# 5 LDP in spaces of functions

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## 5a The simplest case of Mogulskii's theorem

Tossing a fair coin n times we get a random element of  $\{0, 1\}^n$ . We embed all these spaces  $\{0, 1\}^n$  into a single metrizable compact space

(5a1) 
$$K = \{ \varphi \in L_{\infty}(0,1) : \mathbf{0} \le \varphi \le \mathbf{1} \}$$

as follows: given  $\beta = (\beta_1, \ldots, \beta_n) \in \{0, 1\}^n$ , we define  $\varphi_\beta \in K$  by

(5a2) 
$$\varphi_{\beta}(t) = \beta_k \text{ for } t \in \left(\frac{k-1}{n}, \frac{k}{n}\right).$$

The relevant metrizable topology on K, well-known as the weak<sup>\*</sup> topology, may be described as follows: for  $\varphi, \varphi_1, \varphi_2, \dots \in K$ ,

(5a3) 
$$\varphi_k \to \varphi$$
 if and only if  $\forall \eta \in L_1(0,1) \int \varphi_k \eta \to \int \varphi \eta$ .

Here is an example of a metric that generates this topology:

(5a4) 
$$\operatorname{dist}(\varphi,\psi) = \max_{k} \frac{1}{k} \left| \int \varphi \eta_{k} - \int \psi \eta_{k} \right|,$$

where  $\eta_1, \eta_2, \ldots$  are a sequence dense in the unit ball of  $L_1(0, 1)$ . The choice of  $\eta_1, \eta_2, \ldots$  influences the metric but not the topology. Another metric (for the same topology):

(5a5) 
$$\operatorname{dist}(\varphi,\psi) = \max_{t\in[0,1]} \left| \int_0^t \varphi - \int_0^t \psi \right|.$$

We consider the distribution  $\mu_n$  of the random function  $\varphi_\beta$ ,

(5a6) 
$$\mu_n \in P(K), \quad \int f \,\mathrm{d}\mu_n = \frac{1}{2^n} \sum_{\beta \in \{0,1\}^n} f(\varphi_\beta).$$

Large deviations

**5a7 Exercise.** Assume that  $(\mu_n)_n$  satisfies LDP with a rate function *I*. Then

$$\min\{I(\varphi): \varphi \in K, \, \int \varphi = u\} = I_{0.5}(u) \,,$$

where  $I_{0.5}(u) = u \ln \frac{u}{0.5} + (1-u) \ln \frac{1-u}{0.5} = u \ln u + (1-u) \ln(1-u) + \ln 2$  (recall (3a5) and (3a9)).

Prove it.

Hint: the contraction principle (Th. 2b1), and 3a4.

**5a8 Exercise.** Assume that  $(\mu_n)_n$  satisfies LDP with a rate function *I*. Then

$$I(\varphi) = \frac{I(\varphi_{\text{left}}) + I(\varphi_{\text{right}})}{2}$$

for all  $\varphi \in K$ ; here  $\varphi_{\text{left}}, \varphi_{\text{right}} \in K$  are defined by

$$\varphi_{\text{left}}(t) = \varphi(0.5t), \ \varphi_{\text{right}}(t) = \varphi(0.5+0.5t) \text{ for } t \in (0,1).$$

Prove it.

Hint:  $K = K_1 \times K_2$ ,  $K_1 \subset L_{\infty}(0, 0.5)$ ,  $K_2 \subset L_{\infty}(0.5, 1)$ ;  $\mu_{2n} = \mu_n^{(1)} \times \mu_n^{(2)}$ ;  $2I(\varphi) = I_1(\varphi_1) + I_2(\varphi_2)$  by 4d1, 4d2 and 2a17. On the other hand, the natural one-to-one correspondence between K and  $K_1$  transforms  $\mu_n$  to  $\mu_n^{(1)}$ , thus, I to  $I_1$ .

Applying the same formula to  $I(\varphi_{\text{left}})$  and  $I(\varphi_{\text{right}})$  we split  $I(\varphi)$  into four terms. And so on.

Now you could guess the rate function!

**5a9 Theorem.**  $(\mu_n)_n$  satisfies LDP with the rate function

$$I(\varphi) = \int_0^1 I_{0.5}(\varphi(t)) \,\mathrm{d}t \,.$$

See [1, Th. 5.1.2].

Note that I is far from being continuous. In fact,

$$\liminf_{\psi \to \varphi} I(\psi) = I(\varphi) \quad \text{but} \quad \limsup_{\psi \to \varphi} I(\psi) = \ln 2$$

for all  $\varphi \in K$ . Note also that

$$\mu_n\{\varphi \in K : I(\varphi) = \ln 2\} = 1 \quad \text{for all } n.$$

How could we prove the theorem? The approach of 3a does not work here, since the number of atoms of  $\mu_n$  is exponentially large. No binomial coefficients, just  $2^n$  atoms of probability  $2^{-n}$  each. However, we may apply Sanov's theorem to  $\int_0^1 \varphi$ ,  $\int_0^{0.5} \varphi$ ,  $\int_{0.5}^1 \varphi$  and so on. Doing so in the next section, we'll prove the theorem for  $n \in \{1, 2, 4, 8, ...\}$ . Here we just discuss it.

The map  $K \to C[0, 1]$ ,

$$\varphi \mapsto w\,, \quad w(t) = \int_0^t \varphi(s)\,\mathrm{d} s\,,$$

is continuous and one-to-one, therefore (by compactness) a homeomorphism. Thus, the LDP on K leads to LDP on the set of functions  $w: [0,1] \to \mathbb{R}$ such that

(5a10) 
$$0 \le w(t) - w(s) \le t - s$$
 whenever  $0 \le s \le t \le 1$ , and  $w(0) = 0$ 

with the rate function

(5a11) 
$$J(w) = \int_0^1 I_{0.5}(w'(t)) \, \mathrm{d}t \, .$$

(The derivative exists almost everywhere.) Note that the random function  $w_{\beta}$  (corresponding to  $\varphi_{\beta}$ ) is piecewise linear, with the derivative  $\beta_k \in \{0, 1\}$  on  $\left(\frac{k-1}{n}, \frac{k}{n}\right)$ . It is a (rescaled) path of a random walk. Do not hesitate to use Theorem 5a9 in the exercises below.

**5a12 Exercise.** A fair coin is tossed n times, giving  $(\beta_1, \ldots, \beta_n) \in \{0, 1\}^n$ . Consider

$$p_{n,\varepsilon} = \mathbb{P}\left(\forall k = 1, \dots, n \quad \left|\frac{\beta_1 + \dots + \beta_k}{n} - \frac{1}{2}\left(\frac{k}{n}\right)^2\right| \le \varepsilon\right).$$

Prove that

$$\limsup_{n \to \infty} \left| \sqrt[n]{p_{n,\varepsilon}} - \frac{\sqrt{e}}{2} \right| \to 0 \quad \text{as } \varepsilon \to 0 + .$$

Hint: use 4b12.

**5a13 Exercise.** A fair coin is tossed n times, giving  $(\beta_1, \ldots, \beta_n) \in \{0, 1\}^n$ . Given  $c \in [0, 1]$ , we consider

$$p_n = \mathbb{P}\left(\forall k = 1, \dots, n \quad \frac{\beta_1 + \dots + \beta_k}{n} \ge c\left(\frac{k}{n}\right)^2\right).$$

Large deviations

$$\sqrt[n]{p_n} \to 1 \qquad \text{for } 0 \le c \le 0.5 ,$$
  
$$\sqrt[n]{p_n} \to \frac{1}{2c^c(1-c)^{1-c}} \qquad \text{for } 0.5 \le c \le 1$$

 $(0^0 = 1, \text{ as before}).$ 

Hint: use 4b6; guess the extremal function; prove your guess, taking into account that  $\int_0^1 I_{0.5}(\varphi(t)) dt \ge I_{0.5}(\int_0^1 \varphi(t) dt)$ .

**5a14 Exercise.** In the situation of 5a13, formulate and prove a statement about the conditional distribution (in the spirit of 4c5).

Another example:

$$p_n = \mathbb{P}\left(\forall k = 1, \dots, n \quad \frac{\beta_1 + \dots + \beta_k}{n} \ge \frac{k}{n} - \frac{1}{2}\left(\frac{k}{n}\right)^2\right).$$

It appears that

$$\sqrt[n]{p_n} \to \frac{\mathrm{e}^{1/4}}{\sqrt{2}}$$
 as  $n \to \infty$ .

The extremal function is

$$w(t) = \begin{cases} t - 0.5t^2 & \text{for } 0 \le t \le 0.5, \\ 0.5t + 0.125 & \text{for } 0.5 \le t \le 1. \end{cases}$$

In order to prove its extremality, the following lemma helps:  $J(w \wedge v) \leq J(w)$  for every *linear* function  $v : [0,1] \to \mathbb{R}$  such that  $v(0) \geq 0$  and  $v'(\cdot) \geq 0.5$ ; here  $w \wedge v$  is the pointwise minimum.

Two-dimensional random arrays are quite similar. The interval (0,1)and the square  $(0,1) \times (0,1)$  are isomorphic measure spaces, thus,  $L_{\infty}(0,1)$ and  $L_{\infty}((0,1) \times (0,1))$  are isomorphic. But moreover, the natural partition of the interval into  $2^{2n}$  parts corresponds to that of the square. And the natural correspondence between the compact sets K in dimensions 1 and 2 is a homeomorphism. Thus, Theorem 5a9 implies the corresponding result in two (and more) dimensions. Note also that the metric

$$\operatorname{dist}(\varphi, \psi) = \max_{s,t \in [0,1]} \left| \iint_{(0,s) \times (0,t)} (\varphi - \psi) \right|$$

generates the considered topology on the space K (over the square). Thus, we may consider two-dimensional 'paths', getting the rate function

$$J(w) = \iint_{(0,1)\times(0,1)} I_{0.5}\left(\frac{\partial^2}{\partial s \partial t}w(s,t)\right) \mathrm{d}s \mathrm{d}t \,.$$

#### Large deviations

## 5b Infinite dimension as the limit of finite dimensions: the Dawson-Gärtner theorem

We return for a while to the general situation: a compact metrizable space K and a sequence  $(\mu_n)_n$  of probability measures on K.

Given  $g \in C(K)$ , we may consider the distribution  $\nu_n$  of g w.r.t.  $\mu_n$ , that is, the probability measure on  $\mathbb{R}$  defined by  $\nu_n(B) = \mu_n(\{x : g(x) \in B\}) =$  $\mu_n(g^{-1}(B))$  for Borel sets  $B \subset \mathbb{R}$ ; equivalently,  $\int_K f_1(g(\cdot)) d\mu_n = \int_{\mathbb{R}} f_1 d\nu_n$ for all continuous (or bounded Borel) functions  $f_1 : \mathbb{R} \to \mathbb{R}$ . Clearly,  $\nu_n$  are concentrated on the compact set  $g(K) \subset \mathbb{R}$ . If  $(\mu_n)_n$  is LD-convergent (on K) then  $(\nu_n)_n$  is also LD-convergent (on g(K)) by the contraction principle. The opposite is generally wrong.

**5b1 Exercise.** The sequence  $(\nu_n)_n$  is LD-convergent if and only if the limit  $\lim_n \|f\|_{L_n(\mu_n)}$  exists for all  $f \in C(K)$  of the form  $f(\cdot) = f_1(g(\cdot))$  for continuous  $f_1 : \mathbb{R} \to \mathbb{R}$ .

Prove it.

Hint:  $||f||_{L_n(\mu_n)} = ||f_1||_{L_n(\nu_n)}$ .

Given  $g, h \in C(K)$ , we may consider the joint distribution  $\nu_n$  of g, hw.r.t.  $\mu_n$ , that is, the probability measure on  $\mathbb{R}^2$  defined by  $\nu_n(B) = \mu_n(\{x : (g(x), h(x)) \in B\})$  for Borel sets  $B \subset \mathbb{R}^2$ . Similarly to 5b1, LD-convergence of  $(\nu_n)_n$  means convergence of  $||f||_{L_n(\mu_n)}$  for all  $f \in C(K)$  of the form  $f(\cdot) = f_2(g(\cdot), h(\cdot))$  for continuous  $f_2 : \mathbb{R}^2 \to \mathbb{R}$ .

Given  $g_1, g_2, \dots \in C(K)$ , we may consider the joint distribution  $\nu_n^{(j)}$  of  $g_1, \dots, g_j$  w.r.t.  $\mu_n$ . LD-convergence of  $(\nu_n^{(j)})_n$  for all j means convergence of  $||f||_{L_n(\mu_n)}$  for all  $f \in C(K)$  of the form  $f(\cdot) = f_j(g_1(\cdot), \dots, g_j(\cdot))$ , for all j. Are all such f dense in C(K)? They are a subalgebra of C(K), thus, the answer is given by the Stone-Weierstrass theorem:

A subalgebra of C(K) is dense if and only if it separates points of K.

**5b2 Theorem.** Let  $g_1, g_2, \dots \in C(K)$  separate points of K, and  $\nu_n^{(j)}$  be the joint distribution of  $g_1, \dots, g_j$  w.r.t.  $\mu_n$ . Then

(a) If for each j the sequence  $(\nu_n^{(j)})_n$  is LD-convergent (on the image  $K_j \subset \mathbb{R}^j$  of K under the map  $x \mapsto (g_1(x), \ldots, g_j(x))$ ), then the sequence  $(\mu_n)_n$  is LD-convergent.

(b) If for each j the sequence  $(\nu_n^{(j)})_n$  satisfies LDP with a rate function  $I_j$  on  $K_j$  then the sequence  $(\mu_n)_n$  satisfies LDP with the rate function

$$I(x) = \sup_{j} I_j(g_1(x), \dots, g_j(x)).$$

(See also [1, Th. 4.6.1].)

*Proof.* By the Stone-Weierstrass theorem, functions  $f \in C(K)$  of the form  $f(\cdot) = f_j(g_1(\cdot), \ldots, g_j(\cdot))$  are a dense set  $D \subset C(K)$ .

(a) Convergence of  $\|\cdot\|_{L_n(\mu_n)}$  on D implies convergence on the whole C(K), since

$$\limsup_{n} \|f\|_{L_{n}(\mu_{n})} - \liminf_{n} \|f\|_{L_{n}(\mu_{n})} \leq \\ \leq 2\|f - \tilde{f}\|_{C(K)} + \limsup_{n} \|\tilde{f}\|_{L_{n}(\mu_{n})} - \liminf_{n} \|\tilde{f}\|_{L_{n}(\mu_{n})} = 2\|f - \tilde{f}\|_{C(K)}$$

for  $f \in C(K)$ ,  $\tilde{f} \in D$ .

(b) We will prove that

$$e^{I(x)} = \sup\{f(x) : ||f|| \le 1\},\$$

where  $||f|| = \lim_{n \to \infty} ||f||_{L_n(\mu_n)}$ . For each j it is given that

$$e^{I_j(y_j)} = \sup\{f_j(y_j) : \|f_j\|_j \le 1\},\$$

where  $y_j = (g_1(x), \ldots, g_j(x))$  and  $||f_j||_j = \lim_n ||f_j||_{L_n(\nu_n^{(j)})}$ . If  $f(\cdot) = f_j(g_1(\cdot), \ldots, g_j(\cdot))$  then  $||f|| = ||f_j||_j$  (since  $||f||_{L_n(\mu_n)} = ||f_j||_{L_n(\nu_n^{(j)})}$ ) and  $f(x) = f_j(y_j)$ . Thus,  $\sup\{f(x) : ||f|| \le 1\} \ge \sup\{f_j(y_j) : ||f_j|| \le 1\} = e^{I_j(y_j)}$  for all j, therefore

$$\sup\{f(x): ||f|| \le 1\} \ge \sup_{j} e^{I_{j}(y_{j})} = e^{I(x)}.$$

On the other hand,  $f(x) = f_j(y_j) \leq e^{I_j(y_j)} \leq e^{I(x)}$  for  $f \in D$ ,  $||f|| \leq 1$ . More generally,  $f(x) \leq ||f|| e^{I(x)}$  for all  $f \in D$ . Given  $\varepsilon > 0$  and an arbitrary  $f \in C(K)$  such that  $||f|| \leq 1$ , we take  $\tilde{f} \in D$  such that  $||f - \tilde{f}||_{C(K)} \leq \varepsilon$ , then  $f(x) \leq \tilde{f}(x) + \varepsilon \leq ||\tilde{f}|| e^{I(x)} + \varepsilon \leq (1 + \varepsilon) e^{I(x)} + \varepsilon$ . Therefore  $f(x) \leq e^{I(x)}$ , that is,

$$e^{I(x)} \ge \sup\{f(x) : \|f\| \le 1\}.$$

Note that

$$I_j(y_1, \dots, y_j) = \min_{y_{j+1}: (y_1, \dots, y_{j+1}) \in K_{j+1}} I_{j+1}(y_1, \dots, y_{j+1}) \quad \text{for } (y_1, \dots, y_j) \in K_j$$

by the contraction principle. Thus,

(5b3) 
$$I_j(g_1(x), \dots, g_j(x)) \uparrow I(x) \text{ as } j \to \infty$$

It is easy to generalize Theorem 5b2 to the situation where j runs on a subsequence (say,  $j \in \{2, 4, 8, ...\}$ ).

**5b4 Exercise.** Generalize 5b2 to continuous functions  $g_j : K \to K_0$  (rather than  $K \to \mathbb{R}$ ), where  $K_0$  is another compact metrizable space.

**5b5 Exercise.** Let K be a compact metrizable space and  $(\mu_n)_n$  a sequence of probability measures on K. Consider the compact metrizable space

$$K^{\infty} = K \times K \times \dots ;$$

it may be metrized by

$$\operatorname{dist}_{\infty}((x_1, x_2, \dots), (y_1, y_2, \dots)) = \max_k \frac{1}{k} \operatorname{dist}(x_k, y_k).$$

On  $K^{\infty}$  we consider product measures

$$\mu_n^{\infty} = \mu_n \times \mu_n \times \dots$$

(a) The sequence  $(\mu_n^{\infty})_n$  is LD-convergent if and only if the sequence  $(\mu_n)_n$  is LD-convergent.

(b) If  $(\mu_n)_n$  satisfies LDP with a rate function  $I : K \to [0, \infty]$ , then  $(\mu_n^{\infty})_n$  satisfies LDP with the rate function  $I_{\infty} : K^{\infty} \to [0, \infty]$ ,

$$I_{\infty}((x_1, x_2, \dots)) = I(x_1) + I(x_2) + \dots$$

Prove it.

Hint: 4d1, 4d2 and 5b4.

If K is defined by (5a1), (5a3), then (up to a natural isomorphism)

(5b6) 
$$K^{\infty} = \{ \varphi \in L_{\infty}(0, \infty) : \mathbf{0} \le \varphi \le \mathbf{1} \},$$
$$\varphi_{k} \to \varphi \quad \text{if and only if} \quad \forall \eta \in L_{1}(0, \infty) \quad \int \varphi_{k} \eta \to \int \varphi \eta$$

for  $\varphi, \varphi_1, \varphi_2, \dots \in K^{\infty}$ . It is straightforward to adapt (5a4) to  $K^{\infty}$ . However, (5a5) needs a modification, say,

$$\operatorname{dist}(\varphi,\psi) = \max_{t \in [0,\infty)} \frac{1}{t^2 + 1} \left| \int_0^t \varphi - \int_0^t \psi \right|.$$

Now we toss a coin endlessly, getting  $\beta = (\beta_1, \beta_2, ...) \in \{0, 1\}^{\infty}$ , define  $\varphi_{\beta} \in K^{\infty}$  by (5a2) (waiving the restriction  $k \leq n$ ) and observe that this  $\varphi_{\beta}$  is distributed  $\mu_n^{\infty}$  ( $\mu_n$  being defined by (5a6)). By 5b5 and Theorem 5a9 (not proved yet), ( $\mu_n^{\infty}$ )<sub>n</sub> satisfies LDP with the rate function  $I_{\infty} : K^{\infty} \to [0, \infty]$ ,

(5b7) 
$$I_{\infty}(\varphi) = \int_0^{\infty} I_{0.5}(\varphi(t)) \,\mathrm{d}t \,.$$

Large deviations

This time,

$$\liminf_{\psi \to \varphi} I(\psi) = I(\varphi) \quad \text{but} \quad \limsup_{\psi \to \varphi} I(\psi) = \infty$$

for all  $\varphi \in K^{\infty}$ . Also

$$\mu_n \{ \varphi \in K^\infty : I(\varphi) = +\infty \} = 1$$
 for all  $n$ .

### **5c Proof for nice** n

We return to Theorem 5a9. It states LDP, namely, that  $||f||_{L_n(\mu_n)} \to \max(|f|e^{-I})$  as  $n \to \infty$  for all  $f \in C(K)$ . Here we prove a weaker statement (LDP along a subsequence):

$$||f||_{L_{2^m}(\mu_{2^m})} \to \max(|f|e^{-I}) \text{ as } m \to \infty.$$

In order to use 5b, we define  $g_2, g_3, \dots \in C(K)$  by<sup>1</sup>

$$g_j(\varphi) = \frac{1}{\operatorname{mes} I_j} \int_{I_j} \varphi \,,$$

where

$$(I_2, I_3, I_4, I_5...) = ((0, 1), (0, 0.5), (0.5, 1), (0, 0.25), ...)$$

is the sequence of all dyadic intervals. Clearly,  $g_j$  separate points of K. We introduce  $\nu_n^{(j)}$  on  $K_j$  as in 5b2, but we restrict ourselves to

 $j \in \{2, 4, 8, \dots\}, \quad n \in \{2, 4, 8, \dots\}, \quad n \ge j.$ 

The set

$$K_{2j} = \{(g_2(\varphi), \dots, g_{2j}(\varphi)) : \varphi \in K\}$$

lies in  $\mathbb{R}^{2j-1}$ , but only the last j coordinates  $g_{j+1}, \ldots, g_{2j}$  are really needed; they determine  $g_2, \ldots, g_j$  uniquely. (For example,  $g_2(\cdot) = \frac{1}{2}(g_3(\cdot) + g_4(\cdot))$ .)

If  $\varphi$  is distributed  $\mu_n$  then  $g_{j+1}(\varphi), \ldots, g_{2j}(\varphi)$  are independent, identically distributed; namely, each of them is distributed  $\mu_{n/j}^{3a}$ , where  $\mu^{3a}$  means ' $\mu$  of Sect. 3a'. By 3a4,  $(\mu_k^{3a})_k$  satisfies LDP with the rate function  $I_{0.5}$ . Thus (similarly to 2a17), for  $k = j + 1, \ldots, 2j$ ,

$$\|f(g_k(\cdot))\|_{L_n(\mu_n)} = \|f\|_{L_n(\mu_{n/j}^{3a})} = \|f^j\|_{L_{n/j}(\mu_{n/j}^{3a})}^{1/j} \xrightarrow[n \to \infty]{} (\max(|f^j|e^{-I_{0.5}}))^{1/j} = \max(|f|e^{-I_{0.5}/j}),$$

<sup>&</sup>lt;sup>1</sup>The numbers start from 2 for convenience; the natural blocks finish at  $j = 2^k$ .

#### Large deviations

that is,  $I_{0.5}/j$  is the rate function for  $g_k(\cdot)$  (along the subsequence,  $n \in \{j, 2j, 3j, \ldots\} \supset \{j, 2j, 4j, \ldots\}$ ).

Prop. 4d1 (or rather, its evident generalization to the product of j measures, and n restricted to a subsequence) gives us the rate function  $(y_{j+1}, \ldots, y_{2j}) \mapsto \frac{1}{j} (I_{0.5}(y_{j+1}) + \cdots + I_{0.5}(y_{2j}))$  for  $(g_{j+1}, \ldots, g_{2j})$ , therefore, the rate function  $I_{2j}$  on  $K_{2j}$ ,

(5c1) 
$$I_{2j}(y_2, \dots, y_{2j}) = \frac{1}{j} \left( I_{0.5}(y_{j+1}) + \dots + I_{0.5}(y_{2j}) \right)$$

for distributions  $\nu_n^{(2j)}$  of  $g_2, \ldots, g_{2j}$  (along the subsequence, still).

The Dawson-Gärtner theorem 5b2 (or rather, its evident generalization to subsequences) gives us LDP for  $(\mu_n)_n$  with the rate function

$$I(\varphi) = \lim_{j} 2^{-j} \sum_{k=1}^{2^{j}} I_{0.5} \left( 2^{j} \int_{(k-1)2^{-j}}^{k \cdot 2^{-j}} \varphi \right)$$

(recall 5b3). That is,  $I(\varphi) = \lim_{j} \int I_{0.5}(\varphi_j)$ , where  $\varphi_j$  is the orthogonal projection of  $\varphi$  to the  $2^j$ -dimensional space of step functions. However,  $\varphi_j \rightarrow \varphi$  in measure (in fact, almost everywhere), therefore  $I_{0.5}(\varphi_j) \rightarrow I_{0.5}(\varphi)$  in measure, therefore (using boundedness),  $\int I_{0.5}(\varphi_j) \rightarrow \int I_{0.5}(\varphi)$ .

### 5d Measures coming together

A general situation, again:  $(\mu_n)_n$  and  $(\nu_n)_n$  be two sequences of probability measures on a compact metrizable space K. We say that they *come together*, if there exist probability measures  $\lambda_n$  on  $K \times K$  satisfying two conditions.

First,  $\mu_n$  and  $\nu_n$  are the marginals of  $\lambda_n$  (for every *n*). That is,  $\lambda_n(B \times K) = \mu_n(B)$  and  $\lambda_n(K \times B) = \nu_n(B)$  for every Borel set  $B \subset K$ . Or equivalently,  $\int_{K \times K} f(x) \lambda_n(dxdy) = \int_K f d\mu$  and  $\int_{K \times K} f(y) \lambda_n(dxdy) = \int_K f d\nu$  for all  $f \in C(K)$ . (Every such  $\lambda_n$  is called a joining of  $\mu_n$  and  $\nu_n$ .)

Second, there exist  $\varepsilon_n \to 0$  such that  $\lambda_n(\{(x, y) : \operatorname{dist}(x, y) \le \varepsilon_n\}) = 1$  for all n. (The choice of the metric affects the choice of  $\varepsilon_n$ , but the condition is invariant.)

An equivalent definition without joinings exists (but will not be used). Namely,  $(\mu_n)_n$  and  $(\nu_n)_n$  come together, if there exist  $\varepsilon_n \to 0$  such that (recall (4b9), (4b10))  $\mu_n(F) \leq \nu_n(F_{+\varepsilon_n})$  and  $\nu_n(F) \leq \mu_n(F_{+\varepsilon_n})$  for all closed sets  $F \subset K$ . (The same  $(\varepsilon_n)_n$  for all F, of course.)

**5d1 Proposition.** If  $(\mu_n)_n$  and  $(\nu_n)_n$  come together, then

(a)  $(\mu_n)_n$  is LD-convergent if and only if  $(\nu_n)_n$  is LD-convergent;

(b) if  $(\mu_n)_n$  satisfies LDP with a rate function I, then  $(\nu_n)_n$  satisfies LDP with the same rate function I.

*Proof.* Given  $f \in C(K)$ , we introduce  $f_1, f_2 \in C(K \times K)$  by  $f_1(x, y) = f(x)$ and  $f_2(x, y) = f(y)$ . Then  $||f||_{L_n(\mu_n)} = ||f_1||_{L_n(\lambda_n)}$  and  $||f||_{L_n(\nu_n)} = ||f_2||_{L_n(\lambda_n)}$ . However,

$$\max_{\operatorname{dist}(x,y) \le \varepsilon_n} |f_1(x,y) - f_2(x,y)| = \max_{\operatorname{dist}(x,y) \le \varepsilon_n} |f(x) - f(y)| \to 0 \quad \text{as } n \to \infty$$

since f is uniformly continuous (due to compactness). Thus,  $||f_1 - f_2||_{L_n(\lambda_n)} \to 0$ , therefore

$$||f||_{L_n(\mu_n)} - ||f||_{L_n(\nu_n)} = ||f_1||_{L_n(\lambda_n)} - ||f_2||_{L_n(\lambda_n)} \to 0$$

as  $n \to \infty$ ; (a) and (b) follow immediately.

See also [1, Th. 4.2.13].

#### **5e Proof for all** n

Here we finish the proof of Theorem 5a9 by generalizing the argument of 5c from  $n \in \{2, 4, 8, ...\}$  to  $n \in \{1, 2, 3, ...\}$ .

We consider the distribution  $\nu_n^{(j)}$  on  $K_j$ ; still,  $j \in \{2, 4, 8, ...\}$ , but now  $n \in \{1, 2, 3, ...\}$ . It is sufficient to prove that  $(\nu_n^{(j)})_n$  satisfies LDP with the rate function  $I_j$  (recall (5c1)), that is,

(5e1) 
$$\|f\|_{L_n(\nu_n^{(j)})} \to \max_{K_j} \left(|f| \mathrm{e}^{-I_j}\right) \quad \text{as } n \to \infty$$

for all  $f \in K_j$  and all  $j \in \{2, 4, 8, ...\}$ . Recall that the argument of 5c gives us a weaker statement, namely,

$$||f||_{L_{mj}(\nu_{mj}^{(2j)})} \to \max_{K_j} (|f| e^{-I_{2j}}) \text{ as } m \to \infty.$$

(Only  $m \in \{1, 2, 4, ...\}$  are used there, but the argument works for all m.)

Let us start with 2j = 4. The measure  $\nu_n^{(4)}$  is basically the joint distribution of  $g_3(\varphi) = 2 \int_0^{0.5} \varphi$  and  $g_4(\varphi) = 2 \int_{0.5}^1 \varphi$ , when  $\varphi$  is distributed  $\mu_n$ . These two are independent for even n, but not for odd n; this is the problem. The solution:  $\nu_{2m}^{(4)}$  and  $\nu_{2m+1}^{(4)}$  are close enough.

**5e2 Lemma.**  $(\nu_{2m}^{(4)})_m$  and  $(\nu_{2m+1}^{(4)})_m$  come together.

*Proof.* Basically,  $\nu_{2m}^{(4)}$  is the joint distribution of  $(\beta_1 + \cdots + \beta_m)/m$  and  $(\beta_{m+1} + \cdots + \beta_{2m})/m$ , where  $(\beta_1, \ldots, \beta_{2m}) \in \{0, 1\}^{2m}$  is distributed uniformly. Similarly,  $\nu_{2m+1}^{(4)}$  is the joint distribution of  $(\beta_1 + \cdots + \beta_m + 0.5\beta_{m+1})/(m+0.5)$ 

and  $(0.5\beta_{m+1} + \beta_{m+2} + \cdots + \beta_{2m+1})/(m+0.5)$ . We construct a joining  $\lambda_m$  of  $\nu_{2m}^{(4)}$  and  $\nu_{2m+1}^{(4)}$  as the joint distribution of two pairs,

$$\left(\frac{\beta_1 + \dots + \beta_m}{m}, \frac{\beta_{m+2} + \dots + \beta_{2m+1}}{m}\right) \text{ and} \\ \left(\frac{\beta_1 + \dots + \beta_m + 0.5\beta_{m+1}}{m+0.5}, \frac{0.5\beta_{m+1} + \beta_{m+2} + \dots + \beta_{2m+1}}{m+0.5}\right);$$

of course,  $(\beta_1, \ldots, \beta_{2m+1})$  is distributed uniformly on  $\{0, 1\}^{2m+1}$ . We estimate the distance between the two pairs:

$$\left|\frac{\beta_1 + \dots + \beta_m}{m} - \frac{\beta_1 + \dots + \beta_m + 0.5\beta_{m+1}}{m + 0.5}\right| \le \\ \le m \left(\frac{1}{m} - \frac{1}{m + 0.5}\right) + \frac{0.5}{m + 0.5} = \frac{1}{m + 0.5} \to 0;$$

the same holds for the second coordinate.

By 5d1,  $||f||_{L_{2m}(\nu_{2m+1}^{(4)})}$  behaves similarly to  $||f||_{L_{2m}(\nu_{2m}^{(4)})}$ , namely, converges to  $\max(|f|e^{-I_4})$ . The same holds for  $||f||_{L_{2m+1}(\nu_{2m+1}^{(4)})}$ , since  $\frac{2m+1}{2m} \to 1$  (recall the argument of 2a17). Thus,  $||f||_{L_n(\nu_n^{(4)})} \to \max(|f|e^{-I_4})$ . Similarly, for every  $j \in \{2, 4, 8, ...\}$  and every  $k \in \{0, 1, ..., j - 1\}$ ,

Similarly, for every  $j \in \{2, 4, 8, ...\}$  and every  $k \in \{0, 1, ..., j - 1\}$ ,  $(\nu_{jm+k}^{(2j)})_m$  and  $(\nu_{j(m-1)}^{(2j)})_m$  come together, which implies (5e1) and completes the proof of Theorem 5a9.

# References

[1] A. Dembo, O. Zeitouni, *Large deviations techniques and applications*, Jones and Bartlett publ., 1993.