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# A counter-example to the central limit theorem in Hilbert spaces under a strong mixing condition

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#### **Abstract**

We show that in a separable infinite dimensional Hilbert space, uniform integrability of the square of the norm of normalized partial sums of a strictly stationary sequence, together with a strong mixing condition, does not guarantee the central limit theorem.

**Keywords:** Central limit theorem; Hilbert space; mixing conditions; strictly stationary process

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# 1 Introduction and notations

Let  $(\Omega, \mathcal{F}, \mu)$  be a probability space and (S, d) a separable metric space. We say that the sequence of random variables  $(X_n)_{n \in \mathbb{Z}}$  from  $\Omega$  to S is *strictly stationary* if for all integer d and all integer k, the d- uple  $(X_1, \ldots, X_d)$  has the same law as  $(X_{k+1}, \ldots, X_{k+d})$ .

Rosenblatt introduced in [18] the measure of dependence between two sub- $\sigma$ -algebras  $\mathcal{A}$  and  $\mathcal{B}$ :

$$\alpha(\mathcal{A}, \mathcal{B}) := \sup \left\{ \left| \mu(A \cap B) - \mu(A)\mu(B) \right|, A \in \mathcal{A}, B \in \mathcal{B} \right\}.$$

Another one is  $\beta$ -mixing, which is defined by

$$\beta(\mathcal{A}, \mathcal{B}) := \frac{1}{2} \sup \sum_{i=1}^{I} \sum_{j=1}^{J} |\mu(A_i \cap B_j) - \mu(A_i)\mu(B_j)|,$$

where the supremum is taken over the finite partitions  $\{A_1, \ldots, A_I\}$  and  $\{B_1, \ldots, B_J\}$  of  $\Omega$ , which consist respectively of elements of  $\mathcal{A}$  and  $\mathcal{B}$ . It was introduced by Volkonskii and Rozanov in [21].

In order to measure dependence of a sequence of random variables, say  $X:=(X_j)_{j\in\mathbb{Z}}$  (assumed strictly stationary for simplicity), we define  $\mathcal{F}_m^n$  as the  $\sigma$ -algebra generated by the  $X_j$  for  $m\leqslant j\leqslant n$ , where  $-\infty\leqslant m\leqslant n\leqslant +\infty$ .

Then mixing coefficients are defined by

$$\alpha_X(n) := \alpha\left(\mathcal{F}_{-\infty}^0, \mathcal{F}_n^{+\infty}\right)$$
 (1.1)

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$$\beta_X(n) := \beta\left(\mathcal{F}_{-\infty}^0, \mathcal{F}_n^{+\infty}\right),\tag{1.2}$$

which will be simply writen  $\alpha(n)$  (respectively  $\beta(n)$ ) when there is no ambiguity.

We say that the strictly stationary sequence  $(X_j)_j$  is  $\alpha$ -mixing (respectively  $\beta$ -mixing) if  $\lim_{n\to\infty}\alpha(n)=0$  (respectively  $\lim_{n\to\infty}\beta(n)=0$ ). Sequences which are  $\alpha$ -mixing are also called strong-mixing. Notice that the inequality  $2\alpha(\mathcal{A},\mathcal{B})\leqslant\beta(\mathcal{A},\mathcal{B})$  for any two sub- $\sigma$ -algebras  $\mathcal{A}$  and  $\mathcal{B}$  implies that each  $\beta$ -mixing sequence is strong mixing. We refer the reader to Bradley's book [4] for further information about mixing conditions.

Let  $(V, \|\cdot\|)$  be a separable normed space. We can represent a strictly stationary sequence  $(X_j)_j$  by  $X_j = f \circ T^j$ , where  $T \colon \Omega \to \Omega$  is measurable and measure preserving, that is,  $\mu(T^{-1}(S)) = \mu(S)$  for all  $S \in \mathcal{F}$  (see [8], p.456, second paragraph).

that is, 
$$\mu(T^{-1}(S)) = \mu(S)$$
 for all  $S \in \mathcal{F}$  (see [8], p.456, second paragraph). Given an integer  $N$ , we define  $S_N(f) := \sum_{j=0}^{N-1} f \circ T^j$  and  $(\sigma_N(f))^2 := \mathbb{E}\left[\|S_N(f)\|^2\right]$ .

When  $V=\mathbb{R}^d$ ,  $d\in\mathbb{N}^*$  it is well-known that if  $\left(f\circ T^j\right)_{j\geqslant 0}$  satisfies the following assumptions:

- 1.  $\lim_{N\to+\infty} \sigma_N(f) = +\infty$ ;
- 2.  $\int f d\mu = 0$ :
- 3.  $\lim_{n\to+\infty} \alpha(n) = 0$ ;
- 4. the family  $\left\{ \frac{\|S_N(f)\|^2}{(\sigma_N(f))^2}, N \geqslant 1 \right\}$  is uniformly integrable,

then  $\left(\frac{1}{\sigma_N(f)}S_N(f)\right)_{N\geqslant 1}$  converges in distribution to a Gaussian law. It was established for d=1 by Denker [7], Mori and Yoshihara [14] using a blocking argument. Volný [22] gave a proof for d arbitrary based on approximation by an array of independent random variables.

A natural question would be: what if we replace  $\mathbb{R}^d$  by another normed space?

First, we restrict ourselves to separable normed spaces in order to avoid measurability issues of sums of random variables. Corollary 10.9. in [11] asserts that a separable Banach space B with norm  $\|\cdot\|_B$  is isomorphic to a Hilbert space if and only if for all random variables X with values in B, the conditions  $\mathbb{E}\left[\mathbf{X}\right]=0$  and  $\mathbb{E}\left[\|\mathbf{X}\|_B^2\right]<\infty$  are necessary and sufficient for X to satisfy the central limit theorem. By " $\mathbf{X}$  satisfies the CLT", we mean that if  $(\mathbf{X_j})_{j\geqslant 1}$  is a sequence of independent random variables, with the same law as X, the sequence  $\left(n^{-1/2}\sum_{j=1}^n\mathbf{X_j}\right)_{n\geqslant 1}$  weakly converges in B. Hence we cannot expect a generalization in a class larger than separable Hilbert spaces. Such a space is necessarily isomorphic to  $\mathcal{H}:=\ell^2(\mathbb{R})$ , the space of square sumable sequences  $(x_n)_{n\geqslant 1}$  endowed with the inner product  $\langle x,y\rangle_{\mathcal{H}}:=\sum_{n=1}^{+\infty}x_ny_n$ . We shall denote by  $\mathbf{e_n}$  the sequence whose all terms are 0, except the n-th which is 1. Bold letters denote both randoms variables taking their values in  $\mathcal{H}$  and elements of this space.

General considerations about probability measures and central limit theorem in Banach spaces are contained in Araujo and Giné's book [2].

Notation 1. If  $(a_n)_{n\geqslant 1}$ ,  $(b_n)_{n\geqslant 1}$  are sequences of non-negative real numbers,  $a_n\lesssim b_n$  means that  $a_n\leqslant Cb_n$ , where C does not depend on n. In an analogous way, we define  $a_n\gtrsim b_n$ . When  $a_n\lesssim b_n\lesssim a_n$ , we simply write  $a_n\asymp b_n$ .

Our main results are

**Theorem A.** There exists a probability space  $(\Omega, \mathcal{F}, \mu)$  such that given 0 < q < 1, we can construct a strictly stationary sequence  $\mathbf{X} = (\mathbf{f} \circ T^k) = (\mathbf{X_k})_{k \in \mathbb{N}}$  defined on  $\Omega$ , taking its values in  $\mathcal{H}$ , such that:

- a)  $\mathbb{E}[\mathbf{f}] = 0$ ,  $\mathbb{E}[\|\mathbf{f}\|_{\mathcal{H}}^p]$  is finite for each p;
- b) the limit  $\lim_{N\to\infty} \sigma_N(\mathbf{f})$  is infinite;
- c) the process  $(\mathbf{X_k})_{k \in \mathbb{N}}$  is  $\beta$ -mixing, more precisely,  $\beta_{\mathbf{X}}(j) = O\left(\frac{1}{j^q}\right)$ ;
- d) the family  $\left\{\frac{\|S_N(\mathbf{f})\|_{\mathcal{H}}^2}{\sigma_N^2(\mathbf{f})}, N\geqslant 1\right\}$  is uniformly integrable;
- e) if  $I \subset \mathbb{N}$  is infinite, the family  $\left\{ \frac{S_N(\mathbf{f})}{\sigma_N(\mathbf{f})}, N \in I \right\}$  is not tight in  $\mathcal{H}$ ; furthermore, given a sequence  $(c_N)_{N\geqslant 1}$  of real numbers going to infinity, we have either

  - $\lim_{N \to +\infty} \frac{\sigma_N(\mathbf{f})}{c_N} = 0$ , hence  $\left(\frac{S_N(\mathbf{f})}{c_N}\right)_{N \geqslant 1}$  converges to  $\mathbf{0}_{\mathcal{H}}$  in distribution, or  $\limsup_{N \to +\infty} \frac{\sigma_N(\mathbf{f})}{c_N} > 0$ , and in this case the collection  $\left\{\frac{S_N(\mathbf{f})}{c_N}, N \geqslant 1\right\}$  is not

**Theorem A'.** Let  $(b_N)_{N\geqslant 1}$  and  $(h_N)_{N\geqslant 1}$  be sequences of positive real numbers, with  $\lim_{N\to\infty} b_N = 0$  and  $\lim_{N\to\infty} h_N = \infty$ . Then there exists a strictly stationary sequence  $\mathbf{X}:=(\mathbf{f}\circ T^k)_{k\in\mathbb{N}}=(\mathbf{X_k})_{k\in\mathbb{N}}$  of random variables with values in  $\mathcal H$  such that A, A, A of Theorem A and the following two properties hold:

- b') we have  $\sigma_N^2(\mathbf{f}) \lesssim N \cdot h_N$  and  $\frac{\sigma_N^2(\mathbf{f})}{N} \to \infty$ ;
- c') the process  $(\mathbf{X_k})_{k\in\mathbb{N}}$  is  $\beta$ -mixing, and there is an increasing sequence  $(n_k)_{k\geqslant 1}$  of integers such that for each k,  $\beta_{\mathbf{X}}(n_k) \leq b_{n_k}$ .

Remark 2. Theorem A shows that Denker's result does not remain valid in its full generality in the context of Hilbert space valued random variables.

Furthermore, a careful analysis of the proof of Proposition 6 shows that for the construction given in Theorem A, we have  $\sigma_N^2(f) = N \cdot h(N)$  with h slowly varying in the strong sense. Theorem 1 of [12] does not remain valid in the Hilbert space setting. Indeed, the arguments given in pages 654-655 show that the conditions of Denker's theorem together with the assumption that  $\sigma_N^2 = N \cdot h(N)$  with h slowly varying in the strong sense imply those of Theorem 1. These arguments are still true in the Hilbert space setting.

Remark 3. Theorem A' gives a control of the mixing coefficients on a subsequence. When  $b_N := N^{-2}$  for example, the construction gives a better estimation for the considered subsequence than what we get by Theorem A.

Tone has established in [20] a central limit theorem for strictly stationary random fields with values in  $\mathcal{H}$  under  $\rho'$ -mixing conditions. For sequences, these coefficients are defined by

$$\rho'(n) := \sup \left\{ \frac{|\mathbb{E}\left[ \langle \mathbf{f}, \mathbf{g} \rangle_{\mathcal{H}} \right] - \langle \mathbb{E}\left[ \mathbf{f} \right], \mathbb{E}\left[ \mathbf{g} \right] \rangle_{\mathcal{H}}|}{\|\mathbf{f}\|_{\mathbb{L}^{2}(\mathcal{H})} \|\mathbf{g}\|_{\mathbb{L}^{2}(\mathcal{H})}} \right\},$$

where the supremum is taken over all the non-zero functions f and g such that f and g are respectively  $\sigma(X_j, j \in S_1)$  and  $\sigma(X_j, j \in S_2)$ -measurable, where  $S_1$  and  $S_2$  are such that  $\min_{s \in S_1, t \in S_2} |s - t| \geqslant n$ , while  $\mathbb{L}^2(\mathcal{H})$  denote the collection of equivalence classes of random variables  $\mathbf{X} \colon \Omega \to \mathcal{H}$  such that  $\|\mathbf{X}\|_{\mathcal{H}}^2$  is integrable.

So "interlaced index sets" can be considered, which is not the case for  $\alpha$  and  $\beta$ mixing coefficient. Taking f and g as characteristic functions of elements of  $\mathcal{F}_{-\infty}^0$  and  $\mathcal{F}_n^{+\infty}$  respectively, one can see that  $\alpha(n)\leqslant \rho'(n)$ , hence  $\rho'$ -mixing condition is more restrictive than  $\alpha$ -mixing condition.

A partial generalization of the finite dimensional result was proved by Politis and Romano [15], namely, the conditions  $\mathbb{E} \|\mathbf{X_1}\|_{\mathcal{H}}^{2+\delta}$  finite for some positive  $\delta$  and  $\sum_j \alpha_{\mathbf{X}}(j)^{\frac{\delta}{2+\delta}}$  guarantees the convergence of  $n^{-1/2}\sum_{j=1}^n \mathbf{X_j}$  to a Gaussian random variable  $\mathcal{N}$ , whose covariance operator S satisfies

$$\mathbb{E}\left[\langle \mathcal{N}, h \rangle^2\right] = \langle Sh, h \rangle_{\mathcal{H}} = \operatorname{Var}(\langle \mathbf{X_1}, h \rangle) + 2 \sum_{i=1}^{+\infty} \operatorname{Cov}\left(\langle \mathbf{X_1}, h \rangle, \langle \mathbf{X_{1+i}}, h \rangle\right).$$

Similar results were obtained by Dehling [6].

Rio's inequality [16] asserts that given two real valued random variables X and Y with finite two order moments,

$$|\mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]| \leqslant 2 \int_0^{\alpha(\sigma(X), \sigma(Y))} Q_X(u)Q_Y(u)du.$$

It was extented by Merlevède et al. [13], namely, if  $\mathbf{X}$  and  $\mathbf{Y}$  are two random variables with values in  $\mathcal{H}$ , with respective quantile function  $Q_{\|\mathbf{X}\|_{\mathcal{H}}}$  and  $Q_{\|\mathbf{Y}\|_{\mathcal{H}}}$ , then

$$|\mathbb{E}\left[\langle \mathbf{X}, \mathbf{Y} \rangle_{\mathcal{H}}\right] - \langle \mathbb{E}\left[\mathbf{X}\right], \mathbb{E}\left[\mathbf{Y}\right] \rangle_{\mathcal{H}}| \leq 18 \int_{0}^{\alpha} Q_{\|\mathbf{X}\|_{\mathcal{H}}} Q_{\|\mathbf{Y}\|_{\mathcal{H}}} du,$$

where  $\alpha := \alpha(\sigma(\mathbf{X}), \sigma(\mathbf{Y})).$ 

From this inequality, they deduce a central limit theorem for a stationary sequence  $(\mathbf{X_j})_{i \in \mathbb{Z}}$  of  $\mathcal{H}$ -valued zero-mean random variables satisfying

$$\int_0^1 \alpha^{-1}(u) Q_{\|\mathbf{X}_0\|_{\mathcal{H}}}^2(u) \mathrm{d}u < \infty, \tag{1.3}$$

where  $\alpha^{-1}$  is the inverse function of  $x \mapsto \alpha_{\mathbf{X}}(\lfloor x \rfloor)$ .

Discussion after Corollary 1.2 in [17] proves that the later result implies Politis' one. Relative optimality of condition (1.3) (cf. [9]) can give a finite-dimensional counter-example to the central limit theorem when this condition is not satisfied. Here, the condition of uniform integrability prevents such counter-examples.

Defining  $\alpha_{2,\mathbf{X}}(n) := \sup_{i \geqslant j \geqslant n} \alpha(\mathcal{F}^0_{-\infty}, \sigma(\mathbf{X_i}, \mathbf{X_j}))$  and  $Q_{X_0}$  the right-continuous inverse of the function  $t \mapsto \mu\{\|\mathbf{X_0}\|_{\mathcal{H}} > t\}$  (that is,

 $Q_{\mathbf{X_0}}(u) := \inf\{t \in \mathbb{R}, \mu\{\|\mathbf{X_0}\|_{\mathcal{H}} > t\} \leqslant u\}$ ), Dedecker and Merlevède have shown in [5] that under the assumption

$$\sum_{k=1}^{+\infty} \int_0^{\alpha_{2,\mathbf{X}}(k)} Q_{\mathbf{X_0}}^2(u) \mathrm{d}u < \infty,$$

we can find a sequence  $(\mathbf{Z_i})_{i\in\mathbb{N}}$  of Gaussian random variables with values in  $\mathcal H$  such that almost surely,

$$\left\| \mathbf{S_n} - \sum_{i=1}^{n} \mathbf{Z_i} \right\|_{\mathcal{H}} = o\left(\sqrt{n \log \log n}\right).$$

# 2 The proof

### **2.1** Construction of f

In order to construct a counter-example, we shall need the following lemma, which will be proved later.

We will denote U the Koopman operator associated to T, which acts on measurable functions by U(f)(x) := f(T(x)).

**Lemma 4.** Let  $(u_k)_{k\geqslant 1}\subset (0,1)$  be a sequence of numbers. Then there exists a dynamical system  $(\Omega, \mathcal{F}, \mu, T)$  and a sequence of random variables  $(\xi_k)_{k\geqslant 1}$  such that

- 1. for each  $k \ge 1$ ,  $\mu(\xi_k = 1) = \mu(\xi_k = -1) = \frac{u_k}{2}$  and  $\mu(\xi_k = 0) = 1 u_k$ ;
- 2. the random variables  $(U^i\xi_k, k \geqslant 1, i \in \mathbb{Z})$  are mutually independent.

Recall that  $e_k$  is the k-th element of the canonical orthonormal system of  $\mathcal{H}=\ell^2(\mathbb{R})$ . We define

$$f_k := \sum_{i=0}^{n_k - 1} U^{-i} \xi_k \text{ and } \mathbf{f} := \sum_{k=1}^{+\infty} f_k \mathbf{e_k},$$
 (2.1)

where the  $\xi_i$ 's are constructed using to Lemma 4 taking  $u_k := n_k^{-2}$ . Conditions on the increasing sequence of integers  $(n_k)_{k \ge 1}$  will be specified latter.

Then  $\mathbf{X_k} := \mathbf{f} \circ T^k$  is a strictly stationary sequence. Note that  $\|\mathbf{f}\|_{\mathcal{H}}^2$  is an integrable random variable whenever  $\sum_k \frac{1}{n_k}$  is convergent. In the sequel, the choice of  $n_k$  will guarantee this condition.

#### 2.2 Preliminary results

We express  $S_N(f_k)$  as a linear combination of independent random variables. By direct computations, we get

$$f_k = n_k \xi_k + (I - U) \sum_{i=1-n_k}^{-1} (n_k + i) U^i \xi_k,$$
(2.2)

hence

$$S_N(f_k) = n_k \sum_{j=0}^{N-1} U^j \xi_k + \sum_{i=1-n_k}^{-1} (n_k + i) U^i \xi_k - \sum_{i=N-n_k+1}^{N-1} (n_k + i - N) U^i \xi_k.$$

This formula can be simplified if we distinguish the cases  $N \ge n_k$  and  $n_k < N$  (we break the third sum at the index i = 0 if necessary). This gives

$$S_N(f_k) = \sum_{j=0}^{N-1} (N-j)U^j \xi_k + \sum_{j=1-n_k}^{N-n_k} (n_k + j)U^j \xi_k + N \sum_{j=1+N-n_k}^{-1} U^j \xi_k, \quad \text{if } N < n_k, \quad (2.3)$$

$$S_N(f_k) = n_k \sum_{j=0}^{N-n_k} U^j \xi_k + \sum_{j=N-n_k+1}^{N-1} (N-j) U^j \xi_k + \sum_{j=1-n_k}^{-1} (n_k+j) U^j \xi_k, \quad \text{if } N \geqslant n_k. \quad (2.4)$$

The computation of the expectation of the square of partial sums gives

$$\sigma_N^2(f_k) = \begin{cases} \frac{1}{n_k^2} \left( 2\sum_{j=1}^N j^2 + (n_k - N - 1)N^2 \right) & \text{if } N < n_k, \\ \frac{1}{n_k^2} \left( n_k^2 (N - n_k + 1) + 2\sum_{j=1}^{n_k - 1} j^2 \right) & \text{if } N \geqslant n_k. \end{cases}$$
 (2.5)

Notation 5. If N is a positive integer and  $(n_k)_{k\geqslant 1}$  is an increasing sequence of integers, denote by i(N) the unique integer for which  $n_{i(N)}\leqslant N< n_{i(N)+1}$ .

**Proposition 6.** Assume that  $(n_k)_{k\geqslant 1}$  satisfies the condition

there is 
$$p > 1$$
 such that for each  $k$ ,  $n_{k+1} \geqslant n_k^p$ . (C)

Then  $\sigma_N^2(\mathbf{f}) \asymp N \cdot i(N)$ .

*Proof.* Using (2.5), the fact that  $M^3 \asymp \sum_{j=1}^M j^2$  and  $\sigma_N^2(\mathbf{f}) = \sum_{k\geqslant 1} \sigma_N^2(f_k)$ , we have

$$\sigma_N^2(\mathbf{f}) \geqslant \sum_{k=1}^{i(N)} \sigma_N^2(f_k) \approx N \sum_{i=1}^{i(N)} 1 = N \cdot i(N).$$
 (2.6)

From (2.5) in the case  $n_k \geqslant N$ , we deduce

$$\sum_{k \geqslant i(N)+1} \sigma_N^2(f_k) \lesssim \sum_{k \geqslant i(N)+1} \frac{N^2}{n_k} \leqslant \frac{N^2}{n_{i(N)+1}} + \sum_{k \geqslant i(N)+1} \frac{N^2}{n_k} \frac{1}{n_k^{p-1}}.$$
 (2.7)

Since  $n_{i(N)+1} \geqslant N$  and the series  $\sum_{k \geqslant 1} n_k^{1-p}$  is convergent (by the ratio test), we obtain

$$\sum_{k \geqslant i(N)+1} \sigma_N^2(f_k) \lesssim N + N \sum_{k \geqslant i(N)+1} \frac{1}{n_k^{p-1}} \lesssim N.$$
 (2.8)

Combining (2.6) and (2.8), we get

$$N \cdot i(N) \lesssim \sigma_N^2(\mathbf{f}) \lesssim \sum_{k=1}^{i(N)} \sigma_N^2(f_k) + \sum_{k \geqslant i(N)+1} \sigma_N^2(f_k) \lesssim N \cdot i(N) + N \lesssim N \cdot i(N).$$
 (2.9)

**Proposition 7.** Assume that  $\sum_k n_k^{-a}$  is convergent for any positive real number a. Then for each integer p,  $\|\mathbf{f}\|_{\mathcal{H}}$  has a finite moment of order p.

*Proof.* We shall use Rosenthal's inequality (Theorem 3, [19]): there exists a constant C depending only on q such that if M is an integer,  $Y_1, \ldots, Y_M$  are independent real valued zero mean random variables for which  $\mathbb{E}|Y_i|^q < \infty$  for each i, then

$$\mathbb{E}\left|\sum_{j=1}^{M} Y_j\right|^q \leqslant C\left(\sum_{j=1}^{M} \mathbb{E}\left|Y_j\right|^q + \left(\sum_{j=1}^{M} \mathbb{E}\left[Y_j^2\right]\right)^{q/2}\right). \tag{2.10}$$

If q = 2p is given then we have

$$\mathbb{E}|f_k|^{2p} \lesssim n_k^{-1} + n_k^{-p} \lesssim n_k^{-1}.$$
 (2.11)

We provide a sufficient condition for the uniform integrability of the family  $\mathcal{S}:=\left\{\frac{\|S_N(\mathbf{f})\|_{\mathcal{H}}^2}{\sigma_N^2(\mathbf{f})}, N\geqslant 1\right\}$ .

**Proposition 8.** If  $(n_k)_{k\geqslant 1}$  satisfies (C), then S is uniformly integrable.

*Proof.* For  $N \geqslant 1$ , we have:

$$\frac{\|S_N(\mathbf{f})\|_{\mathcal{H}}^2}{\sigma_N^2(\mathbf{f})} = \sum_{j=1}^{i(N)-1} \frac{|S_N(f_j)|^2}{\sigma_N^2(\mathbf{f})} + \frac{\left|S_N(f_{i(N)})\right|^2}{\sigma_N^2(\mathbf{f})} + \frac{\left|S_N(f_{i(N)+1})\right|^2}{\sigma_N^2(\mathbf{f})} + \sum_{j \geqslant i(N)+2} \frac{\left|S_N(f_j)\right|^2}{\sigma_N^2(\mathbf{f})},$$

hence it is enough to prove that the families

$$\begin{split} \mathcal{S}_1 &:= \left\{ \sum_{k=1}^{i(N)-1} \frac{\left|S_N(f_k)\right|^2}{\sigma_N^2(\mathbf{f})}, N \geqslant 1 \right\}, \\ \mathcal{S}_2 &:= \left\{ \frac{\left|S_N(f_{i(N)})\right|^2}{\sigma_N^2(\mathbf{f})}, N \geqslant 1 \right\} =: \left\{ u_N, N \geqslant 1 \right\}, \\ \mathcal{S}_3 &:= \left\{ \frac{\left|S_N(f_{i(N)+1})\right|^2}{\sigma_N^2(\mathbf{f})}, N \geqslant 1 \right\} =: \left\{ v_N, N \geqslant 1 \right\}, \text{ and } \\ \mathcal{S}_4 &:= \left\{ \sum_{k \geqslant i(N)+2} \frac{\left|S_N(f_k)\right|^2}{\sigma_N^2(\mathbf{f})}, N \geqslant 1 \right\} \end{split}$$

are uniformly integrable. For  $S_1$  and  $S_4$ , we shall show that these families are bounded in  $\mathbb{L}^p$  for  $p \in (1,2]$  as in (C).

• for  $S_1$ : using the expression in (2.4) and (2.10) with q:=2p>2, we have

$$\mathbb{E}\left[|S_N(f_k)|^{2p}\right] \leqslant C\left(2\sum_{j=1}^{n_k} \frac{j^{2p}}{n_k^2} + \frac{n_k^{2p}(N-n_k)}{n_k^2}\right) + C\left(2\sum_{j=1}^{n_k} \frac{j^2}{n_k^2} + \frac{(N-n_k)n_k^2}{n_k^2}\right)^p$$

$$\lesssim \frac{1}{n_k^2} \left(n_k^{2p+1} + (N-n_k)n_k^{2p}\right) + \frac{1}{n_k^{2p}} \left(n_k^3 + (N-n_k)n_k^2\right)^p$$

$$= \frac{Nn_k^{2p}}{n_k^2} + \frac{N^p n_k^{2p}}{n_k^{2p}}$$

$$= Nn_k^{2(p-1)} + N^p$$

hence

$$||S_N(f_k)^2||_p \lesssim N^{1/p} n_k^{\frac{2^{p-1}}{p}} + N$$

which gives

$$\left\| \sum_{k=1}^{i(N)-1} \frac{|S_N(f_k)|^2}{\sigma_N^2(\mathbf{f})} \right\|_p \lesssim \frac{\sum_{k=1}^{i(N)-1} (N^{1/p} n_k^{2\frac{p-1}{p}} + N)}{\sigma_N^2(\mathbf{f})}$$

$$\lesssim \frac{i(N) n_{i(N)-1}^{2\frac{p-1}{p}} + Ni(N)}{\sigma_N^2(\mathbf{f})}.$$

From (2.6), we get

$$\left\| \sum_{k=1}^{i(N)-1} \frac{\left| S_N(f_k) \right|^2}{\sigma_N^2(\mathbf{f})} \right\|_p \lesssim \frac{n_{i(N)}^{2\frac{p-1}{p}}}{n_{i(N)}} + 1 = n_{i(N)}^{\frac{p-2}{p}} + 1.$$

Since  $p-2 \leq 0$ , we obtain that  $S_1$  is bounded in  $\mathbb{L}^p$  hence uniformly integrable.

• for  $S_2$ : using (2.4) in the case  $n_k \leq N$  and Proposition 6, we get

$$\|u_N\|_1 \lesssim \frac{N}{\sigma_N^2(\mathbf{f})} \lesssim \frac{1}{i(N)}.$$
 (2.12)

Since  $||u_N||_1 \to 0$  and  $u_N \in \mathbb{L}^1$  for each N, the family  $S_2$  is uniformly integrable.

• for  $S_3$ : using (2.3) in the case  $n_k > N$  and Proposition 6, we get

$$||v_N||_1 \lesssim \frac{N^2}{n_{i(N)+1}\sigma_N^2(\mathbf{f})} \lesssim \frac{N}{N \cdot i(N)}.$$
 (2.13)

Since  $\|v_N\|_1 \to 0$  and  $v_N \in \mathbb{L}^1$  for each N, the family  $S_3$  is uniformly integrable.

• for  $S_4$ : as for  $S_1$ , we shall show that this family is bounded in  $\mathbb{L}^p$  with  $p \in (1,2]$ . We have, using (2.3) and (2.10)

$$\mathbb{E}\left[\left|S_{N}(f_{k})\right|^{2p}\right] \lesssim \frac{1}{n_{k}^{2}} (N^{2p+1} + N^{2p}(n_{k} - N)) + \frac{1}{n_{k}^{2p}} (N^{3} + (n_{k} - N)N^{2})^{p}$$

$$= \frac{N^{2p}}{n_{k}} + \frac{N^{2p}}{n_{k}^{p}}$$

$$\lesssim \frac{N^{2p}}{n_{k}}$$

as  $N \leq n_k$ . We thus get that

$$\left\| \sum_{k \geqslant i(N)+2} |S_N(f_k)|^2 \right\|_p \lesssim N^2 \sum_{k \geqslant i(N)+2} \frac{1}{n_k^{1/p}}.$$

Also, using (2.5), we have

$$\sigma_N^2(\mathbf{f}) \gtrsim N^2 \sum_{k \geqslant i(N)+1} \frac{1}{n_k}.$$

The condition  $n_{k+1} \geqslant n_k^p$  gives boundedness in  $\mathbb{L}^p$  of  $\mathcal{S}_4$ .

This concludes the proof of A.

**Proposition 9.** Assume that  $(n_k)_{k\geqslant 1}$  is such that  $\mathcal{S}$  is uniformly integrable and  $\sum_k n_k^{-1}$  is convergent. Then for each  $I\subset\mathbb{N}$  infinite, the collection  $\left\{\frac{S_N(\mathbf{f})}{\sigma_N(\mathbf{f})}, N\in I\right\}$  is not tight in  $\mathcal{H}$ . Its finite-dimensional distributions converge to 0 in probability.

Furthermore, if  $(c_N)_{N\geqslant 0}$  is a sequence of positive numbers going to infinity, we have either

- $\lim_{N\to+\infty} \frac{\sigma_N(\mathbf{f})}{c_N} = 0$ , hence  $\left(\frac{S_N(\mathbf{f})}{c_N}\right)_{N\geqslant 1}$  converges to  $\mathbf{0}_{\mathcal{H}}$  in distribution, or
- $\limsup_{N \to +\infty} \frac{\sigma_N(\mathbf{f})}{c_N} > 0$ , and in this case the sequence  $\left\{ \frac{S_N(\mathbf{f})}{c_N}, N \geqslant 1 \right\}$  is not tight.

*Proof.* We first prove that the finite dimensional distributions of  $\frac{S_N(\mathbf{f})}{\sigma_N(\mathbf{f})}$  converge weakly to 0.

For each  $d \in \mathbb{N}$ , we have  $\frac{\langle S_N(\mathbf{f}), \mathbf{e_d} \rangle_{\mathcal{H}}}{\sigma_N(\mathbf{f})} \to 0$  in distribution. Indeed, we have by (2.2) that  $\langle S_N(\mathbf{f}), \mathbf{e_d} \rangle_{\mathcal{H}} = n_d \sum_{i=0}^{N-1} U^i \xi_d + (I - U^N) \sum_{i=1-n_d}^{-1} (n_d + i) U^i \xi_d$ . We conclude noticing that  $\sigma_N(\mathbf{f})^{-1} (I - U^N) \sum_{i=1-n_d}^{-1} (n_d + i) U^i \xi_d$  goes to 0 in probability as N goes to infinity, using Proposition 6 and the estimate

$$\mathbb{E}\left(n_d \sum_{i=0}^{N-1} U^i \xi_d\right)^2 = N \lesssim \frac{\sigma_N^2(\mathbf{f})}{i(N)}$$

This can be extended replacing  $e_d$  by any  $v \in \mathcal{H}$  by an application of Theorem 4.2. in [3]. By Proposition 4.15 in [2], the only possible limit is the Dirac measure at  $0_{\mathcal{H}}$ .

Assume that the sequence  $\left\{\frac{S_N(\mathbf{f})}{\sigma_N(\mathbf{f})}, N \geqslant 1\right\}$  is tight. The sequence  $\left(\frac{\|S_N(\mathbf{f})\|_{\mathcal{H}}^2}{\sigma_N^2(\mathbf{f})}\right)_{N \geqslant 1}$  is a uniformly integrable sequence of random variables of mean 1. A weakly convergent subsequence would go to  $0_{\mathcal{H}}$ . According to Theorem 5.4 in [3], we should have that the limit random variable has expectation 1. This contradiction gives the result when  $I=\mathbb{N}\setminus\{0\}$ . Applying this reasonning to subsequences, one can see that for any infinite subset I of  $\mathbb{N}\setminus\{0\}$ , the family  $\left\{\frac{S_N(\mathbf{f})}{\sigma_N(\mathbf{f})}, N\in I\right\}$  is not tight. Let  $(c_N)_{N\geqslant 1}$  be a sequence of positive real numbers such that  $\lim_{N\to +\infty}c_N=+\infty$ .

- first case:  $\frac{\sigma_N(\mathbf{f})}{c_N}$  converges to 0. In this case, the sequence  $\left(\frac{\|S_N(\mathbf{f})\|^2}{c_N^2}\right)_{N>1}$  converges to 0 in  $\mathbb{L}^1$ , hence the sequence  $\left(\frac{S_N(\mathbf{f})}{c_N}\right)_{N\geqslant 1}$  converges in distribution to
- second case:  $\limsup_{N\to\infty} \frac{\sigma_N(\mathbf{f})}{c_N} > 0$ . Hence there is some r>0 and a sequence of integers  $l_i \uparrow \infty$  such that for each i,  $\frac{\sigma_{l_i}(\mathbf{f})}{c_{l_i}} \geqslant \frac{1}{r}$ , that is,  $c_{l_i} \leqslant r\sigma_{l_i}(\mathbf{f})$ .

Assume that the family  $\left\{ \frac{S_{l_i}(\mathbf{f})}{cl_i}, i \geqslant 1 \right\}$  is tight. This means that given a positive  $\varepsilon$ , one can find a compact set  $K=K(\varepsilon)$  such that for each i,  $\mu\left\{\frac{S_{l_i}(\mathbf{f})}{c_{l_i}}\in K\right\}>1-\varepsilon$ . We can assume that this compact set is convex and contains 0 (we consider the closed convex hull of  $K \cup \{0\}$ , which is compact by Theorem 5.35 in [1]). Then we have

$$\left\{ \frac{S_{l_i}(\mathbf{f})}{c_{l_i}} \in K \right\} = \left\{ \frac{S_{l_i}(\mathbf{f})}{\sigma_{l_i}(\mathbf{f})} \in \frac{c_{l_i}}{\sigma_{l_i}(\mathbf{f})} K \right\} \\
\subset \left\{ \frac{S_{l_i}(\mathbf{f})}{\sigma_{l_i}(\mathbf{f})} \in rK \right\},$$

and we would deduce tightness of  $\left\{ \frac{S_{l_i}(\mathbf{f})}{\sigma_{l_i}(\mathbf{f})}, i \geqslant 1 \right\}$ , which cannot happen.

Remark 10. In the second case, it may happen that the finite dimensional distributions does not converge to degenerate ones, for example with  $c_N := N$ .

## 2.3 Proof of Theorem A

Notice that if  $n_{k+1} \geqslant n_k^p$  for some p>1 and  $n_1=2$ , then  $n_k\geqslant 2^{p^k}$ , hence the condition of Proposition 7 is fulfilled. We get A since each  $f_k$  has expectation 0.

We denote  $|x| := \sup \{k \in \mathbb{Z}, k \leq x\}$  the integer part of the real number x.

**Proposition 11.** Let p > 1. With  $n_k := \lfloor 2^{p^k} \rfloor$  (which satisfies (C)), we have for each positive integer l,

$$\beta_{\mathbf{X}}(l) \lesssim \frac{1}{l^{\frac{1}{n}}}.$$

*Proof.* We define  $\beta_k(n)$  as the *n*-th  $\beta$ -mixing coefficient of the sequence  $(f_k \circ T^i)_{i \ge 0}$ .

By Lemma 5 of [10], we have the estimate  $\beta_k(0) \leqslant 4n_k^{-1}$  for each k. Using then Proposition 4 of this paper (cf. [4] for a proof), we get that  $\beta_{\mathbf{X}}(n_k) \lesssim \sum_{j \geqslant k} \frac{1}{n_j}$  for each integer k. Since  $p^i \geqslant i$  for i large enough,

$$\sum_{i \ge k} \frac{1}{n_j} = \sum_{i=0}^{+\infty} \frac{1}{2^{p^{i+k}}} = \sum_{i=0}^{+\infty} \frac{1}{2^{p^i p^k}} \lesssim \sum_{i=0}^{+\infty} \frac{1}{2^i} \frac{1}{2^{p^k}} = \frac{2}{2^{p^k}},$$

we get

$$\beta_{\mathbf{X}}(N) \leqslant \beta_X(n_{i(N)}) \lesssim \frac{1}{n_{i(N)}} = \frac{1}{n_{i(N)+1}^{1/p}} \leqslant \frac{1}{N^{1/p}}.$$

This proves A. For any p, the choice  $n_k := \lfloor 2^{p^k} \rfloor$  satisfies the condition of Proposition 8, which proves A. We conclude the proof by Proposition 9.

Remark 12. For each of these choices,  $\sigma_N^2(\mathbf{f})$  behaves asymptotically like  $N\log\log N$ . Theorem A' shows that we can construct a process which satisfies the same asymptotic behavior of partial sums and has a variance close to a linear one.

A question would be: can we construct a strictly stationary sequence with all the properties of Theorem A, except A which is replaced by an assumption of linear variance?

#### 2.4 Proof of Theorem A'

Let  $(h_N)_{N\geqslant 1}$  be the sequence involved in Theorem A'. We define for an integer u the quantity  $h^{-1}(u):=\inf\{j\in\mathbb{N},h_i\geqslant u\}.$ 

If  $(b_k)_{k\geqslant 1}$  is the given sequence (that can be assumed decreasing), we define inductively

$$n_{k+1} := \max \left\{ n_k^2, \lfloor \frac{2^k}{b_{n_k}} \rfloor, h^{-1}(k) \right\}.$$
 (2.14)

Let N be an integer. We assume without loss of generality that the growth of the sequence  $(h_N)_{N\geqslant 1}$  is slow enough in order to guarantee that there exists k such that  $N=h^{-1}(k)$ . We then have  $i(N)\leqslant k+1\leqslant h_N+1$ , hence using Proposition 6, we get b').

We have  $n_k \geqslant 2^{2^k}$  hence by a similar argument as in the proof of Theorem A, A is satisfied.

By a similar argument as in [10], we get  $\beta_{\mathbf{X}}(n_k) \leqslant b_{n_k}$ , hence c') holds.

Remark 13. By (1.3), we cannot expect the relationship  $\beta_{\mathbf{X}}(\cdot) \leq b$  for the whole sequence.

Since for each k,  $n_{k+1} \ge n_k^2$ , Proposition 8 and 9 apply. This concludes the proof of Theorem A'.

Proof of Lemma 4. Let  $\Omega := [0,1]^{\mathbb{N}^* \times \mathbb{Z}}$ , where [0,1] is endowed with Borel  $\sigma$ - algebra and Lebesgue measure, and  $\Omega$  with the product structure.

For  $(k,j) \in \mathbb{N}^* \times \mathbb{Z}$  and  $S \subset [0,1]$ , let  $P_{k,j}(S) := \prod_{(i_1,i_2) \in \mathbb{N}^* \times \mathbb{Z}} S_{i_1,i_2}$ , where  $S_{i_1,i_2} = S$  if  $(i_1,i_2) = (k,j)$  and [0,1] otherwise. Then we define

$$A_{k,j}^+ := P_{k,j}([0, 2^{-1}(u_k)^{-1}]),$$

$$A_{k,j}^- := P_{k,j}([2^{-1}(u_k)^{-1},(u_k)^{-1}]),$$

$$A_{k,j}^{(0)} := P_{k,j}([(u_k)^{-1}, 1]),$$

the map T by  $T\left((x_{k,j})_{(k,j)\in\mathbb{N}^*\times\mathbb{Z}}\right):=(x_{k,j+1})_{(k,j)\in\mathbb{N}^*\times\mathbb{Z}}$ , and

$$\xi_k := \chi_{A_{k,0}^+} - \chi_{A_{k,0}^-}.$$

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