$ . As an isometry  $\psi$  can be extended to the mapping

$$\psi : \underbrace{\overline{L(f)}}_{=L^2(\mathbb{E}, \nu)} \longrightarrow \overline{L(X)}, \quad \text{where } \overline{L(X)} = \text{closure of } L(X) \text{ in } L^2(\Omega, \mathcal{F}, \mathcal{P}).$$

Now define  $W(B) = \psi(I_B)$  for any  $B \in \mathcal{A} : \nu(B) < \infty$ .  $W$  is an independently scattered random measure on  $(\Omega, \mathcal{F}, \mathcal{P})$  with control measure  $\nu$ , since

$$\begin{aligned} \langle W(A), W(B) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} &= \langle \psi(I_A), \psi(I_B) \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \langle I_A, I_B \rangle_{L^2(\mathbb{E}, \nu)} = \nu(A \cap B), \\ A, B \in \mathcal{A} : \nu(A) < \infty, \quad \nu(B) < \infty. \end{aligned}$$

The measure  $W$  is centered, since  $W(A) \in \overline{L(X)}$  for any  $A \in \mathcal{A} : \nu(A) < \infty$ , and it holds  $\mathbb{E}\xi = 0$  for any  $\xi \in \overline{L(X)}$  due to  $\mathbb{E}X(t) = 0, t \in T$ .

Take the stochastic integral  $J(\cdot)$  on  $L^2(\mathbb{E}, \nu)$  w.r.t.  $W$ . By Lemma 2.3.4, 2)  $J$  is an isometry from  $L^2(\mathbb{E}, \nu)$  onto  $L_W^2 \subset L^2(\Omega, \mathcal{F}, \mathcal{P})$ . Show that  $\psi \equiv J$  (and thus  $\overline{L(f)} = L_W^2$ ).

Since  $\psi(I_B) = J(I_B)$  by their definition for  $B \in \mathcal{A} : \nu(B) < \infty$ , and linear combinations of indicators are dense in  $L^2(\mathbb{E}, \mathcal{A}, \nu)$ , we get  $\psi \equiv J$  as mappings  $L^2(\mathbb{E}, \nu) \longrightarrow \overline{L(f)} = L_W^2$ .

Then,  $X(t) = J(f(t, \cdot)), t \in T$  is the spectral representation we fought for.

Now let us return to the special case of  $(\tilde{\Omega}, \tilde{\mathcal{F}}, \tilde{\mathcal{P}}) \neq (\Omega, \mathcal{F}, \mathcal{P})$ , i.e.  $\{f(t, \cdot) : t \in T\}$  is not

full. In this case,  $\overline{L(f)} \subset L^2(\mathbf{E}, \nu)$ ,  $\overline{L(f)} \neq L^2(\mathbf{E}, \nu)$ . Take the orthogonal complement of  $\overline{L(f)}$  in  $L^2(\mathbf{E}, \nu)$  (denote it by  $\overline{L(f)}^\perp$ ) and consider a basis

$$\{g(s, \cdot) : s \in T'\} \subset L^2(\mathbf{E}, \nu), \quad \text{where } T' \cap T = \emptyset.$$

Introduce the function

$$C_1(s, t) = \int_{\mathbf{E}} g(s, x) \overline{g(t, x)} \nu(dx), \quad s, t \in T'.$$

Since

$$\sum_{i, j=1}^n a_i \overline{a_j} C_1(t_i, t_j) = \int_{\mathbf{E}} \left| \sum_{i=1}^n a_i g(t_i, x) \right|^2 \nu(dx) \geq 0,$$

$C_1$  is positive semi-definite. Hence, there exists a probability space  $(\Omega', \mathcal{F}', \mathcal{P}')$  and a centered (complex-valued) Gaussian random function  $X' = \{X'(t) : t \in T'\}$  on  $(\Omega', \mathcal{F}', \mathcal{P}')$  such that  $X'$  has the covariance function

$$C_1 : C_1(s, t) = \mathbf{E} \left[ X'(s) \overline{X'(t)} \right], \quad s, t \in T'.$$

Introduce the extension of  $(\Omega, \mathcal{F}, \mathcal{P})$  by  $(\tilde{\Omega}, \tilde{\mathcal{F}}, \tilde{\mathcal{P}}) = (\Omega, \mathcal{F}, \mathcal{P}) \times (\Omega', \mathcal{F}', \mathcal{P}')$ .

For any  $t \in T$ ,  $s \in T'$ ,  $X(t)$  and  $X'(s)$  are independent of  $(\tilde{\Omega}, \tilde{\mathcal{F}}, \tilde{\mathcal{P}})$ , where for  $\tilde{\omega} = (\omega, \omega') \in \tilde{\Omega}$  we set  $X(t, \tilde{\omega}) = X(t, \omega)$ ,  $X'(s, \tilde{\omega}) = X'(s, \omega')$ . Introduce the (centered) random function

$\tilde{X} = \{\tilde{X}(t) : t \in T \cup T'\}$  by

$$\tilde{X}(t, \tilde{\omega}) = \left\{ \begin{array}{ll} X(t, \omega), & t \in T \\ X'(t, \omega'), & t \in T' \end{array} \right\}$$

It holds

$$\tilde{C}(s, t) = \mathbf{E} \left[ \tilde{X}(s) \overline{\tilde{X}(t)} \right] = \left\{ \begin{array}{ll} C(s, t), & s, t \in T \\ C_1(s, t), & s, t \in T' \\ 0, & s \in T, t \in T' \text{ or } s \in T, t \in T \end{array} \right\}$$

Hence,

$$\tilde{C}(s, t) = \int_{\mathbf{E}} h(s, x) \overline{h(t, x)} \nu(dx), \quad \text{with}$$

$$h(t, x) = \left\{ \begin{array}{ll} f(t, x), & t \in T \\ g(t, x), & t \in T', \end{array} \right\}$$

$x \in \mathbf{E}$ , since  $\langle f(t, \cdot), g(s, \cdot) \rangle_{L^2(\mathbf{E}, \nu)} = 0$ , for  $t \in T$ ,  $s \in T'$ .

Furthermore,  $\overline{L(h)} = L^2(\mathbf{E}, \nu)$ , because  $\{h(t, \cdot) : t \in T \cup T'\}$  is full in  $L^2(\mathbf{E}, \nu)$ . Then we can use the first part of the proof in 2) and write

$$\tilde{X}(t) = \int_{\mathbf{E}} h(t, x) W(dx), \quad t \in T \cup T',$$

where  $W$  is an independent scattered random measure defined on  $(\tilde{\Omega}, \tilde{\mathcal{F}}, \tilde{\mathcal{P}})$ . For  $t \in T$ , we get

$$X(t, \omega) = \tilde{X}(t, \tilde{\omega}) = \int_{\mathbb{E}} h(t, x) W(dx) = \int_{\mathbb{E}} f(t, x) W(dx).$$

□

Corollary 2.4.1 (Cramér):

Let  $\{X(t) : t \in \mathbb{R}^d\}$  be a centered complex-valued (wide sense) stationary random field on  $(\Omega, \mathcal{F}, \mathcal{P})$  which is continuous in the mean square sense. Let  $\nu$  be its spectral measure from Bochner's theorem. Then, there exists an independently scattered centered random measure  $W = \{W(A) : A \in \mathcal{B}(\mathbb{R}^d)\}$  on  $(\Omega, \mathcal{F}, \mathcal{P})$  with control measure  $\nu$  such that

$$X(t) = \int_{\mathbb{R}^d} e^{i\langle t, x \rangle} W(dx), \quad t \in \mathbb{R}^d. \quad (2.4.4)$$

Proof Since  $X$  is mean square continuous, its covariance function

$$C_0(h) = \mathbb{E} \left[ X(s) \overline{X(s+h)} \right]$$

is continuous at the origin. Hence, by Bochner's theorem, we get

$$C_0(h) = \int_{\mathbb{R}^d} e^{i\langle h, x \rangle} \nu(dx)$$

for a finite (spectral) measure  $\nu$  on  $\mathcal{B}_{\mathbb{R}^d}$ , in other words

$$C(s, t) = \mathbb{E} \left[ X(s) \overline{X(t)} \right] = C_0(s-t) = \int_{\mathbb{R}^d} e^{i\langle s-t, x \rangle} \nu(dx) = \int_{\mathbb{R}^d} e^{i\langle s, x \rangle} \cdot \overline{e^{i\langle t, x \rangle}} \nu(dx).$$

Put  $f(t, x) = e^{i\langle t, x \rangle}$ ,  $t, x \in \mathbb{R}^d$  in the function station (2.4.2),  $\mathbb{E} = \mathbb{R}^d$ . Since the set of functions  $\{e^{i\langle t, \cdot \rangle} : t \in \mathbb{R}^d\}$  is full in  $L^2(\mathbb{R}^d, \mathcal{B}_{\mathbb{R}^d})$ , we can apply Theorem 2.4.1 and get (2.4.4). □

Remark 2.4.1 1. If  $W$  is Gaussian, then so is  $X$ , and vice versa.

2. If  $X$  is real-valued, the spectral representation (2.4.1) can be written in its real form:

$$X(t) = \int_{\mathbb{R}^{d-1} \times \mathbb{R}_+} \cos \langle t, x \rangle W_1(dx) + \int_{\mathbb{R}^{d-1} \times \mathbb{R}_+} \sin \langle t, x \rangle W_2(dx), \quad t \in \mathbb{R}^d,$$

where  $W_1$  and  $W_2$  are independent real-valued independently scattered random measures.

3. The random measure  $W$  in (2.4.1) is called a spectral process corresponding to  $X$ .

The proof of 1) is obvious due to the convolution stability of the usual distribution. The proof of 2) is more involved and will not be given here.

How spectral representations (2.4.1) can be used in direct applications?

Example 2.4.1 (Simulation of Gaussian random fields):

In order to simulate a centered second order stationary Gaussian random field  $X$  with spectral measure  $\nu$  within an observation window  $A \subset \mathbb{R}^d$ ,  $A$  bounded Borel set, it is enough to consider sums

$$\tilde{X}_n(t) = \sum_{i=1}^{m_n} e^{i\langle t, x_i \rangle} W(A_i^n), \quad t \in A, \quad (2.4.5)$$

where

$$A = \bigcup_{i=1}^{m_n} A_i^n \subset \mathbb{R}^d$$

is sufficiently large to approximate

$$X(t) = \int_{\mathbb{R}^d} e^{i\langle t, x \rangle} W(dx) \quad \text{by} \quad X_A(t) = \int_A e^{i\langle t, x \rangle} W(dx)$$

in the mean square sense with a desired accuracy  $\|X(t) - X_A(t)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} < \varepsilon$ ,  $A_i^n \cap A_j^n = \emptyset$ ,  $i \neq j$  are bounded Borel sets in  $\mathbb{R}^d$ ,  $x_i \in A_i$ ,  $W(A_i^n)$  are independent random variables such that  $W(A_i^n) \sim N(0, \nu(A_i^n))$ ,  $i = 1, \dots, m_n$ . Then,  $\tilde{X}_n(t)$  is always a Gaussian random field s.t.

$$\tilde{X}_n(t) \xrightarrow{L^2(\Omega, \mathcal{F}, \mathcal{P})} \int_A e^{i\langle t, x \rangle} W(dx), \quad \text{as } n \rightarrow \infty,$$

i.e., the covariance function  $C_n$  of  $\tilde{X}_n$  tends to the covariance function  $C_A$  of  $X_A$  as  $n \rightarrow \infty$ . If  $A$  is a cube  $[-k; k]^d$ , then  $A_i^n$  can be chosen to be shifts of  $[0, \frac{1}{n}]^d$  and  $x_i$  can be taken to be the diagonal crossing point of  $A_i$ . If the choice of  $x_i$  and  $t$  is appropriate, a fast Fourier transformation for the fast computation of the sums in (2.4.5) can be used.

## 2.5 Orthogonal expansions for random functions

In this section, we would like to prove the following representation of a random function  $X = \{X(t), t \in T\}$  on a Hausdorff (compact) index space  $T$  satisfying some conditions:

$$X(t) = \sum_{i=1}^{\infty} \xi_i \psi_i(t), \quad (2.5.1)$$

where  $\{\xi_i\}_{i \in \mathbb{N}}$  are centered uncorrelated random variables (i.e.,  $\mathbb{E}\xi_i^2 < \infty$ ,  $\mathbb{E}\xi_i = 0$ ,  $\mathbb{E}(\xi_i \xi_j) = \lambda_i \delta_{ij}$ ,  $\lambda_i \geq 0$ ,  $i, j \in \mathbb{N}$ ) and  $\{\psi_i\}_{i \in \mathbb{N}}$  is an orthonormal system of  $L^2(T, \nu)$  with  $\nu$  a finite measure on the Borel- $\sigma$ -Algebra  $\mathcal{B}_T$ .

This convergence is understood in  $L^2(\Omega, \mathcal{F}, \mathcal{P})$ , and it is uniform in  $t$  on  $T$ .

The representation (2.5.1) is known under the name of Karhunen-Loève (named after Kari Karhunen and Michel Loève). In order to prove it, some technical devices are at hand.

### 2.5.1 Mercer's Theorem

Let  $T$  be a compact Hausdorff space equipped with a finite measure  $\nu$  defined on  $\mathcal{B}_T$ .

Let a function  $K : T \times T \rightarrow \mathbb{R}$  be symmetric (i.e.,  $K(s, t) = K(t, s)$ ,  $s, t \in T$ ) and positive semi-definite.

Then it is called a kernel. Let  $K$  be continuous in both arguments. Introduce the operator  $A_K$  on  $L^2(T, \mathcal{B}_T, \nu)$  by

$$[A_K g](t) = \int_T K(t, s)g(s)\nu(ds), \quad t \in T, \quad g \in L^2(T, \mathcal{B}_T, \nu)$$

The following Theorem goes back to James Mercer (1905), who proved it in the case of  $T = [a; b] \subset \mathbb{R}$ .

Theorem 2.5.1

If the kernel  $K$  is continuous, then  $T_K$  has an orthonormal basis of eigenfunctions  $\{\psi_i\}_{i \in \mathbb{N}}$  corresponding to eigenvalues  $\{\lambda_i\}_{i \in \mathbb{N}}$ ,  $\lambda_i \geq 0 \forall i \in \mathbb{N}$  in  $L^2(T, \mathcal{B}_T, \nu)$ , and

$$K(s, t) = \sum_{j=1}^{\infty} \lambda_j \psi_j(s) \psi_j(t), \quad s, t \in T, \quad (2.5.2)$$

where this convergence is absolute and uniform on  $T$ .

The proof of this result can be found in [33]. It is based on the following idea: it is enough to show that  $A_K$  is a compact operator in  $L^2(T, \mathcal{B}_T, \nu)$ . Then, the spectral theorem by Hilbert-Schmidt for compact operators on Hilbert Spaces is applied.

Corollary 2.5.1

Under the assumptions of Theorem 2.5.1, it holds

$$\int_T K(t, t)\nu(dt) = \sum_{i=1}^{\infty} \lambda_i.$$

Proof The statement follows from (2.5.2) and orthonormality of  $\{\psi_i\}_{i \in \mathbb{N}}$ . □

Suppose that the eigenvalues  $\{\lambda_i\}_{i \in \mathbb{N}}$  of  $T_K$  are given in decreasing order:  $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \dots \geq 0$ .

By definition of  $\psi_j$  and  $\lambda_j$ , it holds

$$\int_T K(s, t)\psi_j(s)\nu(ds) = \lambda_j \cdot \psi_j(t), \quad t \in T$$

as well as

$$\int_T \psi_i(t)\psi_j(t)\nu(dt) = \delta_{ij}, \quad i, j \in \mathbb{N}$$

Corollary 2.5.2

If  $K : T \times T \rightarrow \mathbb{R}$  is a covariance function of a (real-valued) random function  $X = \{X(t) : t \in T\}$ , and  $K$  is continuous on  $T$ , then it has expansion (2.5.2), because it is a kernel.

It is not easy to get the expansion (2.5.2) analytically, because the problem of comparing the functions of  $T_K$  is not trivial. There are, however, some special cases, where it can be done explicitly.

Example 2.5.1 1. Let  $T = [0; 1]$ ,  $\nu$  be the Lebesgue measure on  $[0; 1]$ ,  $K(s, t) = \min\{s, t\}$  be the covariance function of the Wiener process  $X = \{X(t) : t \in [0; 1]\}$ .

Let us show that

$$\psi_j(t) = \sqrt{2} \sin\left(\pi\left(j + \frac{1}{2}\right)t\right), \quad t \in [0; 1]$$

with

$$\lambda_j = \frac{1}{\left(j + \frac{1}{2}\right)^2 \pi^2}, \quad j \in \mathbb{N}.$$

Since

$$K(s, t) = sI\{s \leq t\} + tI\{s > t\} \quad (2.5.3)$$

is continuous, Theorem 2.5.1 can be applied to it. Let us solve the equation

$$\int_0^1 K(s, t) \psi(s) ds = \lambda \cdot \psi(t).$$

Indeed we have by (2.5.3)

$$\lambda \psi(t) = \int_0^t s \psi(s) ds + t \int_t^1 \psi(s) ds. \quad (2.5.4)$$

Assume that  $\psi \in C^2[0; 1]$ ,  $\lambda > 0$  and differentiate both sides of the above equation twice. We get the boundary value problem

$$\left\{ \begin{array}{l} \psi''(t) = -\frac{1}{\lambda} \psi(t) \\ \psi(0) = 0 \\ \psi'(1) = 0, \end{array} \right\}$$

because

$$\lambda \psi'(t) = \int_t^1 \psi(s) ds, \quad t \in [0; 1] \quad \text{and} \quad \psi'(1) = 0 \quad \text{follows from it.}$$

$\psi(0) = 0$  follows from (2.5.2) with  $s = t = 0$ . Solving the equation

$$\psi''(t) = -\frac{1}{\lambda} \psi(t), \quad \text{we get}$$

$$\psi(t) = c \cdot \cos\left(-\frac{t}{\sqrt{\lambda}} + a\right), \quad \text{where}$$

$$\psi(0) = 0 \quad \Rightarrow \quad a = \frac{\pi}{2}, \quad \text{i.e.}$$

$$\psi(t) = c \sin\left(\frac{t}{\sqrt{\lambda}}\right), \quad \psi' = \frac{c}{\sqrt{\lambda}} \cos\left(\frac{t}{\sqrt{\lambda}}\right),$$

$$\psi'(1) = \frac{c}{\sqrt{\lambda}} \cos\left(\frac{1}{\sqrt{\lambda}}\right) = 0 \quad \Rightarrow \quad \frac{1}{\sqrt{\lambda}} = \pi\left(j + \frac{1}{2}\right), \quad j \in \mathbb{Z},$$

thus

$$\psi_j(t) = c_j \cdot \sin\left(\pi\left(j + \frac{1}{2}\right)t\right), \quad j \in \mathbb{N}.$$

The constant  $c_j$  can be found from

$$\int_0^1 \psi_j^2(t) dt = 1, \quad j \in \mathbb{N} \cup \{0\}.$$

The eigenvalue  $\lambda_j$  can be obtained from (2.5.4).

2. Let  $T = [0; 1]^d$ ,  $\nu$  is the Lebesgue measure on  $[0; 1]^d$ , and

$$K(s, t) = \prod_{i=1}^d \min\{s_i, t_i\}, \quad s = (s_1 \dots s_d)^T, \quad t = (t_1 \dots t_d)^T \in [0; 1]^d \quad (2.5.5)$$

be the covariance function of the Brownian sheet (which is a centered Gaussian process with this covariance function). The Brownian sheet can be seen as a multidimensional generalization of the univariate Wiener process. Introduce the multiindex  $j = (j_1 \dots j_d)^T$ ,  $j_i \in \mathbb{N}$ .

Exercise 2.5.1

Show that the eigenfunctions of  $A_K$  with given in (2.5.5) are

$$\psi_j(t) = 2^{\frac{d}{2}} \prod_{i=1}^d \sin\left(\pi\left(j_i + \frac{1}{2}\right)t_i\right), \quad j = (j_1 \dots j_d) \in \mathbb{N}^d, \quad t = (t_1 \dots t_d)^T \in [0; 1]^d$$

with eigenvalues

$$\lambda_j = \prod_{i=1}^d \frac{1}{(j_i + \frac{1}{2})^2 \pi^2}.$$

### 2.5.2 Reproducing Kernel Hilbert Spaces

Let  $X = \{X(t) : t \in T\}$  be a (real-valued) random function defined on  $(\Omega, \mathcal{F}, \mathcal{P})$ .  $T$  being a compact separable Hausdorff space. It is often useful to assume that  $T$  is compact w.r.t. the topology induced by the following (pseudo) metric on  $T$ :

$$\rho(s, t) = \sqrt{\mathbb{E}|X(s) - X(t)|^2}.$$



It satisfies all properties of a metric except for

$$\rho(s, t) = 0 \quad \Rightarrow \quad s = t.$$

obviously, there can exist random functions  $X$  with  $X(s) \stackrel{a.s.}{=} X(t)$ , but  $s \neq t$  (e. g. if  $X$  is periodic). This pseudometric  $\rho$  is called a canonical metric for  $X$ . Let  $X$  be centered:  $\mathbf{E}X(t) \equiv 0$ ,  $t \in T$ , and  $\mathbf{E}X^2(t) < \infty$ ,  $t \in T$ .

Let

$$C(s, t) = \mathbf{E}[X(s)X(t)], \quad s, t \in T$$

be the covariance function of  $X$  which is positive definite and continuous on  $T \times T$ . Let us construct the reproducing kernel Hilbert space  $H$  of  $C$  (or  $X$ ) using the following step-by-step procedure:

1. Introduce the space

$$\mathbf{E} = \left\{ g : T \rightarrow \mathbb{R} : g(\cdot) = \sum_{i=1}^n a_i C(s_i, \cdot), \quad a_i \in \mathbb{R}, \quad s_i \in T, \quad i = 1, \dots, n, \quad n \in \mathbb{N} \right\}$$

with the scalar product

$$\langle f, g \rangle_H = \sum_{i=1}^n \sum_{j=1}^m a_i b_j C(s_i, t_j) \quad (2.5.6)$$

on  $\mathbf{E}$ , where  $f, g \in \mathbf{E}$ :

$$f(\cdot) = \sum_{i=1}^n a_i C(s_i, \cdot), \quad g(\cdot) = \sum_{j=1}^m b_j C(t_j, \cdot).$$

Since  $C$  is positive definite, it holds

$$\langle g, g \rangle_H \geq 0, \quad \langle g, g \rangle_H = 0 \quad \Leftrightarrow \quad g \equiv 0, \quad g \in \mathbf{E},$$

i.e.  $\langle \cdot, \cdot \rangle_H$  is indeed a scalar product.

Lemma 2.5.1

The scalar product  $\langle \cdot, \cdot \rangle_H$  has the so-called reproducing kernel property on  $\mathbf{E}$ , i.e.,

$$\langle g, C(t, \cdot) \rangle_H = g(t), \quad t \in T, \quad g \in \mathbf{E}.$$

Proof We write

$$\langle g, C(t, \cdot) \rangle_H = \left\langle \sum_{i=1}^n a_i C(s_i, \cdot), C(t, \cdot) \right\rangle_H = \sum_{i=1}^n a_i C(s_i, t) = g(t), \quad t \in T$$

for

$$g(\cdot) = \sum_{i=1}^n a_i C(s_i, \cdot) \in \mathbf{E}.$$

□

2. Introduce the norm  $\|g\|_H = \sqrt{\langle g, g \rangle_H}$  on  $\mathbf{E}$ .

Definition 2.5.1

The closure of  $\mathbf{E}$  w.r.t. the norm  $\|\cdot\|_H$  is called the reproducing kernel (Hilbert) space:

$$H = \overline{\mathbf{E}}.$$

Lemma 2.5.2 1. The convergence  $g_n \xrightarrow{\|\cdot\|_H} g$ , as  $n \rightarrow \infty$ ,  $g_n \in \mathbf{E}$ , in the norm  $\|\cdot\|_H$  implies the pointwise convergence of functional sequences on  $T$ :

$$g_n(t) \longrightarrow g(t), \quad \text{as } n \rightarrow \infty, \quad t \in T.$$

2.  $H = \overline{\mathbf{E}}$  is indeed a Hilbert space.

Proof 1. Let  $\{g_n\}$  converge to  $g$  in  $\|\cdot\|_H$ ,  $g_n \in \mathbf{E}$ ,  $n \in \mathbb{N}$ , then it is a Cauchy sequence:

$$\forall \varepsilon > 0 \quad \exists N : \quad \forall n, m > N \quad \|g_n - g_m\|_H < \varepsilon.$$

By the reproducing kernel property of  $\langle \cdot, \cdot \rangle_H$ , we have

$$|g_n(t) - g_m(t)| = | \langle g_n - g_m, C(t, \cdot) \rangle_H | \leq \|g_n - g_m\|_H \cdot \|C(t, \cdot)\|_H = \|g_n - g_m\|_H \cdot \sqrt{C(t, t)}, \quad t \in T$$

using Cauchy-Schwarz inequality and the definition (2.5.6) for  $\|C(t, \cdot)\|_H$ . Then,  $\{g_n(t)\}$ ,  $t \in T$  is a Cauchy sequence converging to  $g(t)$ .

2. The only property we have to prove here is that  $H$  is separable. This property follows from the separability of  $T$  and the continuousness of  $C$ .

□

Exercise 2.5.2

Please prove it!

Remark 2.5.1

Since  $\langle \cdot, \cdot \rangle_H$  is continuous on  $H$  and by Lemma 2.3.1, 1) reproducing kernel property extends to the whole space  $H$  :

$$\langle g, C(t, \cdot) \rangle_H = g(t), \quad t \in T, \quad g \in H.$$

Example 2.5.2

Let  $T = [0; 1]$ , and  $X$  be the Wiener process on  $T$  with covariance function  $C(s, t) = \min\{s, t\}$ . Show that the reproducing kernel Hilbert space  $H$  of  $X$ , is given by

$$H = \left\{ g : [0, 1] \rightarrow \mathbb{R} : g'(t) \text{ exists a.e. on } [0; 1], \quad g(t) = \int_0^t g'(s) ds \quad \text{and} \quad \int_0^1 (g'(t))^2 dt < \infty \right\} \quad (2.5.7)$$

with the scalar product

$$\langle f, g \rangle_H = \int_0^1 f'(t)g'(t)dt$$

(Cameron-Martin space).

First, if

$$f(t) = \sum_{i=1}^n a_i C(s_i, t) = \sum_{i=1}^n a_i \min\{s_i, t\} \in \mathbf{E},$$

$$g(t) = \sum_{j=1}^m b_j C(t_j, t) = \sum_{j=1}^m b_j \min\{t_j, t\} \in \mathbf{E}$$

then

$$f'(t) = \sum_{i=1}^n a_i (\min\{s_i, t\})' = \sum_{i=1}^n a_i I_{[0; s_i]}(t), \quad t \in [0; 1]$$

$$g'(t) = \sum_{j=1}^m b_j I_{[0; t_j]}(t)$$

and

$$\begin{aligned} \langle f, g \rangle_H &= \sum_{i=1}^n \sum_{j=1}^m a_i b_j \min\{s_i, t_j\} = \sum_{i=1}^n \sum_{j=1}^m a_i b_j \int_0^1 I_{[0; s_i]}(t) I_{[0; t_j]}(t) dt \\ &= \int_0^1 \sum_{i=1}^n a_i I_{[0; s_i]}(t) \sum_{j=1}^m b_j I_{[0; t_j]}(t) dt = \int_0^1 f'(t)g'(t)dt. \end{aligned}$$

Since  $g(t) = \int_0^t g'(s)ds$  for any  $g \in H$  as above, we get the reproducing kernel property:

$$\langle g, C(t, \cdot) \rangle_H = \int_0^1 g'(s) I_{[0; t]}(s) ds = \int_0^t g'(s) ds = g(t), \quad t \in [0; 1]$$

Hence,  $H$  defined above is indeed the reproducing kernel Hilbert space of  $X$ , cf. the following.

Exercise 2.5.3

Show that  $H$  given in (2.5.7) is indeed a Hilbert space and show that  $H = \overline{E}$  in the norm  $\|\cdot\|_H$ .

## Lemma 2.5.3

Let the covariance function  $C$  be continuous and let  $\{\varphi_n\}_{n \in \mathbb{N}}$  be an orthonormal basis in the reproducing kernel Hilbert space  $H$  for  $C$ . Then, lead  $\varphi_n$  is a continuous function on  $T$ , and

$$C(t, t) = \sum_{n=1}^{\infty} \varphi_n^2(t), \quad t \in T, \quad (2.5.8)$$

whereas the convergence of this series is uniform in  $t \in T$ .

Proof By the kernel reproducing property and Cauchy-Schwarz-inequality, we get  $\forall n \in \mathbb{N}$  and  $s, t \in T$

$$\begin{aligned} |\varphi_n(s) - \varphi_n(t)| &= | \langle \varphi_n(\cdot), C(s, \cdot) \rangle_H - \langle \varphi_n(\cdot), C(t, \cdot) \rangle_H | \\ &= | \langle \varphi_n(\cdot), C(s, \cdot) - C(t, \cdot) \rangle_H | \leq \underbrace{\|\varphi_n\|_H}_{=1} \cdot \|C(s, \cdot) - C(t, \cdot)\|_H = \\ &= \sqrt{\langle C(s, \cdot), C(s, \cdot) \rangle_H - 2 \langle C(s, \cdot), C(t, \cdot) \rangle_H + \langle C(t, \cdot), C(t, \cdot) \rangle_H} = \sqrt{C(s, s) - 2C(s, t) + C(t, t)} \\ &= \sqrt{\mathbf{E}[X(s) - X(t)]^2} = \varphi(s, t) \end{aligned}$$

by relation (1.5.1) on p. 21 and the definition of the canonical metric. Then  $\varphi_n(\cdot)$  is continuous on  $T$ , if so is  $C$ . Expanding  $C(t, \cdot)$  in a Fourier series w.r.t.  $\{\varphi_n\}_{n \in \mathbb{N}}$  and using the reproducing kernel property, we get

$$C(t, \cdot) = \sum_{n=1}^{\infty} \langle C(t, \cdot), \varphi_n(\cdot) \rangle_H \cdot \varphi_n(\cdot) = \sum_{n=1}^{\infty} \varphi_n(\cdot) \cdot \varphi_n(t), \quad t \in T \quad (2.5.9)$$

where the series converges in the  $\|\cdot\|_H$ -norm. For  $s = t$ , we get the pointwise convergence in the formula (2.5.8) by the reproducing kernel property. Now we have to show that this convergence is uniform in  $t \in T$ . The convergence of  $\sum_{n=1}^N \varphi_n^2(t)$  to  $C(t, t)$  as  $N \rightarrow \infty$  is obviously monotone, by Dini's theorem it is uniform in  $t \in T$ .  $\square$

## Remark 2.5.2

Compare formula (2.5.9) with representation (2.5.2) in Mercer's theorem!

## 2.5.3 Canonical isomorphism

Let  $\{X(t) : t \in T\}$  be a centered random real-valued function with a continuous covariance function  $C$  introduced in 2.5.2. Consider the subspace  $\overline{X} \subset L^2(\Omega, \mathcal{F}, \mathcal{P})$ , where  $\overline{X} = \overline{\text{span}\{X(t), t \in T\}}$  is the closure of the linear hull of  $X$  in  $L^2(\Omega, \mathcal{F}, \mathcal{P})$  equipped with the scalar product  $\langle \xi, \eta \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} = \mathbf{E}(\xi\eta)$ . Let  $H$  be the reproducing kernel Hilbert space of  $X$ . Let us show that  $H$  is isomorph to  $\overline{X}$ . For any

$$g(\cdot) = \sum_{i=1}^n a_i C(t_i, \cdot) \in \mathbf{E}$$

define the mapping  $\Delta : \mathbf{E} \mapsto \Delta(\mathbf{E}) \subset \overline{X}$ , by

$$\Delta(g) = \sum_{i=1}^n a_i X(t_i).$$

Evidently,  $\Delta$  is an isometry:

$$\|g\|_H^2 = \sum_{i,j=1}^n a_i a_j C(t_i, t_j) = \left\| \sum_{i=1}^n a_i X(t_i) \right\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})}^2 = \|\Delta(g)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})}^2, \quad g \in E.$$

Consequently,  $\Delta$  extends by limiting procedure to  $H = \overline{E}$  and the whole of  $\overline{X}$ .

So constructed,  $\Delta$  is called the canonical isomorphism. If  $\{\varphi_n\}_{n \in \mathbb{N}}$  is an orthonormal basis in  $H$ , then  $\xi_n = \Delta(\varphi_n) \in L^2(\Omega, \mathcal{F}, \mathcal{P})$  yields a sequence  $\{\xi_n\}_{n \in \mathbb{N}}$  of uncorrelated random variables with  $E\xi_n = 0$ ,  $E\xi_n^2 = 1$ , which forms an orthonormal basis of  $\overline{X}$ . In particular, we have  $\forall t \in T$ .

$$X(t) = \sum_{n=1}^{\infty} \langle X(t), \xi_n \rangle_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \xi_n = \sum_{n=1}^{\infty} \langle C(t, \cdot), \varphi_n \rangle_H \cdot \xi_n = \sum_{n=1}^{\infty} \varphi_n(t) \cdot \xi_n$$

by the isometry property of  $\Delta$  and the reproducing kernel property of  $\langle \cdot, \cdot \rangle_H$ , where the series converges to  $X(t)$  in  $L^2(\Omega, \mathcal{F}, \mathcal{P})$ . We proved the following result:

**Proposition 2.5.1**

If  $\{\varphi_n\}_{n \in \mathbb{N}}$  is an orthonormal basis in  $H$ , then there exists a sequence  $\{\xi_n\}_{n \in \mathbb{N}}$  of pointwise uncorrelated random variables with  $E\xi_n = 0$ ,  $E\xi_n^2 = 1$  such that

$$X(t) = \sum_{n=1}^{\infty} \varphi_n(t) \xi_n \tag{2.5.10}$$

in the  $L^2$ -sense. Hence,  $\xi_n = \Delta(\varphi_n)$ ,  $n \in \mathbb{N}$ .

**Remark 2.5.3**

If  $X$  is Gaussian, then all elements of  $\overline{X}$  are Gaussian random variables as well, and so are  $\{\xi_n\}_{n \in \mathbb{N}}$ . Hence, we get  $\xi_n \sim N(0, 1)$ ,  $\xi_n$  independent,  $n \in \mathbb{N}$ .

Evidently, the choice of random variables  $\xi_n$  heavily depends on the basis  $\{\varphi_n\}_{n \in \mathbb{N}}$ . This is a major difficulty in this theory to find an appropriate basis  $\{\varphi_n\}_{n \in \mathbb{N}}$  in  $H$ .

Mercer's theorem can help us to find such a basis  $\{\varphi_n\}$ , which leads to the so-called Karhunen-Loève expansion of  $X$ .

#### 2.5.4 Karhunen-Loève expansion

By Corollary 2.5.2, let  $\{\psi_n\}_{n \in \mathbb{N}}$  be an orthonormal basis of eigenfunctions of the Fredholm operator  $A_C$  (given by  $A_C g(t) = \int_T C(s, t) g(s) \nu(ds)$ ,  $g \in L^2(T, \mathcal{B}_T, \nu)$ ) with non-increasing eigenvalues  $\lambda_1 \geq \lambda_2 \geq \lambda_3 \cdots \geq 0$  in  $L^2(T, \mathcal{B}_T, \nu)$ .

**Lemma 2.5.4**

The reproducing kernel Hilbert space of  $C$  is given by

$$H = \left\{ g : g(t) = \sum_{n=1}^{\infty} a_n \varphi_n(t), \quad t \in T, \quad \sum_{n=1}^{\infty} a_n^2 < \infty, \quad \varphi_n = \sqrt{\lambda_n} \cdot \psi_n, \quad n \in \mathbb{N} \right\}$$

with the orthonormal basis  $\{\varphi_n\}_{n \in \mathbb{N}}$  and scalar product

$$\langle f, g \rangle_H = \sum_{n=1}^{\infty} a_n b_n, \quad f = \sum_{n=1}^{\infty} a_n \varphi_n, \quad g = \sum_{n=1}^{\infty} b_n \varphi_n, \quad f, g \in H.$$

Proof Let us show that  $\langle \cdot, \cdot \rangle_H$  has the reproducing kernel property: by Mercer's theorem, we get

$$\langle g(\cdot), C(t, \cdot) \rangle_H = \left\langle \sum_{n=1}^{\infty} a_n \varphi_n, \sum_{n=1}^{\infty} \varphi_n(t) \cdot \varphi_n \right\rangle_H = \sum_{n=1}^{\infty} a_n \varphi_n(t) = g(t), \quad t \in T.$$

By Mercer's theorem,  $\{\varphi_n\}_{n=1}^{\infty}$  forms a basis in  $H$ . By the definition of  $\langle \cdot, \cdot \rangle_H$ , it is orthonormal. It reasons to show that  $H$  is a Hilbert space (trivial exercise!).  $\square$

Remark 2.5.4

For

$$g = \underbrace{\sum_{n=1}^{\infty} a_n \varphi_n}_{\sum_{n=1}^{\infty} a_n \sqrt{\lambda_n} \psi_n} \in H,$$

we have  $a_n = \langle g, \varphi_n \rangle_H$ . At the same time, we have

$$\sqrt{\lambda_n} \cdot a_n = \langle g, \psi_n \rangle_{L^2(T, \mathcal{B}_T, \nu)} = \int_T g(t) \psi_n(t) \nu(dt),$$

hence

$$a_n = \sqrt{\lambda_n} \langle g, \psi_n \rangle_{L^2(T, \mathcal{B}_T, \nu)} = \frac{1}{\sqrt{\lambda_n}} \cdot \langle g, \psi_n \rangle_{L^2(T, \mathcal{B}_T, \nu)} \quad \text{for } \lambda_n > 0.$$

Hence,  $H$  consists of  $(L^2, \mathcal{B}_T, \nu)$ -integrable functions for  $g$  with the property

$$\|g\|_H^2 = \sum_{n=1}^{\infty} a_n^2 = \sum_{n=1}^{\infty} \frac{1}{\lambda_n} \left( \int_T g(t) \psi_n(t) \nu(dt) \right)^2 < \infty$$

and is equipped with the inner product

$$\langle f, g \rangle_H = \sum_{n=1}^{\infty} \frac{1}{\lambda_n} \int_T f(t) \psi_n(t) \nu(dt) \cdot \int_T g(t) \psi_n(t) \nu(dt).$$

Now take  $\varphi_n = \sqrt{\lambda_n} \psi_n$  in Proposition 2.5.1 to get the following.

Corollary 2.5.3 (Karhunen-Loève Expansion):

For any centered  $X = \{X(t), t \in T\}$  on a compact  $T$  with continuous covariance function  $C$ , there exists a family  $\{\xi_n\}_{n=1}^{\infty}$  of uncorrelated random variables with  $E\xi_n = 0$ ,  $E\xi_n^2 = 1$  such that

$$X(t) = \sum_{n=1}^{\infty} \sqrt{\lambda_n} \xi_n \psi_n(t), \quad (2.5.11)$$

where  $\{\psi_n\}_{n=1}^{\infty}$  is an orthonormal basis of eigenfunctions of the corresponding Fredholm operator with kernel  $C$  in  $L^2(T, \mathcal{B}_T, \nu)$ ,  $\lambda_n$  are the eigenvalues corresponding to  $\psi_n$ , and the above expansion holds in  $L^2(\Omega, \mathcal{F}, \mathcal{P})$ .

Remark 2.5.5 1. If  $X(\cdot, \omega) \in L_2(T, \mathcal{B}_T, \nu)$ , it holds

$$\xi_n = \frac{1}{\sqrt{\lambda_n}} \int_T X(t) \cdot \psi_n(t) \nu(dt), \quad n \in \mathbb{N}$$

Indeed, this formula follows by applying  $\langle \cdot, \psi_n \rangle_{L^2(T, \mathcal{B}_T, \nu)}$  on both sides of (2.5.11) and using the orthonormality of  $\{\psi_n\}_{n \in \mathbb{N}}$ .

2. Karhunen-Loève expansions hold also for complex-valued random functions with evident (minor) changes.

Example 2.5.3 (Wiener process):

By Example 2.5.1, 1), the Wiener process  $X = \{X(t) : t \in [0, 1]\}$  has the Karhunen-Loève expansion

$$X(t) = \frac{\sqrt{2}}{\pi} \sum_{n=0}^{\infty} \frac{1}{n + \frac{1}{2}} \sin\left(\left[n + \frac{1}{2}\right] \pi t\right) \xi_n, \quad t \in [0, 1]$$

where  $\{\xi_n\}_{n=1}^{\infty}$  are i.i.d.  $N(0, 1)$ -random variables. Later on, it will be shown that this convergence holds even a.s. and uniformly on  $[0, 1]$ .

Now, let us prove that:

Theorem 2.5.2

For Gaussian a.s. continuous random functions, the series (2.5.10) converges a.s. uniformly on  $T$ , whereas  $\{\xi_n\}$  are i.i.d.  $N(0, 1)$ -distributed random variables.

For the proof of this theorem, we need the following:

Lemma 2.5.5 (Itô-Nisio, 1968):

Let  $\{Y_n\}_{n \in \mathbb{N}}$  be a sequence of independent symmetric random elements with values in a separable real Banach space  $B$ , equipped with the mass topology. For

$$S_n = \sum_{i=1}^n Y_i$$

$\{S_n\}_{n \in \mathbb{N}}$  converges a.s. iff there exists a random element  $S$  such that

$$F(S_n) \xrightarrow[n \rightarrow \infty]{P} F(S)$$

for any  $F \in B^*$ , where  $B^*$  is the dual space to  $B$ .

This lemma goes back to Itô and Nisio (without proof).

Proof of Theorem 2.5.2

We know that

$$\sum_{n=1}^m \varphi_n(t) \xi_n$$

converges to Gaussian  $X(t)$  in  $L^2$ -sense, whereas  $X(\cdot)$  is a.s. continuous. Take  $Y_i = \varphi_i(t) \xi_i$ . Since  $\xi_i$  are i.i.d., the  $Y_i$  are independent. For any functional  $F \in (L^2(T, \mathcal{B}_T, \nu))^*$ , we have to show that

$$F(S_n) \xrightarrow[n \rightarrow \infty]{P} F(X(t)).$$

Show that this holds in  $L^2$ -sense:

$$\|F(S_n) - F(X(t))\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} \leq \|F\| \cdot \|S_n - X(t)\|_{L^2(T, \mathcal{B}_T, \nu)} \xrightarrow{n \rightarrow \infty} 0.$$

Then applying Lemma 2.5.5, we get that  $S_n$  a.s. converges to some random variables  $S$ , and  $S = X(t)$ . Now let us show that this convergence is uniform. Introduce the Banach space  $C(T)$  of all continuous functions on  $T$  with sup-norm. Clearly,  $X(\cdot), \xi_n \varphi_n(\cdot) \in C(T)$ .

Define

$$S_n(\cdot) = \sum_{k=1}^n \xi_k \varphi_k(\cdot)$$

and show by lemma 2.5.5 that

$$S_n(\cdot) \xrightarrow[n \rightarrow \infty]{a.s.} X(\cdot) \quad \text{in } C(T).$$

It suffices to show that

$$F(S_n(\cdot)) \xrightarrow[n \rightarrow \infty]{L^1} F(X(\cdot)) \quad \text{for any } F \in C^*(T).$$

It is known that

$$F(g) = \int_T g d\mu,$$

where  $\mu$  is a finite signed Borel measure on  $(T, \mathcal{B}_T)$ . Hence, we get

$$\begin{aligned} \mathbb{E}|F(S_n(\cdot)) - F(X(\cdot))| &= \mathbb{E} \left| \int_T (S_n(t) - X(t)) \mu(dt) \right| \leq \int_T \mathbb{E}|S_n(t) - X(t)| |\mu|(dt) \\ &\leq \int_T \|S_n(t) - X(t)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})} |\mu|(dt) = \int_T \sqrt{\sum_{j=n+1}^{\infty} \varphi_j^2(t)} |\nu|(dt) \end{aligned}$$

by Lyapunov's inequality, where  $|\mu|$  is the total variation measure of  $\mu$ . By lemma 2.5.3,

$$\sum_{j=n+1}^{\infty} \varphi_j^2(t) \xrightarrow[n \rightarrow \infty]{} 0$$

uniformly in  $t \in T$ , hence

$$F(S_n(\cdot)) \xrightarrow[n \rightarrow \infty]{P} F(X(\cdot))$$

and we are done □

### Theorem 2.5.3

We stress that the above decompositions hold only for compact  $T$ . If  $T$  is not compact (say, for stationary complex-valued  $X$ ) then the formally written "Karhunen-Loève expansion" may coincide within the spectral representation of  $X$ , as the following example shows:

Consider a second-order stationary complex-valued random field  $X = \{X(t) : t \in \mathbb{R}^d\}$  with



continuous covariance function  $C(s, t) = C_0(s - t)$ ,  $s, t \in \mathbb{R}^d$  such that it has a discrete spectral measure  $\mu$  in Bochner's theorem:

$$\mu(\cdot) = \sum_{j=1}^{\infty} \delta_{\lambda_j}(\cdot) \cdot \mu_j, \quad \lambda_j \in \mathbb{R}^d, \quad \mu_j > 0, \quad j \in \mathbb{N}.$$

Consider the set of functions  $\{e^{i\langle s, \lambda_j \rangle}\}_{j \in \mathbb{N}}$  as a "basis" on Mercer's theorem (which formally does not hold here, together with its generalizations to non-compact spaces; cf. [16]). Then, the formally written Karhunen-Loève expansion of  $X$  would yield

$$X(t) = \sum_{j=1}^{\infty} \sqrt{\mu_j} \xi_j e^{i\langle t, \lambda_j \rangle}, \quad t \in \mathbb{R}^d$$

where  $\{\xi_j\}$  are uncorrelated random variables with  $E\xi_j = 0$ ,  $E\xi_j^2 = 1$ ,  $j \in \mathbb{N}$ . This expansion coincides however with the spectral representation (2.4.4) of  $X$ , of being a discrete random measure

$$W(\cdot) = \sum_{j=1}^{\infty} \sqrt{\mu_j} \xi_j \delta_{\lambda_j}(\cdot).$$

Theorem 2.5.4 (Simulation of Gaussian random functions):

If the Karhunen-Loève expansion of a Gaussian random function  $X = \{X(t) : t \in T\}$  with a.s. continuous realizations on a compact  $T$  is known, it can be used to simulate  $X$  on  $T$  as follows. By Theorem 2.5.2,

$$X(t) \stackrel{a.s.}{=} \sum_{j=1}^{\infty} \sqrt{\lambda_j} \xi_j \psi_j(t), \quad t \in T$$

where  $\{\xi_j\}$  are i.i.d.  $N(0, 1)$  random variables,  $\lambda_j > 0$  and  $\psi_j(\cdot)$  some known functions. Then, one can simulate  $X(t)$  by taming its approximation

$$\hat{X}_N(t) = \sum_{j=1}^N \sqrt{\lambda_j} \xi_j \psi_j(t), \quad t \in T;$$

it holds

$$\hat{X}_N(t) \xrightarrow[N \rightarrow \infty]{a.s.} X(t)$$

uniformly in  $t \in T$ . For instance this method can be used to simulate the Brownian sheet; cf. Exercise 2.5.1. However, the convergence of  $\hat{X}_N$  to  $X$  may be rather slow, so that the performance of the simulation is poor: indeed, since  $\xi_j$  are i.i.d.  $N(0, 1)$ , we get

$$\begin{aligned} \delta_N(t) &= \|X(t) - \hat{X}_N(t)\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})}^2 = \left\| \sum_{j=N+1}^{\infty} \sqrt{\lambda_j} \xi_j \psi_j(t) \right\|_{L^2(\Omega, \mathcal{F}, \mathcal{P})}^2 \\ &= E \left| \sum_{j=N+1}^{\infty} \sqrt{\lambda_j} \xi_j \psi_j(t) \right|^2 = \sum_{j=N+1}^{\infty} \lambda_j \psi_j^2(t), \quad t \in T. \end{aligned}$$

The rate of convergence of this sum to zero as  $N \rightarrow \infty$  depends heavily on the choice of  $\{\psi_j\}_{j \in \mathbb{N}}$ . For instance, in case of the Brownian motion (cf. Example 2.5.3) for  $t \in [0, 1]$

$$\begin{aligned} \delta_N(t) &= \frac{2}{\pi^2} \sum_{j=N+1}^{\infty} \frac{\sin^2((j + \frac{1}{2})\pi t)}{(j + \frac{1}{2})^2} \leq \frac{2}{\pi^2} \sum_{j=N+1}^{\infty} \frac{1}{j^2} \leq \frac{2}{\pi^2} \int_{N+1}^{\infty} \frac{1}{x^2} dx \\ &= \frac{2}{\pi^2} (-1) \frac{1}{x} \Big|_{N+1}^{\infty} = \frac{2}{\pi^2(N+1)} = \Theta(N^{-1}), \quad N \rightarrow \infty. \end{aligned}$$

Exercise 2.5.4

Show that for the Wiener process  $X = \{X(t) : t \in [0, 1]\}$  the following (alternative to (2.5.11)) Karhunen-Loève representation holds:

$$X(t) = t \cdot \xi_0 + \sqrt{2} \sum_{n=1}^{\infty} \frac{\sin(\pi n t)}{\pi n} \xi_n, \quad t \in [0, 1] \quad (2.5.12)$$

where  $\{\xi_n\}_{n=0,1,\dots}$  is an i.i.d. sequence of  $N(0, 1)$ -distributed random variables. To do this, consider the Brownian bridge  $\varphi = \{\varphi(t) : t \in [0, 1]\}$  defined as a centered Gaussian process with covariance function  $C(s, t) = \min\{s, t\} - st$  and a.s. continuous paths. It can be proven (please check this!) that

$$\varphi(t) \stackrel{d}{=} X(t) - t \cdot X(1), \quad t \in [0, 1],$$

so that  $\varphi(0) = \varphi(1) = 0$  a.s. which justifies the value "Bridge". Then,

$$X(t) \stackrel{d}{=} \varphi(t) + t \cdot X(1) = \varphi(t) + t \cdot \xi_0, \quad t \in [0, 1],$$

where  $\xi_0 \sim N(0, 1)$ . Use this representation of  $X$  to proof (2.5.12) by finding the Karhunen-Loève representation of  $\varphi$ . For that, show as in Example 2.5.1, 1) that

$$\lambda_j = (\pi^2 j^2)^{-1}, \quad \psi_j(t) = \sqrt{2} \sin(\pi_j t), \quad j \in \mathbb{N}$$

Exercise 2.5.5 (Ornstein-Uhlenbeck-process):

The Ornstein-Uhlenbeck-process  $X = \{X(t) : t \in \mathbb{R}\}$  is a stationary centered Gaussian process with covariance function

$$C(s, t) = e^{-|s-t|}, \quad s, t \in \mathbb{R}$$

1. Show that

$$X(t) \stackrel{d}{=} e^{-t} \varphi(e^{2t}), \quad t \in \mathbb{R},$$

where  $\varphi = \{\varphi(t) : t \geq 0\}$  is a Wiener process.

2. Show that the spectral density  $f$  of  $X$  coincides with the Cauchy density:

$$f(x) = \frac{1}{\pi(1+x^2)}, \quad x \in \mathbb{R}$$

3. Find the Karhunen-Loève expansion for  $X$  on  $[-a, a]$  using representation 1).

## 2.6 Additional exercises

Exercise 1 Prove that the characteristic function of any random variable is a valid covariance function, i.e. it is positive definite.

Exercise 2 Prove Pólya's criterion: If  $C : [0; \infty) \rightarrow \mathbb{R}$  is such that  $C(0) = 1$ ,  $C(t)$  is continuous and convex, and  $\lim_{t \rightarrow \infty} C(t) = 0$ , then  $C$  is a positive definite function.

Exercise 3 Are the following functions  $C : \mathbb{R} \rightarrow \mathbb{R}$  valid covariance functions?

a)  $C(t) \equiv 0$

b)  $C(t) \equiv 1$

c) Nugget effect:  $C(t) = \begin{cases} 1, & t = 0 \\ 0, & t \neq 0 \end{cases}$

d)  $C(t) = \begin{cases} 1, & t = 0 \\ 1/2, & t \neq 0 \end{cases}$

e)  $C(t) = \sin(t)$

f)  $C(t) = \begin{cases} \exp(-|t|), & t \in \mathbb{Z} \\ 0, & \text{otherwise} \end{cases}$

Exercise 4 Prove the following statement: A function  $C : \mathbb{R} \rightarrow \mathbb{C}$  is real, continuous, and positive definite, if and only if it is the cosine transform of measure  $F$  on  $[0; \infty)$ , i.e.

$$C(x) = \int_{[0, \infty)} \cos(xt) dF(t) \quad \text{for all } x \in \mathbb{R}.$$

Compute the spectral density  $f$  for the following covariance functions  $C : \mathbb{R} \rightarrow \mathbb{R}$ :

1.  $C(x) = \exp(-x^2)$

2.  $C(x) = \exp(-|x|)$

3.  $C(x) = \begin{cases} 1 - \frac{|x|}{2}, & -2 \leq x \leq 2 \\ 0, & \text{otherwise} \end{cases}$

Exercise 5 Prove that  $\cos(x)$  is a valid covariance function on  $\mathbb{R}$ .

Exercise 6 There are several definitions for a stable random variable. Namely, a random variable  $X$  is said to have a stable distribution, if one of the following properties holds:

1. For each  $n \in \mathbb{N}$  there exist constants  $c_n > 0$ ,  $d_n \in \mathbb{R}$  such that  $X_1 + \dots + X_n \stackrel{d}{=} c_n X + d_n$ , where  $X_1, \dots, X_n$  are independent copies of  $X$ .

2. There are parameters  $\alpha \in (0, 2]$ ,  $\sigma \geq 0$ ,  $\beta \in [-1, 1]$  and  $\mu > 0$  such that the characteristic function  $\phi(t) = \mathbb{E} \exp(itX)$  of  $X$  has the form

$$\phi(t) = \begin{cases} \exp(-\sigma^\alpha |t|^\alpha (1 - i\beta \operatorname{sgn}(t) \tan \frac{\pi\alpha}{2}) + i\mu t) & \text{if } \alpha \neq 1 \\ \exp(-\sigma |t| (1 + i\beta \frac{2}{\pi} \operatorname{sgn}(t) \log |t|) + i\mu t) & \text{if } \alpha = 1. \end{cases}$$

Show that 2) implies 1). (In fact the two definitions are equivalent.)

Exercise 7 (The parameters of a stable random variable) According to the upper definition we can denote stable distributions by  $S_\alpha(\sigma, \beta, \mu)$ . The parameter  $\alpha$  is often called the index of stability because it can be shown that the norming constants  $c_n$  in Exercise 1 are of the form  $c_n = n^{1/\alpha}$  with  $\alpha \in (0, 2]$  (see Feller, 1967).

1. The parameter  $\mu$  is a shift parameter. This is backed by the following property. Let  $X \sim S_\alpha(\sigma, \beta, \mu)$  and let  $c \in \mathbb{R}$  be a constant. Show that  $X + c \sim S_\alpha(\sigma, \beta, \mu + c)$ .
2. The parameter  $\sigma$  is called the scale parameter. The reason lies in the following: Let  $X \sim S_\alpha(\sigma, \beta, \mu)$  and let  $c \in \mathbb{R} \setminus \{0\}$ . Show that

$$cX \sim \begin{cases} S_\alpha(|c|\sigma, \beta \operatorname{sgn}(c), c\mu) & \text{if } \alpha \neq 1, \\ S_1(|c|\sigma, \beta \operatorname{sgn}(c), c\mu - \frac{2}{\pi} c \log |c|\sigma\beta) & \text{if } \alpha = 1. \end{cases}$$

3. The parameter  $\beta$  is a skewness parameter. Show that, for any  $0 < \alpha < 2$  it holds

$$X \sim S_\alpha(\sigma, \beta, 0) \text{ if and only if } -X \sim S_\alpha(\sigma, -\beta, 0).$$

Exercise 8

1. Show that  $X \sim S_\alpha(\sigma, \beta, \mu)$  is symmetric about zero if and only if  $\beta = 0$  and  $\mu = 0$ .
2. Show that the random variable  $X \sim N(\mu, \sigma^2)$  is stable with  $\alpha = 2$ .
3. Show that the Cauchy random variable  $X$  with probability density function  $f_X(x) = \frac{\gamma}{\pi(x^2 + \gamma^2)}$ ,  $\gamma > 0$  is stable. What is the value of  $\alpha$ ?

Exercise 9

1. Find a simple formula for the variogram  $\gamma(s, t)$  of a random field  $X = \{X(t), t \in \mathbb{R}^d\}$  with mean value function  $\mu(t)$  and covariance function  $C(s, t)$ ,  $s, t \in \mathbb{R}^d$ ,  $d \geq 1$ .
2. Now assume that  $X$ , defined on a compact  $T \subset \mathbb{R}^d$  and  $\operatorname{diam} T := \sup_{s, t \in T} d(s, t) < \infty$  with the canonical pseudo-metric  $d(s, t) := \sqrt{2\gamma(s, t)} < \infty$ . The smoothness of the random field  $X$  is closely related to the behavior of  $\gamma(s, t)$  for points  $s, t \in \mathbb{R}^d$  with infinitesimal small distance. We now try to find a sufficient condition for the a.s. continuity of the field  $X$ . It is known that Gaussian random fields are a.s. continuous and bounded with probability one if there exists a  $\delta > 0$  such that

$$\int_\delta^\infty p(e^{-u^2}) du < \infty,$$

where  $p^2(u) = \sup_{|s-t| \leq u} 2\gamma(s, t)$ . Show that the existence of a constant  $K \in (0, \infty)$  and  $\alpha, \eta > 0$  such that

$$\gamma(s, t) \leq \frac{K}{|\log |s - t||^{1+\alpha}}$$

for all  $s, t$  with  $|s - t| < \eta$  is a sufficient condition for the a.s. continuity of  $X$ .

**Exercise 10** Let  $\nu$  be a finite measure, given on  $(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$ ,  $d \geq 1$ . Let  $Y, X_1, X_2, \dots$  be independent random elements on a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  such that  $Y \sim \text{Poi}(\nu(\mathbb{R}^d))$  and  $X_1, X_2, \dots$  i.i.d.  $d$ -dimensional  $\mathcal{F}|\mathcal{B}(\mathbb{R}^d)$ -measurable random vectors such that  $\mathbb{P}_{X_1}(B) = \nu(B)/\nu(\mathbb{R}^d)$ ,  $B \in \mathcal{B}(\mathbb{R}^d)$ . We introduce the Poisson random measure  $W : \mathcal{B}(\mathbb{R}^d) \times \Omega$  by

$$W(B, \omega) = \sum_{j=1}^{Y(\omega)} 1_B(X_j(\omega)), \quad B \in \mathcal{B}(\mathbb{R}^d).$$

Show that the Poisson random measure given on a semiring of bounded Borel sets in  $\mathbb{R}^d$  is an orthogonal non-centered random measure.

**Exercise 11** Let  $\{W_t, t \in \mathbb{R}\}$  be a complex-valued  $L^2$ -process such that

- i)  $E|W_s - W_t|^2 \rightarrow 0$  for any  $s \in \mathbb{R}$  with  $s \downarrow t$ ,
- ii) it has independent increments, i.e.  $E(W_{t_2} - W_{t_1})\overline{(W_{t_3} - W_{t_2})} = 0$  for any  $t_1 < t_2 < t_3$ .

We introduce the family of random variables  $W((a, b]) := W(b) - W(a)$  on the semiring  $\mathcal{K} = \{(a, b], -\infty < a \leq b < \infty\}$ , where  $(a, a] = \emptyset$ . Show that  $W$  is an orthogonal random measure on  $\mathcal{K}$ .

**Exercise 12** Let  $E$  be a measurable space, and  $\nu$  a  $\sigma$ -finite measure given on a semiring  $\mathcal{K}(E)$  of subsets of  $E$ . Show that simple functions of the form  $f : E \rightarrow \mathbb{C}$ ,  $f = \sum_{i=1}^m c_i 1_{B_i}$ , where  $c_i \in \mathbb{C}$ ,  $B_i \in \mathcal{K}(E)$ ,  $i = 1, \dots, m$ ,  $\bigcup_{i=1}^m B_i = E$ ,  $B_i \cap B_j = \emptyset$  for  $i \neq j$ , are dense in  $L^2(E, \nu)$ .

**Exercise 13** Show Lemma 2.3.4 4): Let  $E$  be a measurable space, and  $\nu$  a  $\sigma$ -finite measure given on a semiring  $\mathcal{K}(E)$  of subsets of  $E$ . Let  $W$  be a centered orthogonal random measure, i.e.  $EW(A) = 0$ ,  $A \in \mathcal{K}(E)$ . Show that  $EJ(f) = 0$  for  $f \in L^2(E, \nu)$ .

**Exercise 14** An illustrative example of the Karhunen Theorem (1)

1. Show that the Wiener process  $W = \{W(t), t \in [0, 2\pi]\}$  has the representation

$$W(t) = \frac{1}{\sqrt{2\pi}} \sum_{k=-\infty}^{\infty} \frac{1 - e^{-ikt}}{ik} z_k, \quad t \in [0, 2\pi],$$

where the  $z_k$  are uncorrelated centered random variables with unit variance and the series converges in the mean-square sense for every  $t \in [0, 2\pi]$

(for  $k = 0$  we set  $(1 - e^{-ikt})/ik = -t$ ). Use the following steps:

**Step 1:** Determine the values  $f(t, k)$ ,  $t \in [0, 2\pi]$ ,  $k \in \mathbb{Z}$  of the function  $f$  in the representation of the covariance function of the stochastic process, which are given as the coefficients of the Fourier series of  $1_{[0, t]}(u)$ .

**Step 2:** Determine the value of the covariance function  $C(s, t)$ ,  $s, t \in [0, 2\pi]$ , which arises by taking the space  $E = \mathbb{Z}$ , the counting measure  $\nu$  on  $\mathbb{Z}$ , i.e.  $\nu(\{k\}) = 1$ ,  $k \in \mathbb{Z}$  and the function  $f$  from step 1. Hint: Apply the Parseval equality.

Step 3: Apply the Karhunen Theorem.

Exercise 15 An illustrative example of the Karhunen Theorem (2)

Show that the Wiener process  $W = \{W(t), t \in [0, 1]\}$  has the representation

$$W(t) = \sum_{k=1}^{\infty} S_k(t) z_k, \quad t \in [0, 1],$$

where the  $S_k(t), t \in [0, 1], k \geq 1$  are the Schauder functions and the  $z_k$  are uncorrelated centered random variables with unit variance and the series converges in the mean-square sense for every  $t \in [0, 1]$ . Use the same steps as in the preceding exercise.

Exercise 16

Let  $W$  be a Gaussian white noise based on Lebesgue measure, and use it to define a random field on  $\mathbb{R}_+^d = \{(t_1, \dots, t_d) : t_i \geq 0\}$  by setting

$$W(t) = W([0, t]),$$

where  $[0, t]$  is the rectangle  $\prod_{i=1}^d [0, t_i]$ .  $W_t$  is called the Brownian sheet on  $\mathbb{R}_+^d$ , or multiparameter Brownian motion. If  $d = 1$ , it is the standard Brownian motion.

(a) Show that  $W$  is a centered Gaussian field on  $\mathbb{R}_+^d$  with covariance

$$E(W_s W_t) = \min(s_1, t_1) \times \cdots \times \min(s_d, t_d).$$

(b) Suppose  $d > 1$ , and fix  $d - k$  of the index variables  $t_i$ . Show that  $W$  is a scaled  $k$ -parameter Brownian sheet in the remaining variables.

(c) Find the Karhunen-Loève expansion for  $W$  on  $[0, 1]^d$ .

Exercise 17

Let  $T \in \mathbb{N}$  and  $X = \{X(t), t \in [0, T]\}$  be a real-valued process on  $[0, T]$  with  $EX(t) = 0$  and  $EX(t)^2 < \infty$  for all  $t \in [0, T]$ .

(a) Suppose that  $C(s, t) = \cos(2\pi(t - s))$ . Show that the Karhunen-Loève expansion has only two summands and determine the terms of the expansion.

(b) Suppose that  $C(s, t) = (1 - |t - s|)1\{0 \leq t - s \leq 2T\}$ . Determine the Karhunen-Loève expansion.

(c) Suppose that  $C(s, t) = \sum_{n=0}^{\infty} \frac{1}{1+n^2} \cos(n \frac{2\pi}{T}(t - s))$ . Find the eigenvalues and eigenfunctions of the Fredholm operator  $A$  from Exercise 1.

Exercise 18 Let  $\{X(t), t \in [0, 1]\}$  be the Brownian motion with covariance function  $C(s, t) = \min\{s, t\}$  for  $s, t \in [0, 1]$ . Show that

$$\mathcal{H} = \{g : [0, 1] \rightarrow \mathbb{R} \text{ cont.} : \exists g'(t) \text{ for almost all } t \in [0, 1], g(s) = \int_0^s g'(t) dt, \int_0^1 (g'(t))^2 dt < \infty\}$$

is the corresponding reproducing kernel Hilbert space.

Exercise 19 Let  $X = \{X_t, t \in \mathbb{R}\}$  be a random polynomial with  $X_t = Y_0 + Y_1 t + \dots + Y_n t^n$ ,  $Y_i \sim \mathcal{N}(0, 1)$  i.i.d.,  $i = 0, \dots, n$ . Determine the expected value, the variance, the covariance function and the characteristic function of  $X_t$ .

Exercise 20

- (a) Calculate the spectral density of a random process  $X = \{X_t, t \in \mathbb{R}\}$  with
- triangular covariance function  $C(h) = (1 - |h|)1\{|h| \leq 1\}$ ,
  - covariance function  $C(h) = \frac{1}{8}e^{-|h|} (3 \cos(h) + \sin |h|)$ .
- (b) Show that the spectral density of the Ornstein-Uhlenbeck process with covariance function  $C(s, t) = \exp\{-\alpha|t - s|\}$ ,  $s, t \in \mathbb{R}$ ,  $\alpha > 0$ , is given by

$$f(u) = \frac{1}{\pi} \frac{\alpha}{1 + \alpha^2 u^2}, \quad u \in \mathbb{R},$$

and verify that it can be interpreted as a Gamma(1/2)-mixture of Gaussian distributions, i. e.

$$f(u) = \int_0^\infty \left(\frac{t\alpha^2}{\pi}\right)^{\frac{1}{2}} e^{-t\alpha^2 u^2} \frac{1}{\sqrt{\pi}} e^{-t} t^{\frac{1}{2}-1} dt, \quad u \in \mathbb{R}.$$

- (c) Calculate the spectral density of a random field  $X = \{X_t, t \in \mathbb{R}^2\}$  with Gaussian covariance function  $C(h) = e^{-\|h\|_2^2}$ .

#### Exercise 21

Let  $T$  be a separable and compact Hausdorff space. Let  $\mathcal{H}$  be a Hilbert space of functions  $g : T \rightarrow \mathbb{R}$  which admits a reproducing kernel. Show that the reproducing kernel is uniquely determined by the Hilbert space  $\mathcal{H}$ .

#### Exercise 22

Show that under the same assumptions of Exercise 3, the reproducing kernel of a reproducing kernel Hilbert space is positive semi-definite.

#### Exercise 23

A stochastic process  $\{B(t), t \in [0, 1]\}$  is called a Brownian bridge if

- the joint distribution of  $B(t_1), B(t_2), \dots, B(t_n)$ ,  $t_1, \dots, t_n \in [0, 1]$ ,  $n \in \mathbb{N}$  is Gaussian with  $EB(t) = 0$  for all  $t \in [0, 1]$ ,
- the covariance function of  $B(t)$  is given by

$$C(s, t) = \min\{s, t\} - st,$$

- the sample path function of  $B(t, \omega)$  is continuous in  $t$  with probability one.

- (a) Find the Karhunen-Loève expansion of the Brownian bridge.
- (b) Show that  $B(t) = W(t) - tW(1) = (1 - t)W\left(\frac{t}{1-t}\right)$ ,  $t \in [0, 1]$ , where  $\{W(t), t \in [0, 1]\}$  is the Brownian motion.
- (c) Find a representation of the Brownian bridge based on the Karhunen-Loève expansion of the Brownian motion. Compare this representation with the Karhunen-Loève expansion of the Brownian bridge.

#### Exercise 24

A stochastic process  $\{X(t), t \geq 0\}$  is called Ornstein-Uhlenbeck process if it is a centered Gaussian process with covariance function  $C(s, t) = \exp\{-\alpha|t - s|\}$ ,  $s, t \geq 0$ ,  $\alpha > 0$ . Show that  $X$  is a transformed Brownian motion and determine the corresponding (transformed) Karhunen-Loève expansion.

## 3 Models of random fields

Starting with a more detailed treatment of the basics of Gaussian random functions, we shall introduce more general classes of random functions such as stable, infinitely divisible and self-similar (fractal) random functions.

### 3.1 Gaussian random fields

In Definition 1.2.2, Gaussian random functions were introduced by giving all their finite-dimensional distributions, which are multivariate normal ones. It has been shown that the probability base of Gaussian random functions is fixed by their mean value and covariance functions. In this section, we are going to consider some of the properties of Gaussian random functions such as a.s. boundedness, a.s. continuity of realisations, differentiability, etc. in more detail. However, we shall not be able to cover many important aspects of their theory, on which excellent specialized monographs already exist (cf. [1], [15], [37], [44]).

First of all, consider the properties of paths of Gaussian random functions. Then, let us deepen some of the examples of Gaussian random functions which we already encountered in Chapters 1 and 2.

#### 3.1.1 Properties of paths of Gaussian random functions

Let  $X = \{X(t) : t \in T\}$  be a real-valued random function on a topological space  $T$ .

Definition 3.1.1

$X$  is called separable, if there exists a countable dense subset  $D \subset T$  and a fixed event  $A$  with  $P(A) = 0$  such that

$$\{\omega \in \Omega : X(t) \in B, t \in I \cap D\} \setminus \{\omega \in \Omega : X(t) \in B, t \in I\} \subset A$$

for any closed subset  $B \subset \mathbb{R}$  and open  $I \subset T$ .

It can be proven (cf. [43]) that any random function  $X$  with index space  $T$  being a metrical space and values in a compact set  $K \subset \mathbb{R}$  has a separable modification. Later on, we assume that  $X$  be always separable. Separability is introduced in order to study the properties of  $\sup X(t)$ ,  $I$ -open subset of  $T$ . Indeed, we first need to prove that  $\sup X(t)$  is a random variable, i.e. is  $\mathcal{F}|\mathcal{B}_{\mathbb{R}}$ -measurable. This holds true, since

$$\sup_{t \in I} X(t) \stackrel{a.s.}{=} \sup_{t \in I \cap D} X(t)$$

due to separability of  $X$ , and  $\sup_{t \in I \cap D}$  is measurable, since this supremum is taken over a countable set of random variables  $X(t)$ ,  $t \in I \cap D$ . Now assume that  $T$  is a compact metric space with distance function  $\Delta$  on  $T$ . Then, for separable  $X$ ,  $\sup_{t \in T} X(t) \stackrel{a.s.}{=} \sup_{t \in D} X(t)$  is a valid random



variable. Let  $X$  be a (real-valued separable) Gaussian random function on  $T$ . Considering a.s. boundedness and continuity of  $X$ , first let us show that the choice of the metric  $\Delta$  is irrelevant, since it can be always replaced by the canonical metric

$$\rho(s, t) = \sqrt{\mathbb{E}(X(s) - X(t))^2}, \quad s, t \in T.$$

Lemma 3.1.1

Let  $X$  be a random function as above with  $\sup_{t \in T} \mathbb{E}X^2(t) < \infty$ , which is a.s. continuous:

$$\forall t \in T, \quad \lim_{s \xrightarrow{\Delta} t} X(s) = X(t) \quad \text{a.s.}$$

Then,  $X$  is mean square continuous as well. In other words,  $\rho$  is a continuous function.

$$\lim_{s \xrightarrow{\Delta} t} \rho(s, t) = 0, \quad t \in T.$$

Hence  $s \xrightarrow{\Delta} t$  means that  $\Delta(s, t) \rightarrow 0$ .

To prove this lemma, we need the following two facts from the basic probability course:

Definition 3.1.2

A family of random variables  $\{\xi_n\}_{n \in \mathbb{N}}$  is uniformly integrable, if

$$\sup_{n \in \mathbb{N}} \mathbb{E} [|\xi_n| I(|\xi_n| > x)] \xrightarrow{x \rightarrow \infty} 0.$$

Lemma 3.1.2

A family of random variables  $\{\xi_n\}_{n \in \mathbb{N}}$  is uniformly integrable iff

1. Uniform boundedness:

$$\sup_{n \in \mathbb{N}} \mathbb{E}|\xi_n| < \infty$$

2. Uniform absolute continuity:

$$\sup_{n \in \mathbb{N}} \mathbb{E} [|\xi_n| I(A_m)] \rightarrow 0,$$

if  $P(A_m) \rightarrow 0$

Without Proof; see e.g. [9], p. 190.

Theorem 3.1.1

If  $\{\xi_n\}_{n \in \mathbb{N}}$  is uniformly integrable and

$$\xi_n \xrightarrow[n \rightarrow \infty]{a.s.} \xi, \quad \text{then } \mathbb{E}|\xi| < \infty \quad \text{and} \quad \mathbb{E}\xi_n \xrightarrow[n \rightarrow \infty]{} \mathbb{E}\xi, \quad \mathbb{E}|\xi_n - \xi| \xrightarrow[n \rightarrow \infty]{} 0.$$

Without Proof; see [9], p. 188.

Proof of Lemma 3.1.1 Fix a  $t \in T$ . Introduce a random field  $Y(s) = (X(s) - X(t))^2$ ,  $s \in T$ . It holds

$$\sup_{s \in T} EY(s) \leq 2 \sup_{s \in T} EX^2(s) < \infty.$$

To show that  $\{Y(s) : s \in T\}$  is uniformly integrable, it is sufficient (by Lemma 3.1.2) to prove that

$$\sup_{s \in T} E[Y(s)I(A_m)] \rightarrow 0, \quad \text{if } P(A_m) \xrightarrow{m \rightarrow \infty} 0.$$

By the inequality of Cauchy-Schwarz, we have

$$\sup_{s \in T} E[Y(s)I(A_m)] \leq \sup_{s \in T} \sqrt{EY^2(s)}P(A_m) \rightarrow 0,$$

since

$$\sup_{s \in T} \sqrt{EY^2(s)} < \infty$$

due to the Gaussianity of  $X$ . Then,  $\{Y(s) : s \in T\}$  is uniformly integrable and then by Theorem 3.1.1 it holds

$$EY(s) \xrightarrow{s \rightarrow t} 0 \quad \text{since } Y(s) \xrightarrow{s \rightarrow t} 0;$$

□

In the sequel, assume that  $\rho$  is always continuous with respect to the  $\Delta$ -convergence.

Lemma 3.1.3

Let  $X$  be a centered separable real-valued Gaussian process on a compact metric space  $(T, \Delta)$ . Then  $X$  is a.s. continuous w.r.t. the topology induced by  $\Delta$ , iff it is a.s. continuous w.r.t. the topology induced by  $\rho$ .

Proof We have to show that

$$\lim_{s, \Delta(s, t) \rightarrow 0} |X(s) - X(t)| \stackrel{a.s.}{=} 0 \quad \Leftrightarrow \quad \lim_{s: \rho(s, t) \rightarrow 0} |X(s) - X(t)| = 0, \quad t \in T.$$

Fix any  $t \in T$ . Since  $\rho$  is  $\Delta$ -continuous, we have

$$\Delta(s, t) \rightarrow 0 \quad \Rightarrow \quad \rho(s, t) \rightarrow 0$$

and then

$$\lim_{s: \rho(s, t) \rightarrow 0} |X(s) - X(t)| \stackrel{a.s.}{=} 0 \quad \Rightarrow \quad \lim_{s: \Delta(s, t) \rightarrow 0} |X(s) - X(t)| \stackrel{a.s.}{=} 0$$

Let us prove the reverse statement. Let  $X$  be a.s.  $\Delta$ -continuous. For any  $\delta > 0$ , introduce

$$A_\delta = \{(s, t) \in T \times T : \rho(s, t) \leq \delta\} \subset T \times T.$$

Since  $T$  is compact. Hence so is  $T \times T$ . Since  $\rho$  is  $\Delta$ -continuous  $A_\delta$  is  $\Delta$ -closed in  $T \times T$  (and hence a compact in  $T \times T$ ). Take

$$A_0 = \bigcap_{\delta > 0} A_\delta.$$

Then  $A_0$  is compact as well, and by the properties of compactness  $\forall \varepsilon > 0 \exists$  an finite  $\varepsilon$ -network of balls with centers in  $A_0$  covering  $A_0$ :

$$A_0 \subset \bigcup_{(s',t') \in B} \{(s,t) \in T \times T : \Delta(s,s') \leq \varepsilon, \quad \Delta(t,t') \leq \varepsilon\}$$

for a finite subset  $B \subset A_0$ . By  $\Delta$ -continuity of  $\rho$ , there exists  $\delta(\varepsilon) \rightarrow 0$  such that  $A_{\delta(\varepsilon)}$  is covered by this finite  $\varepsilon$ -network as well, i.e., for any

$$(s,t) \in A_{\delta(\varepsilon)} \quad \exists \quad (s',t') \in B : \quad \Delta(s,s') \leq \varepsilon, \quad \Delta(t,t') \leq \varepsilon.$$

Since

$$|X(s) - X(t)| \leq |X(s) - X(s')| + \underbrace{|X(s') - X(t')|}_{=0} + |X(t') - X(t)|$$

\*a.s., since  $s',t' \in B \subset A_0$

we get

$$\sup_{s,t \in T: \rho(s,t) \leq \eta(\varepsilon)} |X(s) - X(t)| \leq 2 \sup_{s,t \in T: \Delta(s,t) \leq \varepsilon} |X(s) - X(t)|,$$

hence  $X$  is a.s.  $\rho$ -continuous as well. □

**Remark 3.1.1**

The assertion of this lemma is obviously true for  $\sigma$ -compact metric spaces  $T$ .

**Definition 3.1.3**

Let  $X$  be a centered Gaussian random field on a  $\rho$ -compact  $T$ . For any  $\varepsilon > 0$ , let  $N(\varepsilon)$  be the smallest number of  $\rho$ -balls of radius  $\varepsilon$  covering  $T$ :  $N(\varepsilon) = N(T, \rho, \varepsilon)$ . Then  $N(\varepsilon)$  is called the (metric) entropy of  $T$  (or  $X$ ).  $H(\varepsilon) = \log N(\varepsilon)$  is a log-entropy of  $T$ . Since  $T$  is  $\rho$ -compact, it follows that  $N(\varepsilon) < \infty$ ,  $\varepsilon > 0$ . Introduce

$$\text{diam}_\rho(T) = \sup_{s,t \in T} \rho(s,t).$$

For  $\varepsilon \geq \text{diam}_\rho(T)$ , we obviously have  $N(\varepsilon) = 1$ . Introduce the modulus of continuity of  $X$  by

$$\omega_{X,\rho}(\delta) = \sup_{s,t \in T: \rho(s,t) \leq \delta} |X(s) - X(t)|, \quad \delta > 0.$$

We would like to state the following results without proof. For proofs, see [1], p.14 ff.

**Theorem 3.1.2**

Let  $X = \{X(t) : t \in T\}$  be centered separable Gaussian random field on a  $\rho$ -compact  $T$  with the metric entropy  $H(\varepsilon)$ . Then,

$$\mathbb{E} \sup_{t \in T} X(t) \leq K \cdot \int_0^{\frac{\text{diam}(T)}{2}} \sqrt{H(\varepsilon)} d\varepsilon,$$

where  $K \geq 0$  is a constant.

Theorem 3.1.3

Under conditions of Theorem 3.1.2 there exists a random variable  $\eta$  such that

$$\omega_{X,\rho}(\delta) \leq K \cdot \int_0^\delta \sqrt{H(\varepsilon)} d\varepsilon$$

for all  $\delta \leq \eta$ , where  $K \geq 0$  is a constant.

Theorem 3.1.4

Let  $X$  be a centered Gaussian random field with

$$P(\sup_{t \in T} X(t) < \infty) = 1.$$

$X$  is a.s. uniformly  $\rho$ -continuous on  $T$  iff  $\varphi(\delta) \rightarrow 0$  as  $\delta \rightarrow 0$  with

$$\varphi(\delta) = E \sup_{\rho(s,t) \leq \delta} (X(s) - X(t)).$$

Furthermore, if  $\varphi(\delta) \rightarrow 0$  as  $\delta \rightarrow 0$ , then for all  $\varepsilon > 0 \exists$  an a.s. finite random variable  $\eta > 0$  such that

$$\omega_{X,\rho} \leq \varphi(\delta) \cdot |\ln \varphi(\delta)|^\varepsilon,$$

for all  $\delta \leq \eta$

Now consider the special case of  $T$  being a compact subset of  $\mathbb{R}^d$ . Introduce

$$p(u) = \sqrt{\sup_{|s-t| \leq u} 2\gamma(s,t)} = \sqrt{\sup_{|s-t| \leq u} E|X(s) - X(t)|^2},$$

where  $|\cdot|$  is the Euclidean metric. For stationary  $X$ , it holds

$$p(u) = \sqrt{2 \sup_{|t| \leq u} |C(0) - C(t)|}.$$

Let  $\omega_X(\delta)$  be the modulus of continuity of a random field  $X$  with respect to the Euclidean metric.

Corollary 3.1.1

If either

$$\int_0^\delta \sqrt{-\log u} dp(u) < \infty \quad \text{or} \quad \int_\delta^\infty p(e^{-u^2}) du < \infty$$

for some  $\delta > 0$ , then the centered Gaussian random field  $X$  on  $T$  is a.s. continuous and bounded. Furthermore there exists a constant  $K = K(d)$  and a random variable  $\eta$  such that

$$\omega_X(\delta) \leq K \cdot \int_0^{p(\delta)} \sqrt{-\log u} dp(u)$$

for all  $\delta < \eta$ .

Proof Let us show that our assertion follows from Theorem 3.1.3, if we prove that

$$\int_0^\delta \sqrt{H(\varepsilon)} d\varepsilon \leq K \cdot \int_0^{p(\delta)} \sqrt{-\log u} dp(u)$$

for small  $\delta$ . First of all, since  $p(u)$  is non-decreasing, the Riemann integral

$$\int_0^\delta \sqrt{-\log u} dp(u)$$

is well-defined.

Let  $L$  be the side length of the smallest centre  $c_L$  containing a compact  $T$ . Since

$$p(u) = \sqrt{\sup_{|s-t| \leq u} \rho^2(s, t)} = \sup_{|s-t| \leq u} \rho(s, t),$$

$c_L$  (and hence  $T$ ) can be covered by at least  $\left(\frac{L}{\Delta}\right)^d$  Euclidean Balls of radius  $\Delta > 0$ ; if  $p(\Delta) = \varepsilon \Rightarrow \Delta = p^{-1}(\varepsilon)$  where  $p^{-1}(\varepsilon) = \sup\{u : p(u) \leq \varepsilon\}$  is a generalised inverse of a non-decreasing function  $p$ . Hence,

$$N(\varepsilon) \leq \left(\frac{L}{\Delta}\right)^d = \left(\frac{L}{p^{-1}(\varepsilon)}\right)^d \Rightarrow H(\varepsilon) = \log N(\varepsilon) \leq d \log \left(\frac{L}{p^{-1}(\varepsilon)}\right)$$

and

$$\begin{aligned} \int_0^\delta \sqrt{H(\varepsilon)} d\varepsilon &\leq \sqrt{d} \int_0^\delta \sqrt{\log L - \log p^{-1}(\varepsilon)} d\varepsilon \stackrel{u=p^{-1}(\varepsilon), \varepsilon=p(u)}{=} \sqrt{d} \int_0^{p(\delta)} \sqrt{\log L - \log u} dp(u) \\ &\leq \underbrace{2\sqrt{d}}_K \int_0^{p(\delta)} \sqrt{-\log u} dp(u), \end{aligned} \quad (3.1.1)$$

for small enough  $\delta$  because

$$\exists \delta > 0 : \quad \log L \leq -3 \log u \quad \text{for } |u| \leq p(\delta),$$

and hence

$$\sqrt{\log L - \log u} \leq \sqrt{-4 \log u} = 2\sqrt{-\log u}.$$

□

Remark 3.1.2

A sufficient condition for the integrals in Corollary 3.1.1 to be finite is

$$\rho(s, t) \leq \frac{c}{|\log |s-t||^{\frac{1}{2}+\alpha}}, \quad c, \alpha > 0, \quad \forall s, t : |s-t| < \beta.$$

Proof If

$$\rho(s, t) \leq \frac{c}{|\log |s-t||^{\frac{1}{2}+\alpha}}, \quad s, t : |s-t| \leq \beta,$$

then

$$p(u) \leq \frac{c}{|\log u|^{\frac{1}{2}+\alpha}}, \quad 0 \leq u \leq \beta,$$

and

$$\begin{aligned} \int_0^\delta \sqrt{-\log u} dp(u) &= p(u) \cdot \sqrt{-\log u} \Big|_0^\delta - \int_0^\delta p(u) d(-\log u)^{\frac{1}{2}} \stackrel{p(0)=0}{=} p(\delta) \sqrt{-\log \delta} \\ &+ \int_0^\delta p(u) \frac{1}{2} \frac{1}{\sqrt{-\log u}} d \log u \leq p(\delta) \sqrt{-\log \delta} + \int_0^\delta \frac{c \cdot d \log u}{|\log u|^{1+\alpha}} \\ &= p(\delta) \sqrt{-\log \delta} + c \int_{-\infty}^{\log \delta} \frac{dx}{|x|^{1+\alpha}} < \infty \text{ for } \delta \leq \beta. \end{aligned}$$

□

The above necessary conditions are quite sharp in the stationary case, as it can be seen from the following.

**Proposition 3.1.1**

If  $X = \{X(t) : t \in T\}$  is a stationary centered Gaussian random field,  $T \subset \mathbb{R}^d$  is open and for the covariance function  $C$  of  $X$  the inequality

$$\frac{K_1}{(-\log |t|)^{1+\alpha_1}} \leq C(0) - C(t) \leq \frac{K_2}{(-\log |t|)^{1+\alpha_2}}$$

holds for  $|t|$  small enough. Then  $X$  has a.s. continuous realizations if  $\alpha_2 > 0$ , and a.s. discontinuous realizations, if  $\alpha_1 < 0$ .

(Without proof; see the proof in [1], p. 47-48)

**Exercise 3.1.1**

Show that conditions of Corollary 3.1.1 are satisfied for the Brownian motion  $X = \{X(t) : t \in [0; 1]\}$ .

Conditions for a.s. continuity can be also formulated in terms of the spectral measure of  $X$ :

**Proposition 3.1.2**

Let  $X = \{X(t) : t \in T\}$  be a centered Gaussian process on a compact  $T \subset \mathbb{R}$  with spectral measure  $\mu$ . If

$$\int_0^\infty (\log(1 + \lambda))^{1+\alpha} \mu(d\lambda) < \infty$$

for some  $\alpha > 0$ , then  $X$  has a.s. continuous paths. If this integral diverges for some  $\alpha < 0$  then  $X$  is a.s. discontinuous.

(Without proof; see [4])

Now suppose that  $X$  is a centered Gaussian random field on  $T \subset \mathbb{R}^d$  and examine the question of a.s. differentiability of its realisations.

**Definition 3.1.4**

Let  $t \in \mathbb{R}^d$ . For any  $k \in \mathbb{N}$  directions  $h_1, \dots, h_k \in \mathbb{R}^d$ , introduce the  $L^2$ -partial derivative of  $X$  in  $t$  in direction  $h = (h_1, \dots, h_k)$  (or mean-square partial derivative) of order  $k$  by

$$\frac{\partial^k X(t)}{\partial h} = \lim_{\delta_1, \dots, \delta_k \rightarrow 0} \frac{\Delta^k X(t, (\delta_i, h_i))}{\delta_1 \cdot \dots \cdot \delta_k},$$

where

$$\Delta^k X(t, y) = \sum_{s \in \{0,1\}^k, s=(s_1 \dots s_k)} (-1)^{k-\sum_{i=1}^k s_i} X(t + \sum_{i=1}^k s_i y_i), \quad y = (y_1, \dots, y_k),$$

is the symmetrical difference of  $X$  and the limit is understood sequentially in the mean square sense: first  $\delta_1 \rightarrow 0$ , then  $\delta_2 \rightarrow 0$  and so on.

Lemma 3.1.4

Furthermore:

1. A random field  $X$  is mean square differentiable of order  $k$  in all directions in a region  $T \subset \mathbb{R}^d$ , if

$$\lim_{\delta_1, \dots, \delta_k, \delta'_1, \dots, \delta'_k \rightarrow 0} \frac{1}{\delta_1 \dots \delta_k \cdot \delta'_1 \dots \delta'_k} \mathbb{E}(\Delta^k X(t, \delta_1 h_1 \dots \delta_k h_k) \cdot \Delta^k X(s, \delta'_1 h'_1 \dots \delta'_k h'_k)) \quad (3.1.2)$$

exists for all  $s, t \in T$  and directions  $h, h' \in (\mathbb{R}^d)^k$ .

2. If  $X$  is Gaussian then  $\frac{\partial^k X}{\partial h^k}$  is Gaussian as well for any  $h \in (\mathbb{R}^d)^k$ .

Proof Property 2. is obvious since a  $L^2$ -limit of Gaussian random variables is Gaussian.

1. For any random variables  $\{Y_n\}_{n \in \mathbb{N}}$  with  $\mathbb{E}Y_n^2 < \infty$ ,  $n \in \mathbb{N}$  it holds that  $\{Y_n\}$  converges in  $L^2$ -sense as  $n \rightarrow \infty$  iff  $\mathbb{E}(Y_n Y_m)$  converges as  $nm \rightarrow \infty$ . Indeed,

$$\mathbb{E}|Y_n - Y_m|^2 \xrightarrow{n, m \rightarrow \infty} 0 \quad \text{iff} \quad \mathbb{E}(Y_n \cdot Y_m) \xrightarrow{n, m \rightarrow \infty} c,$$

since

$$\mathbb{E}|Y_n - Y_m|^2 = \mathbb{E}Y_n^2 - 2\mathbb{E}(Y_n \cdot Y_m) + \mathbb{E}Y_m^2, \quad \forall n, m \in \mathbb{N}.$$

Then

$$\frac{\Delta^k X(t, (\delta_1 h_1, \dots, \delta_k h_k))}{\delta_1 \cdot \dots \cdot \delta_k}$$

converges to a limit as  $\delta_1, \dots, \delta_k \rightarrow 0$  in  $L^2$ -sense if condition (3.1.2) holds true.  $\square$

Now take the space  $\mathbb{R}^d \times (\mathbb{R}^d)^k$  with the norm  $\|\cdot\|_{d,k}$  given by  $\|(t, y)\|_{d,k} = |t|_{\mathbb{R}^d} + |y|_{\mathbb{R}^{dk}}$ , where  $|x|_{\mathbb{R}^n}$  is the Euclidean norm in  $\mathbb{R}^n$ . Let  $B_r(t, y)$  be the ball of radius  $r > 0$  with center at  $(t, y)$  in some space  $\mathbb{R}^d \times (\mathbb{R}^d)^k$ . Introduce the set  $T_\varepsilon = T \times \{y : 1 - \varepsilon < |y|_{\mathbb{R}^{dk}} < 1 + \varepsilon\}$

Theorem 3.1.5

Let  $X$  be a centered Gaussian random field given on a open index set  $T \subset \mathbb{R}^d$  which has all  $k$ th-order  $L^2$ -partial derivatives in all directions everywhere in  $T$ .  $X$  is  $k$  times continuously differentiable with probability one, i.e.,  $X \in C^k(T)$  a.s., if  $\exists C \in (0; \infty)$  and  $\varepsilon, \gamma, r_0 > 0$  such that

$$\mathbb{E}(\Delta^k X(t, \delta_1 \cdot y_1) - \Delta^k X(s, \delta_2 \cdot y_2))^2 \leq C [-\log(\|(t, y_1) - (s, y_2)\|_{d,k} + |\delta_1 - \delta_2|)]^{-(1+\gamma)} \quad (3.1.3)$$

for all  $((t, y_1), (s, y_2)) \in T_\varepsilon \times T_\varepsilon : (s, y_2) \in B_r(t, y_1)$  and some  $0 < \delta_1, \delta_2, r < r_0$ .

Proof Define a new Gaussian random field  $\tilde{X} = \{\tilde{X}(t, y, \delta) : (t, y, \delta) \in \tilde{T}\}$ , where  $\tilde{T} = T_\varepsilon \times (-r; r)$  is an open subset of  $\mathbb{R}^d \times (\mathbb{R}^d)^k \times \mathbb{R}$  with the norm  $\|(t, y, \delta)\|_{d,k,1} = \|(t, y)\|_{d,k} + |\delta|$  and

$$\tilde{X}(t, y, \delta) = \begin{cases} \frac{\Delta^k X(t, \delta y)}{\partial^k}, & \delta \neq 0 \\ \frac{\partial^k X(t)}{\partial y}, & \delta = 0 \end{cases} \quad (t, y, \delta) \in \tilde{T}.$$

$X \in C^k(T)$  a.s. iff  $\tilde{X} \in C(\tilde{T})$ . Moreover, it is clearly enough if  $\tilde{X} \in C$  (hyperplane  $\delta = 0$  in  $\tilde{T}$ ). But condition (3.1.3) being true, our assertion follows from Corollary 3.1.1 and Remark 3.1.2.  $\square$

### 3.1.2 Gaussian random polynomials

Let  $X = \{X(t) : t \in \mathbb{R}^d\}$  be a random field given by

$$X(t) = \sum_{|\alpha| \leq n} a_\alpha \cdot t^\alpha, \quad t = (t_1 \dots t_d)^T \in \mathbb{R}^d,$$

where  $\alpha = (\alpha_1, \dots, \alpha_d)^T$  is a multiindex with  $\alpha_i \in \mathbb{N} \cup \{0\}$ ,  $i = 1, \dots, d$ ,  $|\alpha| = \alpha_1 + \dots + \alpha_d$ ,  $t^\alpha = t_1^{\alpha_1} \cdot t_2^{\alpha_2} \cdot \dots \cdot t_d^{\alpha_d}$ , and  $\{a_\alpha\}$  is a sequence of i.i.d.  $N(0, 1)$ -distributed random variables. This is a random polynomial of degree  $n \in \mathbb{N}$  with Gaussian coefficients  $a_\alpha$ .

For  $d = 1$ , we get  $X(t) = a_0 + a_1 t + \dots + a_{n-1} t^{n-1} + a_n t^n$ ,  $t \in \mathbb{R}$ . Such polynomials form a special case of Gaussian linear functions introduced in Example 2.2.1, 2):

$X(t) = \langle \vec{a}, \vec{t} \rangle$ , where  $\vec{a} = (a_\alpha : |\alpha| \leq n)^T$  and  $\vec{t} = (t^\alpha : |\alpha| \leq n)^T$  are the vectors of coefficients and of variables respectively. It holds obviously  $X(t) \sim N(0, |\vec{t}|^2)$ , with

$$|\vec{t}|^2 = \sum_{|\alpha| \leq n} t^{2\alpha}, \quad t^{2\alpha} = t_1^{2\alpha_1} \cdot t_2^{2\alpha_2} \cdot \dots \cdot t_d^{2\alpha_d}$$

and covariance function

$$C(s, t) = \sum_{|\alpha| \leq n} s^\alpha \cdot t^\alpha.$$

Evidently,  $X(t)$  has an integral representation of Example 1.2.1.

$$X(t) = \int_{\mathbb{R}^d} g(t, x) W(dx), \quad t \in \mathbb{R}^d, \quad (3.1.4)$$

where

$$g(t, x) = \sum_{|\alpha| \leq d} t^\alpha I(x \in A_\alpha),$$

and  $\{A_\alpha\}$  is a family of pairwise disjoint subsets of  $\mathbb{R}^d$  with unit volume  $\lambda_d(A_\alpha) = 1$ ,  $\forall \alpha$ .  $W$  is a Gaussian white noise with Lebesgue control measure; cf. Sections 2.3.1 and 2.3.2 for the definition of  $W$  and the integral in (3.1.4).

One of the classical questions for random Gaussian polynomials is the problem about the mean



vector of real (or complex) roots of  $X$  in a compact domain  $T \subset \mathbb{R}^d$ . If  $d = 1$ , then the classical result of M. Kac (1943) says that

$$\mathbb{E}N_n = \frac{2}{\pi} \log n(1 + o(1)), \quad n \rightarrow \infty, \quad (3.1.5)$$

where  $N_n$  is the number of real roots of  $X(t)$  of degree  $n$ . Moreover,

$$\mathbb{E}N_n(a, b) = \frac{1}{\pi} \int_a^b \left( 1 - \left( \frac{nt^{n-1}(1-t^2)}{1-t^{2n}} \right)^2 \right) \frac{dt}{1-t^2}, \quad (3.1.6)$$

where  $N_n(a, b)$  is the number of real roots of  $X$  in  $(a, b)$ .

**Remark 3.1.3**

The asymptotic of the mean number of real roots heavily depends on that form of the joint distribution of all coefficients

$$\vec{a} = (a_\alpha : |\alpha| \leq n)^T.$$

If all  $a_\alpha$  are independent and id. distributed the asymptotic (3.1.5) holds essentially for distributions of  $a_0$  which belongs to the domain of attraction of  $\alpha$ -stable laws. [23] with another constant factor  $c$  on the place of  $\frac{2}{\pi}$ . [41] could prove that if  $\Theta$  is a class of all non-degenerated distributions of  $a_0$ , then

$$\inf_{\Theta} \sup_{n \in \mathbb{N}} \mathbb{E}(N_n | X(t) \neq 0) = 1.$$

Let  $\Theta_{a,b}$  be the class of distributions of  $a_0$  such that

$$P(a_0 > 0) = a, \quad P(a_0 < 0) = b, \quad a, b \geq 0 : 0 < a + b \leq 1.$$

Then Nazarov and Zaporozhets would show that

$$\inf_{\Theta_{a,b}} \sup_{n \in \mathbb{N}} \mathbb{E}(N_n | X(t) \neq 0) = 1 + \frac{1 - |a - b|}{a + b}.$$

For instance, for symmetric distributions ( $a = b = \frac{1}{2}$ ) we get

$$\inf_{\Theta_{\frac{1}{2}, \frac{1}{2}}} \sup_{n \in \mathbb{N}} \mathbb{E}(N_n | X(t) \neq 0) = 2.$$

In order to prove formula (3.1.6), let us do it in a more general setting:

**Theorem 3.1.6**

Let

$$X(t) = a_0 + a_1 t + a_2 t^2 + \dots + a_n t^n, \quad t \in \mathbb{R},$$

be a random polynomial, where the random coefficients  $a_0, \dots, a_n$  have a joint density  $p(x_0, \dots, x_n)$ . Let  $g(t)$  be any smooth function on  $\mathbb{R}$ ,  $g \in C^1(\mathbb{R})$ . Denote by  $N_n(g; a, b)$  the number of real solutions of the equation  $X(t) = g(t)$ ,  $t \in [a; b]$ . Then

$$\mathbb{E}N_n(g; a, b) = \int_a^b \int_{\mathbb{R}^n} p(g(t) - x_n t^n - \dots - x_1 t, x_1, \dots, x_n) |n x_n t^{n-1} + \dots + x_1 - g'(t)| dx_1 \dots dx_n dt$$

Proof If  $X$  is a polynomial of degree  $n$ , then the probability measure on such polynomials is introduced by

$$dX = p(x_0, x_1, \dots, x_n) dx_0 dx_1 \dots dx_n.$$

Let us try to pass to more convenient coordinates. If  $X$  intersects the graph of  $g$  at a point with an abscissa  $s$ , then we can write

$$0 = X(s) = a_0 + a_1 s + \dots + a_n s^n - g(s) \quad \Rightarrow \quad a_0 = g(s) - a_1 s - \dots - a_n s^n;$$

hence, perform a change of coordinates

$$\begin{cases} x_0 = g(t) - y_1 t - \dots - y_n t^n \\ x_1 = y_1 \\ \vdots \\ x_n = y_n \end{cases}$$

We get

$$\begin{aligned} dX &= p(x_0, x_1, \dots, x_n) dx_0 \dots dx_n = p(g(t) - y_1 t - \dots - y_n t^n, y_1, \dots, y_n) \\ &|g'(t) - y_1 - \dots - n y_n t^{n-1}| dt dy_1 \dots dy_n \end{aligned}$$

Let  $H = \{\text{all polynomials } X \text{ of degree } n: \text{ graph of } X \text{ intersects the graph of } g \text{ within } [a; b] \times \mathbb{R}\}$

Then integrate  $I(X \in H)$  with respect to  $dX$ :

we get

$$\begin{aligned} EN_n(g; a, b) &= \int_{X \in H} N_n(g; a, b) dX = \int_a^b \int_{\mathbb{R}^n} p(g(t) - y_1 t - \dots - y_n t^n, y_1, \dots, y_n) \\ &|g'(t) - y_1 - \dots - n y_n t^{n-1}| dy_1 \dots dy_n dt, \end{aligned}$$

since any polynomial is counted as new times on the left-hand side as often it intersects the graph of  $g$ .  $\square$

Corollary 3.1.2

For i.i.d.  $N(0, 1)$ -distributed coefficients  $a_i$ ,  $i = 0, \dots, n$ , the above theorem yields formula (3.1.6).

Proof Take

$$g(t) \equiv 0, \quad p(x_0, x_1, \dots, x_n) = \frac{1}{(2\pi)^{\frac{n+1}{2}}} \exp\left(-\frac{1}{2}(x_0^2 + \dots + x_n^2)\right)$$

Then

$$p(g(t) - x_n t^n - \dots - x_1 t, x_1, \dots, x_n) = \frac{1}{(2\pi)^{\frac{n+1}{2}}} \exp\left(-\frac{1}{2}((x_1 t + \dots + x_n t^n)^2 + x_1^2 + \dots + x_n^2)\right)$$

If we can prove that

$$\begin{aligned} &\frac{1}{(2\pi)^{\frac{n+1}{2}}} \int_{\mathbb{R}^n} \exp\left(-\frac{1}{2}((x_1 t + \dots + x_n t^n)^2 + x_1^2 + \dots + x_n^2)\right) \cdot |nt^{n-1} x_n + \dots + x_1| dx_1 \dots dx_n \\ &= \frac{1}{1-t^2} \left(1 - \left(\frac{nt^{n-1}(1-t^2)}{1-t^{2n}}\right)^2\right), \quad t \in (a; b), \end{aligned}$$

we are done. □

Exercise 3.1.2  
Show this!

Another possibility to get formula (3.1.6) is by means of the so-called Rice's formula. Let

$$N_u^+(0, T) = \#\{t \in [0; T] : X(t) = u, X'(t) > 0\}$$

be the number of up-crossings of the smooth stochastic process  $X$ - of level  $u \in \mathbb{N}$  over  $[0; T]$ . Then, Rice's formula states, that under some assumptions on  $X$  that will be given in detail later it holds

$$\mathbb{E}N_u^+(0, T) = \int_0^T \int_0^\infty xp_t(u, x) dx dt,$$

where  $p_t$  is the probability density of the distribution of random vector  $(X(t), X'(t))^T$ . Actually, the name "Rice's formula" attributes to the whole class of similar integral formulae for the moments of  $N_u^+$  and related quantities.

$$\begin{aligned} N_u(0, T) &= \#\{t \in [0; T] : X(t) = u\}, \\ N_u^-(0, T) &= \#\{t \in [0; T] : X(t) = u, X'(t) < 0\} \quad (\text{number of downcrossings}), \end{aligned}$$

and so on. Then formulae go back to Rice and Kac in the 1940s who proved them for stationary Gaussian processes. (cf. [1], p. 264-265, [3], p. 69 ff for discussion). The classical Rice's formula (1944, 1945) states that for a stationary centered Gaussian process  $X = \{X(t) : t \in \mathbb{R}\}$  with unit variance and second spectral moment  $\lambda_2$  it holds

$$\mathbb{E}N_u(0, T) = \frac{\sqrt{\lambda_2}}{\pi} e^{-\frac{u^2}{2}} T, \quad \mathbb{E}N_u^+(0, T) = \frac{\mathbb{E}N_u(0, T)}{2}.$$

$\lambda_2$  is defined as

$$\lambda_2 = \int_{\mathbb{R}^d} x^2 \mu_X(dx),$$

where  $\mu_X$  is the spectral measure of  $X$ .

Now let us formulate and prove Rice's formula for the case of Gaussian processes. The same formula holds for a much more general class of processes: see [3], p. 74-79.

Generalizations for the case of vector-valued random fields are also available; see [3], Chapter 6 and [1], 11.2.

Theorem 3.1.7 (Gaussian Rice formula):

Let  $X = \{X(t) : t \in I\}$  be a Gaussian process with  $C^1$ -smooth paths, and  $I$  be an interval on  $\mathbb{R}$ . Let  $u \in \mathbb{N}$ ,  $t_1, \dots, t_k \in I$  be any pairwise distinct points and the distribution of  $(X(t_1), \dots, X(t_k))$  is not degenerate with density  $p_{X(t_1)\dots X(t_k)}$ . Denote by  $\mathbb{E}N_u^{[k]}$  the  $k$ -th factorial moment of

$$N_u = N_u(I) : \mathbb{E}N_u^{[k]} = \mathbb{E}[N_u(N_u - 1) \cdot \dots \cdot (N_u - k + 1)I(N_u \geq k)].$$

Then it holds

$$\mathbb{E}N_u^{[k]} = \int_{I^k} \mathbb{E}[|X'(t_1) \cdots X'(t_k)| |X(t_1) = u, \dots, X(t_k) = u] p_{X(t_1) \dots X(t_k)}(u, \dots, u) dt_1 \dots dt_k \quad (3.1.7)$$

Before we begin to prove this Theorem, some remarks are in order.

1. An equivalent form of (3.1.7) is

$$\mathbb{E}N_u^{[k]} = \int_{I^k} dt_1 \dots dt_k \int_{\mathbb{R}^k} |x'_1 \cdots x'_k| p_{X(t_1) \dots X(t_k) X'(t_1) \dots X'(t_k)}(u, \dots, u, x'_1, \dots, x'_k) dx'_1 \dots dx'_k,$$

where  $p_{X(t_1) \dots X(t_k) X'(t_1) \dots X'(t_k)}$  is the joint probability density of  $X(t_j)$ ,  $i = 1, \dots, k$  and  $X'(t_j)$ ,  $j = 1, \dots, k$ .

2. In particular, for  $k = 1$  it holds

$$\mathbb{E}N_u(I) = \int_I \int_{\mathbb{R}} |x| p_{X(t), X'(t)}(u, x) dx dt \quad (3.1.8)$$

It can be shown that this formula holds also for non-Gaussian processes  $X$  satisfying the following conditions:

- a) Function  $(t, x) \mapsto p_{X(t)}(x)$  is continuous for  $t \in T$ ,  $x$  in a neighborhood of  $u$ .
- b)  $(t, x, x') \mapsto p_{X(t), X'(t)}(x, x')$  is continuous for  $t \in I$  in a neighborhood of  $u$  and  $x' \in \mathbb{R}$ .
- c) When  $\omega_{X'}(\delta)$  is the modulus of continuity of  $X'$  then

$$\mathbb{E}[\omega_{X'}(\delta)] \xrightarrow{\delta \rightarrow 0} 0.$$

3. It follows from formula (3.1.8) that  $\mathbb{E}N_u(I)$  is finite for Gaussian processes, since the right-hand side is always finite. Unfortunately, this may not be the case for  $\mathbb{E}(N_u^{[k]}(I)) < \infty$ ,  $k > 1$ .
4. It is in general not easy to show that the distribution of  $X(t_1) \dots X(t_k)$  is non-degenerate. However, in the case of stationary Gaussian  $X$ , an easy sufficient condition for that is that there exists no countable set  $A : \mu_X(A^c) = 0$ , where  $\mu_X$  is the spectral measure of  $X$ .

For the Proof of Theorem 3.1.7 we need the following lemma:

Lemma 3.1.5 (Kac's counting formula):

Let  $f \in C^1(I)$  be a real-valued function defined on an interval  $I = [t_1, t_2]$ ,  $f(t_1) \neq u$ ,  $f(t_2) \neq u$ , such that there are no critical points of  $f$  at level  $u : \nexists t \in I : f(t) = u, f'(t) = 0$ . Then

$$N_u(f, I) = \lim_{\delta \rightarrow 0} \frac{1}{2\delta} \int_{t \in I : |f(t) - u| < \delta} |f'(t)| dt \quad (3.1.9)$$

Proof Since  $f \in C^1(I)$ ,  $N_u(f, I)$  is finite. Let  $N_u(f, I) = n \in \mathbb{N} \cup \{0\}$ . If  $n = 0$ , then both sides of (3.1.9) are zero, since the integration such in (3.1.9) is empty for  $\delta > 0$  small enough. Let  $n \geq 1$  and  $s_1, \dots, s_n \in I$  be the points where  $f(s_i) = u$ ,  $i = 1, \dots, n$ . Since  $f'(s_i) \neq 0$ ,  $i = 1, \dots, n$ , we have for small enough  $\delta > 0$  that

$$f^{-1}(u - \delta, u + \delta) = \bigcup_{j=1}^n J_j$$

where  $J_j$  are disjoint intervals and  $s_i \in J_i$ ,  $i = 1, \dots, n$ .  $f|_{J_i}$  is a one-to-one mapping, a diffeomorphism, so that one gets

$$\int_{J_i} |f'(t)| dt = 2\delta$$

by an exchange of variables. Then for small enough  $\delta > 0$ , it holds

$$\frac{1}{2\delta} \int_{t \in I: |f(t) - u| < \delta} |f'(t)| dt = \frac{1}{2\delta} \sum_{i=1}^n \int_{J_i} |f'(t)| dt = \frac{n \cdot 2\delta}{2\delta} = n.$$

□

Proof of Theorem 3.1.7. We prove only the case  $k = 1$ . For  $k > 1$  see [3], p. 73. Without loss of generality we assume that  $I = [0, 1]$ . Let  $X^{(n)}$  be the dyadic approximation of  $X$ , i.e. the graph of  $X^{(n)}$  is a polygonal line with vertices  $\{(\frac{k}{2^n}, X(\frac{k}{2^n}))\}$ ,  $k = 0, \dots, 2^n$  one can easily show that

$$\sup_{t \in [0, 1]} |X^{(n)}(t) - X(t)| \xrightarrow[n \rightarrow \infty]{a.s.} 0,$$

$$\left| X^{(n)}(t) - X(t) \right| \stackrel{a.s.}{\leq} 2 \sup_{t \in I} |X(t)|, \quad \forall n \in \mathbb{N}, t \in I,$$

whereas

$$\mathbb{E} \left[ \sup_{t \in I} |X(t)| \right]^m < \infty$$

for all  $m \in \mathbb{N}$ , since  $X$  is a Gaussian process. By Lebesgue's theorem on dominated convergence

$$\text{var} X^{(n)} \xrightarrow[n \rightarrow \infty]{} \text{var} X(t)$$

uniformly on  $t \in I$ . Hence, for large  $n$

$$\text{var}(X^{(n)}(t)) \leq b > 0$$

for all  $t \in I$  and some  $b > 0$ , since  $X$  is non-degenerate process. For such large  $n$ , it holds

$$X^{(n)}\left(\frac{k}{2^n}\right) \neq u \quad \text{a.s.}, \quad k = 0, \dots, 2^n,$$

since  $X(t)$  has a (Gaussian) density,  $t \in I$ . Since the result of lemma 3.1.5 holds also for polygonal  $f$  (although they are only piecewise from  $C^1(I)$ ) by additivity of left and right-hand side of formula (3.1.9) we get

$$N_u(X^{(n)}, I) \stackrel{\text{a.s.}}{=} \lim_{\delta \rightarrow 0} \frac{1}{2\delta} \int_{t \in I: |X^{(n)}(t) - u| < \delta} |X^{(n)'}(t)| dt \quad (3.1.10)$$

for any  $n$  large enough, where the right-hand side of (3.1.10) is obviously bounded by the total number of segments in  $X^{(n)}$ , which is  $2^n$ . Applying dominated convergence theorem, we get

$$\begin{aligned} \mathbb{E}N_u(X^{(n)}, I) &= \lim_{\delta \rightarrow 0} \frac{1}{2\delta} \int_I \underbrace{\mathbb{E}(|X^{(n)'}(t)| \cdot I\{|X^{(n)}(t) - u| < \delta\})}_{\mathbb{E}(|X^{(n)'}(t)| \cdot I\{|X^{(n)}(t) - u| < \delta\})} \\ &= \mathbb{E}(I\{|X^{(n)}(t) - u| < \delta\} \mathbb{E}(|X^{(n)'}(t)| | X^{(n)}(t))) dt \\ &= \lim_{\delta \rightarrow 0} \int_I dt \frac{1}{2\delta} \int_{u-\delta}^{u+\delta} \mathbb{E}(|X^{(n)'}(t)| | X^{(n)}(t) = x) p_{X^{(n)}(t)}(x) dx. \end{aligned}$$

Since  $X, X^{(n)}$  has continuous sample paths and is Gaussian, its expectation and covariance functions are continuous as well. Since for  $t \in (\frac{k}{2^n}, \frac{k+1}{2^n}]$  it holds

$$\begin{aligned} X^{(n)}(t) &= (k+1 - 2^n t) X\left(\frac{k}{2^n}\right) + (2^n t - k) X\left(\frac{k+1}{2^n}\right) \\ &= 2^n \underbrace{\left(X\left(\frac{k+1}{2^n}\right) - X\left(\frac{k}{2^n}\right)\right)}_{\xi^{(k)}} t + \underbrace{(k+1)X\left(\frac{k}{2^n}\right) - kX\left(\frac{k+1}{2^n}\right)}_{\eta^{(k)}}, \end{aligned}$$

we get  $X^{(n)'}(t) = \xi^{(k)}$  and hence

$$\mathbb{E}(|X^{(n)'}(t)| | X^{(n)} = x) = \mathbb{E}(|\xi^{(k)}| | \xi^{(k)}t + \eta^{(k)} = x) = \mathbb{E}\left(\left|\frac{x - \eta^{(k)}}{t}\right|\right).$$

Thus,

$$\mathbb{E}(|X^{(n)'}(t)| | X^{(n)}(t) = x) p_{X^{(n)}(t)}(x)$$

is a continuous function of  $(t, x)$  on  $[\frac{k}{2^n}, \frac{k+1}{2^n}] \times [u - \delta_0, u + \delta_0]$  for some  $\delta_0 > 0$ , and hence

$$\begin{aligned} \mathbb{E}N_u(X^{(n)}, I) &= \int_I \lim_{\delta \rightarrow 0} \frac{1}{2\delta} \int_{u-\delta}^{u+\delta} \mathbb{E}(|X^{(n)'}(t)| | X^{(n)}(t) = x) p_{X^{(n)}(t)}(x) dx dt \\ &= \int_I \mathbb{E}(|X^{(n)'}(t)| | X^{(n)}(t) = u) p_{X^{(n)}(t)}(u) dt \end{aligned}$$

by the mean value theorem. Now take the limit as  $n \rightarrow \infty$  on both sides of the last equality. Since

$$N_u(X^{(n)}, I) \uparrow N_u(X, I)$$

as  $n \rightarrow \infty$ , we get

$$\mathbf{E}N_u(X^{(n)}, I) \xrightarrow{n \rightarrow \infty} \mathbf{E}N_u(X, I)$$

by the theorem on monotone convergence. The monotone convergence  $N_u(X^{(n)}, I)$  to  $N_u(X, I)$  takes place, since with probability one there are no extremal points of  $X$  at level  $u$ . [Ylvisaker Theorem]. As  $n \rightarrow \infty$ , the expectation and the covariance matrix of  $(X^{(n)}(t), X^{(n)'(t)})^T$  converges to the corresponding expressions of  $X$ , that is why

$$\int_I \mathbf{E}(|X^{(n)'(t)}| \mid X^{(n)}(t) = u) p_{X^{(n)}(t)}(u) dt \xrightarrow{n \rightarrow \infty} \int_I \mathbf{E}(|X'(t)| \mid X(t) = u) p_{X(t)}(u) dt.$$

□

### Exercise 3.1.3

Show that (3.1.6) holds using Rice's formula!

Another problem of interest is the location of all complex zeros of

$$X = \{X(t) : t \in \mathbb{C}\}, \quad X(t) = \sum_{i=0}^n a_i t^i$$

on the complex plane  $\mathbb{C}$ . Let  $R_n(a, b) = \#\{z \in \mathbb{C} : a \leq |z| \leq b, X(z) = 0\}$ ,  $0 \leq a < b < \infty$  be the number of zeros of  $X$  on the ring. Let  $S_n(\alpha, \beta) = \#\{z \in \mathbb{C} : \alpha \leq \arg z \leq \beta, X(z) = 0\}$ ,  $-\pi \leq \alpha < \beta \leq \pi$  be the number of zeros of  $X$  in the sector. The following result can be proven (see [25]) for arbitrary distributions of i.i.d. coefficients  $a_i$ ,  $i = 0, \dots, n$  of  $X$ :

### Theorem 3.1.8

Furthermore:

1. It holds

$$\frac{1}{n} R_n(1 - \delta, 1 + \delta) \xrightarrow[n \rightarrow \infty]{a.s.} 1$$

for any  $\delta \in (0, 1)$  iff

$$\mathbf{E} \log(1 + |a_0|) < \infty. \tag{3.1.11}$$

2. For any distribution of  $a_0$ , it holds

$$\frac{1}{n} S_n(\alpha, \beta) \xrightarrow[n \rightarrow \infty]{a.s.} \frac{\beta - \alpha}{2\pi}.$$

This result shows that all complex zeros of random polynomials satisfying conditions of Theorem 3.1.8 asymptotically lie (with probability one) around the unit circle  $|z| = 1$ . Moreover, they are spread over  $|z| = 1$  uniformly.

For Gaussian coefficients  $a_0$ , a more exact result can be proven (see [51]): for any  $\delta > 0$

$$\frac{1}{n} \mathbf{E} R_n \left( e^{-\frac{\delta}{n}} \cdot e^{\frac{\delta}{n}} \right) \xrightarrow{n \rightarrow \infty} \frac{1 + e^{-2\delta}}{1 - e^{-2\delta}} - \frac{1}{\delta}.$$

This asymptotic was extended to distributions of  $a_0$  belonging to domains of attraction of  $\alpha$ -stable laws by [26]. It is worth noting that the behavior of complex roots can be very different from those stated in Theorem 3.1.8, 1) if the condition (3.1.11) does not hold. There are examples of polynomials such that on average  $\frac{n}{2} + o(1)$  of its  $n$  roots concentrate near the origin, whereas another half goes to infinity as  $n \rightarrow \infty$  (see [59]).

Now let us consider the case of dimension  $d$  of index space greater than one, i.e.

$$X(t) = \sum_{|\alpha| \leq n} a_\alpha \cdot t^\alpha$$

is a polynomial of  $d$  variables  $t \in \mathbb{R}^d$ . Let  $M_n$  be the random hypersurface defined by the equation  $X(t) = 0$ ; let  $\mathcal{H}^{d-1}$  be the Hausdorff measure of dimension  $d - 1$ .

Theorem 3.1.9

If  $a_\alpha$  are i.i.d.  $N(0, 1)$ -distributed random variables, then for any compact set  $K \in \mathbb{R}^d$  it holds

$$\mathbb{E}\mathcal{H}^{d-1}(M_n \cap K) = \frac{\Gamma(\frac{d+1}{2})}{2\pi^{\frac{d+1}{2}}} \int_K \int_0^\pi \cdots \int_0^{2\pi} \sqrt{\sum_{i=1}^d \frac{\varphi(x_i)}{(1-x_i^2)} v_i^2} \cdot D(\varphi) d\varphi dx,$$

where  $dx = dx_1 \dots dx_d$ ,  $d\varphi = d\varphi_1 \dots d\varphi_{d-1}$ ,

$$D(\varphi) = \sin^{d-2} \varphi_1 \sin^{d-3} \varphi_2 \cdots \sin \varphi_{d-2}$$

$$\varphi(x_i) = 1 - \left( \frac{(n+1)x_i^n(1-x_i^2)}{1-x_i^{2n+2}} \right)^2, \quad i = 1, \dots, d$$

$$\left\{ \begin{array}{l} v_1(\varphi) = \cos \varphi_1 \\ v_2(\varphi) = \sin \varphi_1 \cdot \cos \varphi_2 \\ \vdots \\ v_{d-1}(\varphi) = \sin \varphi_1 \cdot \sin \varphi_2 \cdots \sin \varphi_{d-2} \cdot \cos \varphi_{d-1} \\ v_d(\varphi) = \sin \varphi_1 \cdot \sin \varphi_2 \cdots \sin \varphi_{d-2} \sin \varphi_{d-1} \end{array} \right.$$

Moreover, it holds

$$\mathbb{E}\mathcal{H}^{d-1}(M_n \cap K) = \frac{\log n}{\pi} \mathcal{H}_{d-1}(K \cap K_0)(1 + o(1)), \quad n \rightarrow \infty,$$

where

$$K_0 = \bigcup_{i=1}^d \{x = (x_1, \dots, x_d) \in \mathbb{R}^d : |x_i| = 1\}$$

The proof of this result can be found in [24].

The asymptotic result above means that almost the whole surface  $M_n$  concentrates around  $K_0$  for  $n \rightarrow \infty$ . More generally, it holds  $\mathbb{E}\mathcal{H}^{d-1}(M_n \cap K) = \mathcal{O}(1)$ , as  $n \rightarrow \infty$  for polynomials  $X$  with i.i.d. coefficients  $a_\alpha$  that have a density  $p$  with  $\text{supp}(x) < \infty$  and  $\mathbb{E}a_0 < \infty$ , if compact  $K$  is chosen so that  $\text{dist}(K, K_0) > 0$ . Here  $\text{dist}(\cdot, \cdot)$  is the Euclidean distance between two sets (see [22]).



In the same paper, the statement of Theorem [3.1.9](#) is generalized to symmetric strictly  $\alpha$ -stable distributions of  $a_\alpha$ .

# Bibliography

- [1] R. Adler and J. Taylor. Random Fields and Geometry. Springer, New York, 2007.
- [2] R. Askey. Refinements of abel summability for jacobi series, in: Harmonic analysis on homogeneous spaces, ed. by C.C. More. Proc. Symp. Pure Math. XXVI, pages 335–338, 1973.
- [3] J.-M. Azaïs and M. Wschebor. Level Sets and Extrema of Random Processes and Fields. Wiley, New York, 2009.
- [4] Goldie C. M. Tengels J. L Bingham, N. H. Regular variable. Cambridge Univ. Press, 1987.
- [5] S. Bochner. Lectures on Fourier integrals. Princeton Univ. Press, 1959.
- [6] V. I. Bogachev. Gaussian Measures. AMS, 1998.
- [7] P. Bremaud. Markov Chains, Gibbs Fields, Monte Carlo Simulation and Queues. Springer, 1999.
- [8] A. V. Bulinski and A. P. Shashkin. Limit theorems for associated random fields and related systems. World Scientific, Singapore, 2007.
- [9] A. V. Bulinski and A. N. Shiryaev. Theory of stochastic processes. Fizmatlit, 2005. (in Russian).
- [10] J.-P. Chiles and P. Delfiner. Geostatistics: Modeling Spatial Uncertainty. Wiley, New York, 1999.
- [11] H. Cramér and M. Leadbetter. Stationary and Related Stochastic Processes. Wiley, New York, 1967.
- [12] N. Cressie. Statistics for spatial data. World Scientific, Singapore, 2007.
- [13] J. L. Doob. Stochastic Processes. Wiley, 1953.
- [14] R. M. Dudley. Uniform Central Limit Theorems. Cambridge Univ. Pr., 1999.
- [15] X. Fernique. Fonctions aléatoires gaussiennes, vecteurs aléatoires gaussiens. CRM, Montreal, 1997.
- [16] J.C. Ferreira and V. A. Menegatto. "Eigenvalues of integral operators defined by smooth positive definite kernels" Integral and operator Theory. Birkhäuser Basel, Volume 64, No. 1, p. 61-61, 2009.
- [17] H.-O. Georgii. Gibbs Measures and Phase Transitions. de Gruyter, Berlin, 1988.

- [18] H.-O. Georgii. *Random Fields on a Network*. Springer, 1995.
- [19] I. I. Gikhman and A. V. Skorokhod. *The Theory of Stochastic Processes*. Springer, Berlin, 1974.
- [20] T. Gneiting. Radial positive definite functions generated by Euclid's hat. *J. Multivar. Anal.*, 69:88–119, 1999.
- [21] T. Gneiting and Z. Sasvári. The characterization problem for isotropic covariance functions. *Math. Geol.*, 31:105–111, 1999.
- [22] I. Ibragimov, F. Götze, and D. Zaporozhets. On a random algebraic surfaces. Preprint, 2003.
- [23] I. Ibragimov and N.B. Maslova. The mean number of real zeros of random polynomials, I. Coefficients with zero mean, volume 16. *Theory of Probability and its Applications*, 1971.
- [24] I. Ibragimov and S. Podkorytov. On random real algebraic surfaces. *Dokl. Akad. Nauk*, 343 edition, 1995.
- [25] I. Ibragimov and D. Zaporozhets. On the distribution of roots of random polynomials. Preprint, The, Bielefeld, 2006.
- [26] I. Ibragimov and O. Zeitouni. On roots of random polynomials. *Trans. AMS*, 347 edition, 1995.
- [27] K. Itô and M. Nisio. On the convergence of sums of independent Banach space valued random variables. *Osaka J. Math.* 5, 35-48, 1968.
- [28] A. V. Ivanov and N. N. Leonenko. *Statistical Analysis of Random Fields*. Kluwer, 1989.
- [29] H. S. Janzer, F. Raudies, H. Neumann, and F. Steiner. Image processing and feature extraction from a perspective of computer vision and physical cosmology. to be published in *Mathematical Analysis of Evolution, Information and Complexity*.
- [30] M. Kac. On the average number of real roots of a random algebraic equation. *Bull. Amer. Math. Sve.* 49, 1943.
- [31] D. Khoshnevisan. *Multiparameter Processes: An Introduction to Random Fields*. Springer, 2002.
- [32] A. N. Kolmogorov and S. V. Fomin. *Elements of the Theory of Functions and Functional Analysis*. Graylock Press, Rochester, 1961.
- [33] H. König. *Eigenvalue distribution of compact operators*. Birkhäuser, 1986.
- [34] C. Lantuejoul. *Geostatistical Simulation - Models and Algorithms*. Springer, 2002.
- [35] M. Ledoux and M. Talagrand. *Probability in Banach Spaces: Isoperimetry and Processes*. Springer, 1991.
- [36] M. Leonenko. *Limit Theorems for Random Fields with Singular Spectrum*. Kluwer, 1999.
- [37] M. A. Lifshits. *Gaussian Random Functions*. Kluwer, 1995.

- [38] W. Magnus, F. Oberhettinger, and R. P. Soni. Stable non-Gaussian random processes. Chapman & Hall/CRC, 1994.
- [39] V. A. Malyshev and R. A. Minlos. Gibbs Random Fields: Cluster Expansions. Kluwer, 1991.
- [40] B. Matern. Spatial Variation. Springer, second edition, 1986.
- [41] A. Nazarov and D. Zaporozhets. What is the least expected number of real roots of a random polynomial?, volume 53. Theory of Probability and Applications, 2009.
- [42] H. H. Ng. Semiinvariants in the theory of characterization of probability distributions. J. Math. Sci., 35(2):2437–2438, 1986.
- [43] K. Norio. Recent development on random fields and their sample paths. Part I: sample path continuity of random fields, volume 16. Soochow J. Math., 1990.
- [44] V. I. Piterbarg. Asymptotic Methods in the Theory of Gaussian Processes and Fields. AMS, 1996.
- [45] A. Ramm. Random Fields Estimation. World Scientific, 2005.
- [46] G. Samorodnitsky and M. Taqqu. Stable non-Gaussian random processes. Chapman & Hall/CRC, 1994.
- [47] A. Sasvári. Positive definite and definitizable functions. Akademie-Verlag, 1994.
- [48] M. Schlather. Construction of positive definite functions. Lecture at 15<sup>th</sup> Workshop on Stoch. Geometry, Stereology and Image Analysis, Blaubeuren, 22.-27.03.2009.
- [49] M. Schlather. Introduction to positive definite functions and to unconditional simulation of random fields. Technical Report ST-99-10, Lancaster University, UK, 1999.
- [50] I. J. Schoenberg. Metric spaces and complete monotone functions. Anna. Math., 39(4):811–841, 1938.
- [51] L. Shepp and R. J. Vanderbei. The complex zeros of random polynomials. Trans. AMS, 347 edition, 1995.
- [52] D. Stoyan, W. Kendall, and J. Mecke. Stochastic Geometry and its Applications. Wiley and Sons, second edition, 1995.
- [53] H. Wackernagel. Multivariate Geostatistics. Springer, second edition, 1998.
- [54] A.D. Wentzel. Theorie zufälliger Prozesse. Birkhäuser, Basel, 1979.
- [55] D. V. Widder. Necessary and sufficient conditions for the representation of a function as Laplace integral. Trans. of the American Math. Soc., vol. 33 edition, 1932.
- [56] G. Winkler. Image Analysis, Random Fields and Markov Chain Monte Carlo Methods. Springer, 2003.
- [57] A. M. Yaglom. Correlation Theory of Stationary and Related Random Functions, Volume I. Springer, 1987.

- [58] A. M. Yaglom. Correlation Theory of Stationary and Related Random Functions, Volume II. Springer, 1987.
- [59] D. Zaporoshets. An example of a random polynomial with unusual zeros behaviour, volume 50. Theory Probability Application, 2006.

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