## 11 Random real zeroes: no derivatives

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## 11a Exponential concentration in general

**11a1 Definition.** <sup>1</sup> (a) A sequence  $(x_n)_n$  of real numbers is *exponentially decaying*, if

$$\exists \delta > 0, \ C < \infty \ \forall n \ |x_n| \le C e^{-\delta n}$$
.

- (b) A sequence  $(X_n)_n$  of random variables  $X_n : \Omega_n \to \mathbb{R}$  is exponentially concentrated at zero, if for every  $\varepsilon > 0$  the sequence of numbers  $\mathbb{P}(|X_n| > \varepsilon)$  is exponentially decaying.
- (c) A sequence  $(X_n)_n$  of random variables  $X_n : \Omega_n \to \mathbb{R}$  is exponentially concentrated, if there exist  $x_n \in \mathbb{R}$  such that  $(X_n x_n)_n$  is exponentially concentrated at zero.

Notation:

$$(X_n)_n \in \operatorname{ExpConZero}; \quad (X_n)_n \in \operatorname{ExpCon}.$$

Only the distributions of these  $X_n$  matter. For a sequence  $(\mu_n)_n$  of probability measures on  $\mathbb{R}$  we define the relations  $(\mu_n)_n \in \operatorname{ExpConZero}$  and  $(\mu_n)_n \in \operatorname{ExpConZero}$  evidently, getting  $(X_n)_n \in \operatorname{ExpConZero}$   $\iff$   $(\mu_n)_n \in \operatorname{ExpConZero}$  where  $\mu_n$  is the distribution of  $X_n$ ; and the same for ExpCon. However, the language of random variables is more appropriate in many cases below.

**11a2 Exercise.** (a) All exponentially decaying sequences of real numbers are a linear space.

(b) ExpConZero is a linear space (for given  $(\Omega_n)_n$ ).

<sup>&</sup>lt;sup>1</sup>Not a standard definition.

(c) Let  $(X_n)_n \in \text{ExpConZero}$  and  $x_n \in \mathbb{R}$ . Then  $(X_n - x_n)_n \in \text{ExpConZero}$  if and only if  $x_n \to 0$ . Prove it.

Thus, the condition  $(X_n - x_n)_n \in \text{ExpConZero determines } (x_n)_n$  up to o(1).

Recall that a number x is called a median of a random variable X if

$$\mathbb{P}(X < x) \le \frac{1}{2} \le \mathbb{P}(X \le x).$$

All medians of X are in general a compact nonempty interval (often a single point). Also, x is a median of X if and only if (-x) is a median of (-X).

**11a3 Exercise.** The following three conditions are equivalent for every sequence of random variables  $X_n$ :

- (a)  $(X_n)_n \in \text{ExpCon};$
- (b) there exist medians  $x_n$  of  $X_n$  such that  $(X_n x_n)_n \in \text{ExpConZero}$ ;
- (c) all medians  $x_n$  of  $X_n$  satisfy  $(X_n x_n)_n \in \text{ExpConZero}$ . Prove it.

In this sense,

$$(X_n)_n \in \text{ExpCon}$$
 if and only if  $(X_n - \text{Me}(X_n))_n \in \text{ExpConZero}$ .

The median interval of  $X_n$  is of length o(1) whenever  $(X_n)_n \in \text{ExpCon}$ . Medians cannot be replaced with expectations...

**11a4 Exercise.** (a) ExpCon is a linear space (for given  $(\Omega_n)_n$ ).

(b) Let  $(X_n)_n$ ,  $(Y_n)_n \in \text{ExpCon}$ , then  $\text{Me}(X_n + Y_n) = \text{Me}(X_n) + \text{Me}(Y_n) + o(1)$ .

Formulate it accurately, and prove.

**11a5 Exercise.** ("Sandwich") Let random variables  $Y_n : \Omega_n \to \mathbb{R}$  be such that for every r > 0 there exist  $X_n, Z_n : \Omega_n \to \mathbb{R}$  satisfying

$$(X_n)_n, (Z_n)_n \in \operatorname{ExpCon},$$
  
 $\forall n \ (X_n \leq Y_n \leq Z_n \text{ a.s.}),$   
 $\forall n \ \operatorname{Me}(Z_n) - \operatorname{Me}(X_n) \leq r.$ 

Then  $(Y_n)_n \in \text{ExpCon}$ . Prove it. Gaussian concentration usually ensures  $\mathbb{E}|X_n| < \infty$  (integrability) and  $\operatorname{Me}(X_n) - \mathbb{E} X_n \to 0$ . Thus, we define ExpConInt (for given  $\Omega_n$ ) as the set of all sequences  $(X_n)_n$  where  $X_n : \Omega_n \to \mathbb{R}$  are integrable, and

$$(X_n - \mathbb{E} X_n)_n \in \operatorname{ExpConZero}$$
.

This is a linear space.

**11a6 Lemma.** Let random variables  $Y_n : \Omega_n \to \mathbb{R}$  be such that for every  $\varepsilon > 0$  there exist  $X_n, Z_n : \Omega_n \to \mathbb{R}$  satisfying

$$(X_n)_n, (Z_n)_n \in \text{ExpConInt},$$
  
 $\forall n \ (X_n \leq Y_n \leq Z_n \text{ a.s.}),$   
 $\forall n \ \mathbb{E} Z_n - \mathbb{E} X_n < \varepsilon.$ 

Then  $(Y_n)_n \in \text{ExpConInt}$ .

It can be proved similarly to 11a5. However, we need a quantitative version.

First, we note that the relation  $(X_n)_n \in \text{ExpConInt}$  may be reformulated as follows: there exist families  $(\delta_{\varepsilon})_{\varepsilon}$  and  $(C_{\varepsilon})_{\varepsilon}$  of numbers  $\delta_{\varepsilon} > 0$ ,  $C_{\varepsilon} < \infty$  given for  $\varepsilon > 0$  such that for all n,

$$\forall \varepsilon > 0 \quad \mathbb{P}(|X_n - \mathbb{E} X_n| > \varepsilon) \le C_{\varepsilon} e^{-\delta_{\varepsilon} n}.$$

Second, in order to get  $\mathbb{P}(|Y_n - \mathbb{E} Y_n| > \varepsilon) \leq C_{\varepsilon} e^{-\delta_{\varepsilon} n}$  in the conclusion of "Sandwich", we require  $\mathbb{P}(|X_n - \mathbb{E} X_n| > \varepsilon) \leq C_{r,\varepsilon} e^{-\delta_{r,\varepsilon} n}$  (and the same for  $Z_n$ ) in the assumption; here r is the parameter denoted by r in 11a5.

The lemma below constructs  $\delta_{\varepsilon}$  and  $C_{\varepsilon}$  for given  $\delta_{r,\varepsilon}$  and  $C_{r,\varepsilon}$ . The formulas are simple, but will not be used; rather, their existence will be used.

**11a7 Lemma.** ("Sandwich") Let positive numbers  $\delta_{r,\varepsilon}$  and  $C_{r,\varepsilon}$  be given for all positive r and  $\varepsilon$ . Let random variables  $Y_n:\Omega_n\to\mathbb{R}$  be such that for every r>0 there exist  $X_n,Z_n:\Omega_n\to\mathbb{R}$  satisfying

$$\forall n, \varepsilon \quad \mathbb{P}(|X_n - \mathbb{E} X_n| > \varepsilon) \leq C_{r,\varepsilon} e^{-\delta_{r,\varepsilon} n},$$

$$\forall n, \varepsilon \quad \mathbb{P}(|Z_n - \mathbb{E} Z_n| > \varepsilon) \leq C_{r,\varepsilon} e^{-\delta_{r,\varepsilon} n},$$

$$\forall n \quad (X_n \leq Y_n \leq Z_n \text{ a.s.}),$$

$$\forall n \quad \mathbb{E} Z_n - \mathbb{E} X_n \leq r.$$

Then

$$\forall n, \varepsilon \quad \mathbb{P}(|Y_n - \mathbb{E}Y_n| > \varepsilon) \le C_{\varepsilon} e^{-\delta_{\varepsilon} n}$$

where  $\delta_{\varepsilon} = \delta_{\varepsilon/2,\varepsilon/2}$  and  $C_{\varepsilon} = 2C_{\varepsilon/2,\varepsilon/2}$ .

11a8 Exercise. Prove Lemma 11a7.

**11a9 Lemma.** ("Approximation") Let integrable random variables  $X_n: \Omega_n \to \mathbb{R}$  be such that for every  $\varepsilon > 0$  there exist  $Y_n: \Omega_n \to \mathbb{R}$  satisfying

$$(Y_n)_n \in \text{ExpConInt}$$
,

the sequence of numbers  $\mathbb{P}(|X_n - Y_n| > \varepsilon)$  is exponentially decaying,  $\forall n \mid \mathbb{E} X_n - \mathbb{E} Y_n | \le \varepsilon$ .

Then  $(X_n)_n \in \text{ExpConInt}$ .

11a10 Exercise. Prove Lemma 11a9.

Here is a quantitative version. The assumption  $(Y_n)_n \in \text{ExpConInt}$  is weakened (to a single  $\varepsilon$ ...). The same  $\delta_{\varepsilon}$ ,  $C_{\varepsilon}$  are used in two assumptions, which is not a problem (just take the minimum of two  $\delta_{\varepsilon}$  and the sum of two  $C_{\varepsilon}$ ).

**11a11 Lemma.** ("Approximation") Let positive numbers  $\delta_{\varepsilon}$  and  $C_{\varepsilon}$  be given for all positive  $\varepsilon$ . Let random variables  $X_n : \Omega_n \to \mathbb{R}$  be such that for every  $\varepsilon > 0$  there exist  $Y_n : \Omega_n \to \mathbb{R}$  satisfying

$$\forall n \quad \mathbb{P}(|Y_n - \mathbb{E} Y_n| > \varepsilon) \le C_{\varepsilon} e^{-\delta_{\varepsilon} n},$$
  
$$\forall n \quad \mathbb{P}(|X_n - Y_n| > \varepsilon) \le C_{\varepsilon} e^{-\delta_{\varepsilon} n},$$
  
$$\forall n \quad |\mathbb{E} X_n - \mathbb{E} Y_n| \le \varepsilon.$$

Then

$$\forall n, \varepsilon \quad \mathbb{P}(|X_n - \mathbb{E} X_n| > \varepsilon) \le 2C_{\varepsilon/3} e^{-\delta_{\varepsilon/3} n}.$$

11a12 Exercise. Prove Lemma 11a11.

# 11b Exponential concentration over Gaussian measures

If a function  $\xi : \mathbb{R}^d \to \mathbb{R}$  is  $\operatorname{Lip}(\sigma)$  for a given  $\sigma > 0$  then Theorem 1a2 gives  $\xi[\gamma^d] = f[\gamma^1]$  for an increasing  $f : \mathbb{R} \to \mathbb{R}$ ,  $f \in \operatorname{Lip}(\sigma)$ . Let us denote by GaussLip $(\sigma)$  the set of all such random variables. Clearly, f(0) is the only median of  $\xi$ , and<sup>1</sup>

$$\begin{split} \mathbb{P}\left(|\xi - \operatorname{Me}(\xi)| > \varepsilon\right) &= \mathbb{P}\left(|f(\zeta) - f(0)| > \varepsilon\right) \leq \\ &\leq \mathbb{P}\left(|\zeta| > \varepsilon/\sigma\right) \leq C \exp\left(-\frac{\varepsilon^2}{2\sigma^2}\right) \end{split}$$

 $<sup>^{1}\</sup>zeta \sim \gamma^{1}$  as before.

for some absolute constant C.<sup>1</sup> Also,  $|\text{Me}(\xi) - \mathbb{E}\xi| = |f(0) - \int f \,d\gamma^1| \le C\sigma$  for another absolute constant C.<sup>2</sup> It follows easily that

(11b1) 
$$\mathbb{P}(|\xi - \mathbb{E}\xi| > \varepsilon) \le C \exp\left(-c\frac{\varepsilon^2}{2\sigma^2}\right)$$

for some absolute constants  $c, C^{3}$  and, of course,

(11b2) 
$$\mathbb{E}\left|\xi - \mathbb{E}\,\xi\right| \le C\sigma$$

for some absolute constant C.

## 11c Using assumption $A_n$

We consider the Gaussian random function  $X(\cdot)$  introduced in Sect. 2a as a linear function of the independent N(0,1) random variables  $X_1, \ldots, X_{2n}$  (via  $a_1, \ldots, a_N$  and  $\lambda_1, \ldots, \lambda_N$ ) under the assumption  $A_n$  (also introduced in Sect. 2a). Here is a non-probabilistic property of the linear operator  $\mathbb{R}^{2n} \to L_2[0,1]$ .

#### 11c1 Proposition.

$$\int_0^1 X^2(t) \, \mathrm{d}t \le \frac{C}{n} (X_1^2 + \dots + X_{2N}^2)$$

for some absolute constant C.

**11c2 Remark.** Assumption  $A_n$  requires also assumption A, namely  $\sum_k a_k^2 = 1$ , but we do not need it here; we use only the assumption

$$\forall \lambda \in [0, \infty)$$
  $\sum_{k: \lambda_k \in [\lambda, \lambda+1]} a_k^2 \le \frac{1}{n}.$ 

Given  $f \in L_2[0,1]$ , we consider the random variable

$$\langle f, X \rangle = \int_0^1 f(t)X(t) dt;$$

this is a linear combination of  $X_1, \ldots, X_{2n}$ , thus  $\langle f, X \rangle \sim N(0, \operatorname{Var}\langle f, X \rangle)$ .

$$\frac{{}^{1}C = \sup_{t>0} \mathrm{e}^{t^{2}/2} \cdot 2 \int_{t}^{\infty} (2\pi)^{-1/2} \mathrm{e}^{-u^{2}/2} \, \mathrm{d}u = 2 \sup_{t>0} (2\pi)^{-1/2} \int_{0}^{\infty} \exp(-\frac{s^{2}}{2} - ts) \, \mathrm{d}s = 1. }$$

<sup>5</sup>But under assumption A only, the operator need not be of small norm; just try N=1.

<sup>&</sup>lt;sup>3</sup>Here and henceforth, constants c and C (possibly with indices) are positive. They may be different in different formulas.

<sup>&</sup>lt;sup>4</sup>In fact, c=1 and C=2. Moreover,  $\mathbb{P}(\xi - \mathbb{E}\xi > \varepsilon) \leq 2\mathbb{P}(\sigma\zeta > \varepsilon)$  (Cirel'son, Ibragimov, Sudakov 1976), thus,  $\mathbb{P}(\xi - \mathbb{E}\xi > \varepsilon) \leq \exp(-\frac{\varepsilon^2}{2\sigma^2})$ .

11c3 Exercise. Deduce 11c1 from the following claim (to be proved soon):

$$\operatorname{Var}\langle f, X \rangle \le \frac{C}{n} ||f||^2$$
.

11c4 Exercise. Prove that

$$\operatorname{Var}\langle f, X \rangle = \sum_{k=1}^{N} a_k^2 |g(\lambda_k)|^2,$$

where  $g(\lambda) = \int_0^1 e^{i\lambda t} f(t) dt$ .

It is well-known that  $||g||_2^2 = 2\pi ||f||_2^2$ . Thus, the claim in 11c3 boils down to<sup>1</sup>

$$\sum a_k^2 |g(\lambda_k)|^2 \le C ||g||^2 \sup_{\lambda} \sum_{k: \lambda_k \in [\lambda, \lambda+1]} a_k^2,$$

which may be rewritten as

(11c5) 
$$\int |g|^2 d\mu \le C \left( \int |g|^2 dm \right) \sup_{\lambda} \mu([\lambda, \lambda + 1])$$

where  $\mu = \sum_{k} a_k^2 \delta_{\lambda_k}$  (a discrete measure), and m is the Lebesgue measure.

The idea is, roughly, that g cannot be nearly concentrated on a short interval, because f is concentrated on an interval of length 1. The proof, given below, uses Fourier transform  $(\varphi \mapsto \hat{\varphi})$  and convolution (\*). If you are familiar with these, keep reading. Otherwise feel free to skip the rest of 11c.

**11c6 Lemma.** There exist even real-valued functions  $\varphi \in L_{\infty}[-0.5, 0.5] \subset L_1(\mathbb{R})$  and  $\psi \in L_1(\mathbb{R})$  such that  $\hat{\varphi}(x)\hat{\psi}(x) = 1$  for all  $t \in [-1, 1]$ .

*Proof.* We take  $\varphi(t) = \text{const}$  on [-0.5, 0.5] (and 0 outside),  $\hat{\varphi}(t) = \frac{1}{t} \sin \frac{t}{2}$ , note that  $\hat{\varphi}(\cdot)$  does not vanish on [-1, 1],  $1/\hat{\varphi}(\cdot)$  is smooth on [-1, 1] and therefore can be extended to a smooth compactly supported function  $\hat{\psi}(\cdot)$ ; its Fourier transform is integrable, since it decays fast enough.

Proof of the proposition. The function  $|g(\cdot)|^2$  is the Fourier transform of a function supported on [-1,1] and therefore invariant under multiplication by  $\hat{\varphi}\hat{\psi}$ . It means that  $|g|^2 = |g|^2 * \varphi * \psi$ . Thus,

$$\int |g|^2 d\mu = \langle |g|^2 * \psi, \mu * \varphi \rangle \le ||g|^2 * \psi||_1 ||\mu * \varphi||_{\infty};$$

$$||g|^2 * \psi||_1 \le ||g|^2 ||_1 ||\psi||_1 = ||g||_2^2 ||\psi||_1 \le C ||g||_2^2;$$

$$||\mu * \varphi||_{\infty} \le ||\varphi||_{\infty} \sup_{\lambda} \mu ([\lambda - 0.5, \lambda + 0.5]) \le C \sup_{\lambda} \mu ([\lambda, \lambda + 1]),$$

which gives (11c5).

 $<sup>^{1}</sup>$ Do not forget that C may be different in different formulas.

### 11d Proving Theorem 2a2

If  $\xi: L_2[0,1] \to \mathbb{R}$  is Lip(1) then  $\xi(X)$ , treated as a function of  $X_1, \ldots, X_{2N}$ , is a Lip $(C/\sqrt{n})$  function  $\mathbb{R}^{2N} \to \mathbb{R}$  (by 11c1). Thus,  $\xi(X) \in \text{GaussLip}(C/\sqrt{n})$ . By (11b1),<sup>1</sup>

(11d1) 
$$\mathbb{P}(|\xi - \mathbb{E}\xi| > \varepsilon) \le C \exp(-c\varepsilon^2 n)$$

for some absolute constants c, C. In this sense, abusing the language, we write (under assumption  $A_n$ )

$$\xi \in \operatorname{ExpConInt}(n)$$

whenever  $\xi$  is Lip(1) on  $L_2[0,1]$ , or Lip(C) for some C not depending on n. Usually, a stronger condition will be satisfied:  $\xi$  is Lip(C) on  $L_1[0,1]$ .

11d2 Exercise. Prove Lemma 2a1.

**11d3 Exercise.** Let  $\varphi : \mathbb{R} \to \mathbb{R}$  be Lip(1). Then the function  $\xi : L_1[0,1] \to \mathbb{R}$ ,

$$\xi(x) = \int_0^1 \varphi(x(t)) \, \mathrm{d}t \,,$$

is well-defined and Lip(1).

Prove it.

Thus, for such  $\varphi$  the random variable

$$\xi = \int_0^1 \varphi(X(t)) \, \mathrm{d}t$$

satisfies

$$\xi \in \text{GaussLip}(C/\sqrt{n}); \quad \xi \in \text{ExpConInt}(n)$$

with absolute constants (as in (11d1)).

Now let  $\varphi$  be as in Theorem 2a2 (continuous a.e., of linear growth). We introduce for every k

$$\varphi_k^-(x) = \inf_y (\varphi(y) + k|y - x|), \quad \varphi_k^+(x) = \sup_y (\varphi(y) - k|y - x|).$$

**11d4 Exercise.** (a)  $\varphi_k^-, \varphi_k^+$  are Lip(k) functions  $\mathbb{R} \to \mathbb{R}$  for all k large enough:<sup>2</sup>

(b)  $\varphi_k^- \uparrow \varphi$  and  $\varphi_k^+ \downarrow \varphi$  almost everywhere;

<sup>&</sup>lt;sup>1</sup>I often write just  $\xi$  instead of  $\xi(X)$ .

 $<sup>^{2}</sup>$ Do you understand why not just "for all k"?

(c) there exists  $C_{\varphi}$  such that for all k large enough and all x

$$-C_{\varphi}(1+|x|) \le \varphi_k^-(x) \le \varphi_k^+(x) \le C_{\varphi}(1+|x|).$$

Prove it.

It follows (using Fubini and the dominated convergence theorem) that  $\mathbb{E}\,\xi_k^- \uparrow \mathbb{E}\,\xi$  and  $\mathbb{E}\,\xi_k^+ \downarrow \mathbb{E}\,\xi$  a.s., where  $\xi_k^{\pm} = \int_0^1 \varphi_k^{\pm}(X(t)) \,\mathrm{d}t$ . We have a "sandwich"; and so, Theorem 2a2 follows by 11a7. (The upper bound  $2\mathrm{e}^{-c_{\varepsilon,\varphi}n}$  is not stronger than  $C_{\varepsilon,\varphi}\mathrm{e}^{-c_{\varepsilon,\varphi}n}$  since  $c_{\varepsilon,\varphi}$  can be made smaller.)

### 11e Proving Theorem 2a3

The function T was defined in Sect. 2a on C[0,1], but the same definition works on  $L_1[0,1]$  and evidently gives a Lip(1) function  $T:L_1[0,1]\to [0,\infty)$ . It follows that  $T(X)\in \operatorname{ExpConInt}(n)$ . However, Theorem 2a3 states that  $T(X)\in \operatorname{ExpConZero}(n)$ . Thus, it is sufficient to prove that  $\mathbb{E} T(X)\leq \varepsilon_n\to 0$ .

We modify T as follows:

$$T_k(f) = \inf_{g} \|\psi_k(f(\cdot)) - \psi_k(g(\cdot))\|_1$$

where g is as before (distributed  $\gamma^1$ ), and  $\psi_k(x) = \text{mid}(-k, x, k)$ , that is, -k for  $x \in (-\infty, -k]$ ; x for  $x \in [-k, k]$ ; and k for  $x \in [k, \infty)$ . We have

$$\mathbb{E} |T_k(X(\cdot)) - T(X(\cdot))| \le \mathbb{E} \|\psi_k(X(\cdot)) - X(\cdot)\|_1 + \|\psi_k(g(\cdot)) - g(\cdot)\|_1 =$$

$$= 2 \int |\psi_k(x) - x| \, \gamma^1(\mathrm{d}x) \to 0$$

as  $k \to \infty$ . It remains to prove that  $\mathbb{E} T_k(X) \le \varepsilon_{k,n} \to 0$  as  $n \to \infty$ .

**11e1 Exercise.** For every  $f \in L_1[0,1]$  and every Lip(1) function  $\varphi : \mathbb{R} \to \mathbb{R}$ ,

$$\left| \int_0^1 \varphi(f(t)) dt - \int \varphi d\gamma^1 \right| \le T(f).$$

Prove it.

It is well-known that  $^1$ 

$$\sup_{\varphi} \left| \int_{0}^{1} \varphi(f(t)) dt - \int \varphi d\gamma^{1} \right| = T(f),$$

where the supremum is taken over all Lip(1) functions  $\mathbb{R} \to \mathbb{R}$ . (I use this fact without proof.) Clearly we may demand  $\varphi(0) = 0$ .

<sup>&</sup>lt;sup>1</sup>Kantorovich-Rubinstein theorem. This T(f) is nothing but the transportation distance between  $\gamma^1$  and the distribution of f. This fact is evident when f is a step function. It extends to the whole  $L_1[0,1]$  by continuity.

**11e2 Exercise.** For every k and  $\varepsilon$  there exists a finite set of Lip(1) functions  $\varphi_1, \ldots, \varphi_N : [-k, k] \to \mathbb{R}$  such that  $\varphi_1(0) = 0, \ldots, \varphi_N(0) = 0$ , and every Lip(1) function  $\varphi : [-k, k] \to \mathbb{R}$  such that  $\varphi(0) = 0$  is  $\varepsilon$ -close to some  $\varphi_i$  uniformly on [-k, k].

Prove it.

11e3 Exercise. Prove that

$$T_k(f) \leq 2\varepsilon + \max_{i=1,\dots,N} \left| \int_0^1 \varphi_i(\psi_k(f(t))) dt - \int \varphi_i(\psi_k(\cdot)) d\gamma^1 \right|.$$

The function  $\varphi_i(\psi_k(\cdot))$  is Lip(1), thus the random variable  $\xi_{i,k} = \int_0^1 \varphi_i(\psi_k(X(t))) dt$  belongs to GaussLip $(C/\sqrt{n})$ . By (11b2),  $\mathbb{E} |\xi_{i,k} - \mathbb{E} \xi_{i,k}| \le C/\sqrt{n}$ . Thus,

$$\mathbb{E} T_k(X) \le 2\varepsilon + \mathbb{E} \max_{i=1,\dots,N} |\xi_{i,k} - \mathbb{E} \xi_{i,k}| \le 2\varepsilon + N_{k,\varepsilon} \cdot \frac{C}{\sqrt{n}},$$

which can be made small enough by choosing  $\varepsilon$  first and n afterwards. That is,  $\mathbb{E} T_k(X) \leq \varepsilon_{k,n} \to 0$  as  $n \to \infty$ , which completes the proof.<sup>1</sup>

## 11f Dimension two, and higher

Returning to the definition of  $X(\cdot)$  given in Sect. 2a via  $a_1, \ldots, a_N$  and  $\lambda_1, \ldots, \lambda_N$ , we replace the numbers  $a_1, \ldots, a_N > 0$  with vectors  $a_1, \ldots, a_N \in \mathbb{R}^2$ , thus getting  $X : \mathbb{R} \to \mathbb{R}^2$ ; we endow  $\mathbb{R}^2$  with the Euclidean norm  $x \mapsto |x|$ . Further, all occurrences of  $a_k^2$  (in assumptions A and  $A_n$ , and everywhere) turn into  $|a_k|^2$ , and all occurrences of  $X^2(t)$  (in Prop. 11c1, and everywhere) into  $|X(t)|^2$ . We also replace the requirement  $0 < \lambda_1 < \cdots < \lambda_N < \infty$  with a weaker requirement  $0 < \lambda_1 \le \cdots \le \lambda_N < \infty$ , thus allowing a single frequency to cover more than one dimension. The distribution of the process X fails to determine uniquely the vectors  $a_k$ , but still determines the measure  $\sum_k |a_k|^2 \delta_{\lambda_k}$ , since

$$\mathbb{E}\langle X(0), X(t)\rangle = \sum_{k=1}^{N} |a_k|^2 \cos \lambda_k t.$$

<sup>&</sup>lt;sup>1</sup>In fact,  $\mathbb{P}(T(X) \geq \varepsilon) \leq \exp(-c((\varepsilon - \alpha_n)^+)^2 n)$  for some absolute constant c and some  $\alpha_n \to 0$  (depending on n only). It is like the large deviations principle with the rate function  $I(\varepsilon) \geq c\varepsilon^2$ .

<sup>&</sup>lt;sup>2</sup>Think, what does it change in the one-dimensional case.

Still, 11c3 and 11c4 hold, but  $f \in L_2[0,1]$  turns into  $f \in L_2([0,1] \to \mathbb{R}^2)$ , and 11c4 becomes

$$\operatorname{Var}\langle f, X \rangle = \sum_{k=1}^{N} |\langle a_k, g(\lambda_k) \rangle|^2 \le \sum_{k=1}^{N} |a_k|^2 |g(\lambda_k)|^2.$$

Nothing changes in the rest of Sect. 11c (it is about the measure  $\mu = \sum_{k} |a_{k}|^{2} \delta_{\lambda_{k}}$ ).

Thus, 11c1 gives us a linear operator  $\mathbb{R}^{2N} \to L_2([0,1] \to \mathbb{R}^2)$  of norm  $\leq C/\sqrt{n}$ . If  $\xi: L_2([0,1] \to \mathbb{R}^2) \to \mathbb{R}$  is Lip(1) then  $\xi(X) \in \text{GaussLip}(C/\sqrt{n})$ .

The function  $\varphi : \mathbb{R} \to \mathbb{R}$  in 2a1, 2a2, 11d3, 11d4 (as well as  $\varphi_k^{\pm}$  in 11d4) turns into  $\varphi : \mathbb{R}^2 \to \mathbb{R}$ ;  $\gamma^1$  in 2a1 turns into  $\gamma^2$ . And of course,  $L_1[0,1]$  in 11d3 turns into  $L_1([0,1] \to \mathbb{R}^2)$ .

Theorem 2a2 is thus generalized.

About Theorem 2a3. The definition of T(f) is generalized evidently  $(\gamma^1 \text{ turns into } \gamma^2)$ ; now T is a Lip(1) function  $L_1([0,1] \to \mathbb{R}^2) \to [0,\infty)$ . The functions  $\psi_k : \mathbb{R}^2 \to \mathbb{R}^2$  may be defined by  $\psi_k(x) = x$  if  $|x| \le k$ , otherwise  $\psi_k(x) = kx/|x|$ . The Kantorovich-Rubinstein theorem holds for all metric spaces, in particular  $\mathbb{R}^2$ . Exercise 11e2 generalizes for a disk of  $\mathbb{R}^2$  (and in fact for every precompact metric space). Exercise 11e3 and the rest of the proof remain valid.<sup>2</sup>

Theorem 2a3 is thus generalized.

All said about  $\mathbb{R}^2$  holds equally well for  $\mathbb{R}^d$ ,  $d = 3, 4, \dots$ 

#### 11g Hints to exercises

11d2: Fubini.

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 $<sup>^{1}</sup>$ And so, the absolute constant C in 11c1 remains intact.

<sup>&</sup>lt;sup>2</sup>Still,  $\mathbb{P}(T(X) \ge \varepsilon) \le \exp(-c((\varepsilon - \alpha_n)^+)^2 n)$  for the same absolute constant c as in dimension one, and another (worse) sequence  $\alpha_n \to 0$ .