

ERNST MORITZ ARNDT  
UNIVERSITÄT GREIFSWALD



Wissen  
lockt.  
Seit 1456

# The empirical process of a random walk in random scenery

Martin Wendler

Conference on Random Processes, Random Media  
November 21st to 24th, 2016



Institut für  
Mathematik und Informatik

# Outline

## Introduction

Sequential Empirical Process  
Random Walks in Random Scenery

## Main Result

Limit Theorem  
Application to  $U$ -Statistics

# Empirical Distribution Function

- ▶  $(X_n)_{n \in \mathbb{N}}$  stationary sequence of real valued random variables
- ▶ distribution function:  $F : \mathbb{R} \rightarrow [0, 1]$  with  $F(s) := P(X_i \leq s)$

empirical distribution function:  $F_n : \mathbb{R} \rightarrow [0, 1]$

- ▶  $F_n(s) := \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{X_i \leq s}$
- ▶ natural estimator for  $F$

## Theorem (Glivenko-Cantelli)

Let  $(X_n)_{n \in \mathbb{N}}$  be ergodic, then

$$\sup_{s \in \mathbb{R}} |F(s) - F_n(s)| \rightarrow 0$$

*almost surely.*

# Sequential Empirical Process

- ▶  $(X_n)_{n \in \mathbb{N}}$  stationary sequence of real valued random variables
- ▶ sequential empirical process: two parameter process

$$(W_n(s, t))_{s, t \in [0, 1]}$$

with

$$W_n(s, t) := \sum_{i=1}^{\lfloor nt \rfloor} (\mathbb{1}_{\{X_i \leq s\}} - F(s))$$

- ▶ fixed  $s$ : partial sum process
- ▶ fixed  $t$ : empirical process
- ▶ without loss of generality:  $F(s) = s$  for  $s \in [0, 1]$

# First Result on Sequential Empirical Process

## Theorem (Müller, 1970)

Let  $(X_n)_{n \in \mathbb{N}}$  be iid, then

$$\left( \frac{1}{\sqrt{n}} W_n(s, t) \right)_{s, t \in [0, 1]} \Rightarrow (K(s, t))_{s, t \in [0, 1]}$$

where  $K$  is a centered Gaussian process with  
 $\text{Cov}(K(s, t), K(s', t')) = \min\{t, t'\}(\min(s, s') - ss')$

limit process called Kiefer-Müller-process

**extensions to short range dependence:**

e.g. Berkes, Philipp (1977): approximating functionals of strongly mixing sequences

# Sketch of Proof

- ▶ for fixed  $s, t$ :

$$W_n(s, t) + E [W_n(s, t)] = \sum_{i=1}^{\lfloor nt \rfloor} \mathbb{1}_{\{X_i \leq s\}}$$

binomial( $\lfloor nt \rfloor, s$ ) distributed

- ▶ finite-dimensional convergence: De Moivre-Laplace theorem
- ▶ tightness: exponential inequality
- ▶ note: Müller used  $C_{D[0,1]}([0, 1])$ , but proof in  $D([0, 1]^2)$  possible

# Properties of Kiefer-Müller-process

- ▶ for fixed  $s$ :  $(K(s, t))_{t \in [0,1]}$  Brownian motion
- ▶ for fixed  $t$ :  $(K(s, t))_{s \in [0,1]}$  Brownian bridge
- ▶ self-similarity with exponent  $\frac{1}{2}$ :  
 $(K(s, at))_{s,t \in [0,1]}$  and  $(a^{1/2}K(s, t))_{s,t \in [0,1]}$  have same distribution
- ▶ rough paths:  $(K(s, t))_{s,t \in [0,1]}$  not Lipschitz-continuous,  
 $\gamma$ -Hölder-continuous for any  $\gamma \in (0, \frac{1}{2})$

# Long Range Dependent Gaussian Sequences

$X_i = G(\xi_i)$ , where  $(\xi_n)_{n \in \mathbb{N}}$  stationary, Gaussian process with  $E[\xi_i] = 0$ ,  $\text{Var}[\xi_i] = 1$  and

$$r(k) := \text{Cov}(\xi_1, \xi_{1+k}) = k^{-D}L(k)$$

$D \in (0, 1)$  and slowly varying function  $L(k)$

**Hermite polynomials:** orthogonal with respect to Gaussian measure

$$H_1(x) = x, H_2(x) = x^2 - 1, H_3(x) = x^3 - 3x, \dots$$

Hermite rank:

$$r := \min \{k \mid E[G(\xi_1)H_k(\xi_1)] \neq 0\}$$



# Hermite Expansion

$L_2$ -approximation of  $G(\xi_i)$

$$G(\xi_i) \stackrel{L_2}{\approx} \sum_{k=r}^{\infty} \frac{c_k}{k!} H_k(\xi_i)$$
$$\Rightarrow \sum_{i=1}^n G(\xi_i) \stackrel{L_2}{\approx} \sum_{k=r}^{\infty} \frac{c_k}{k!} \left( \sum_{i=1}^n H_k(\xi_i) \right)$$

with

$$c_k = E[G(\xi_1)H_k(\xi_1)]$$

and

$$\sum_{k=r}^{\infty} \frac{c_k^2}{k!} < \infty$$

# Reduction Principle

- ▶ correlation of Hermite polynomials:

$$\text{Cov}(H_k(\xi_1), H_k(\xi_{1+i})) = k! (\text{Cov}(\xi_1, \xi_{1+i}))^k$$

- ▶ variance of sums of Hermite polynomials:

$$\text{Var} \left[ \left( \sum_{i=1}^n H_k(\xi_i) \right) \right] \approx \begin{cases} \beta_k n^{2-kD} L^k(n) & \text{if } kD < 1 \\ Ck!n & \text{if } kD > 1 \end{cases}$$

- ▶ sum of higher order Hermite polynomials: lower order of variance
- ▶ reduction principle: limit behaviour of  $\sum_{i=1}^n G(\xi_i)$  dominated by  $\frac{c_k}{k!} \left( \sum_{i=1}^n H_r(\xi_i) \right)$

# Sequential Empirical Process under Long Memory

Hermite rank:  $m := \min \{k | \exists s : E [(\mathbb{1}_{\{X_1 \leq s\}} - F(s))H_k(\xi_1)] \neq 0\}$

$$W_n(s, t) := \sum_{i=1}^{\lfloor nt \rfloor} (\mathbb{1}_{\{X_i \leq s\}} - F(s))$$

Theorem (Dehling, Taqqu, 1989)

If  $D \in (0, \frac{1}{m})$

$$\left( n^{\frac{mD-2}{2}} L^{-1/2}(n) W_n(s, t) \right)_{s,t \in [0,1]} \Rightarrow \left( C_{m,D} J_m(s) Z_m(t) \right)_{s,t \in [0,1]}$$

with  $J_m(s) = E [(\mathbb{1}_{\{X_1 \leq s\}} - F(s))H_m(\xi_1)]$  and  $Z_m$ : Hermite process of order  $m$

Ho and Hsing (1996): linear processes with long memory

## Idea of Proof

## Lemma (Uniform Reduction Principle)

$$\sup_{s,t \in [0,1]} \left| n^{\frac{mD-2}{2}} L^{-1/2}(n) \sum_{i=1}^{[nt]} \sum_{k=m+1}^{\infty} J_k(s) H_k(\xi_i) \right| \Rightarrow 0$$

$$\begin{aligned} \left( \frac{n^{\frac{mD-2}{2}}}{L^{m/2}(n)} W_n(s, t) \right)_{s,t \in [0,1]} &\stackrel{L_2}{\approx} \left( \frac{n^{\frac{mD-2}{2}}}{L^{m/2}(n)} \sum_{i=1}^{[nt]} \frac{J_m(s)}{m!} H_m(\xi_i) \right)_{s,t \in [0,1]} \\ &\Rightarrow (C_{m,D} J_m(s) Z_m(t))_{s,t \in [0,1]} \end{aligned}$$

# Properties of Dehling-Taqqu-Type Limit

- ▶ for fixed  $s$ :  $(G(s, t))_{t \in [0,1]}$  Hermite process
- ▶ for fixed  $t$ :  $(G(s, t))_{s \in [0,1]}$  deterministic function with random factor (semi-degenerate limit)
- ▶ self-similarity with exponent  $\frac{2-mD}{2}$
- ▶ not Gaussian, if  $mD < 1$ ,  $m \geq 2$
- ▶ rough paths in  $t$  direction:  $(G(s, t))_{t \in [0,1]}$  not Lipschitz-continuous,  $\gamma$ -Hölder-continuous for any  $\gamma < \frac{2-mD}{2}$
- ▶ smooth paths in  $s$  direction:  $(G(s, t))_{s \in [0,1]}$  Lipschitz-continuous if  $F$  Lipschitz continuous

**Do all processes with long memory have a Dehling-Taqqu-type limit of the sequential empirical process?**

# Definition of Random Walk in Random Scenery

**random walk:**  $(X_n)_{n \in \mathbb{N}}$  iid  $\mathbb{Z}$ -valued random variables in the normal domain of attraction of an  $\alpha$ -stable law  $F_\alpha$  with  $0 < \alpha \leq 2$

$$S_n := \sum_{m=1}^n X_m$$

**scenery:**  $(\xi(i))_{i \in \mathbb{Z}}$  iid  $\mathbb{R}$ -valued random variables in the normal domain of attraction of an  $\beta$ -stable law  $F_\beta$  with  $0 < \beta \leq 2$

**random walk in random scenery:**

$$(\xi(S_i))_{i \in \mathbb{N}}$$

# Properties of Random Walk in Random Scenery

- ▶ ergodic
- ▶ not absolutely regular ( $\beta$ -mixing)
- ▶ long range dependent  
if  $S_n$  simple random walk,  $\beta = 2$ , then

$$\begin{aligned}\text{Cov}(\xi(S_i), \xi(S_{i+2k})) &= P(S_i = S_{i+2k}) \text{Cov}(\xi(1), \xi(1)) \\ &\approx \frac{1}{\sqrt{k}} \frac{1}{\sqrt{\pi}} \text{Var}(\xi(1))\end{aligned}$$

- ▶ heavy tails, if  $(\xi(i))_{i \in \mathbb{Z}}$  has heavy tails

# Limit Theorem for Partial Sums

## Theorem (Kesten, Spitzer, 1979)

For  $1 < \alpha \leq 2$

$$\left( n^{-1 + \frac{1}{\alpha} - \frac{1}{\alpha\beta}} \sum_{i=1}^{\lfloor nt \rfloor} \xi(S_i) \right)_{t \in [0,1]} \Rightarrow (\Delta_t)_{t \in [0,1]}$$

### properties of $\Delta$

- ▶ self-similar with exponent  $1 - \frac{1}{\alpha} + \frac{1}{\alpha\beta}$
- ▶ non Gaussian even if  $\beta = 2$  (scenery has Gaussian limit)
- ▶ continuous even if  $\beta < 2$  (scenery has limit with jumps)



# Definition of Limit Process

$$\sum_{i=1}^n \xi(S_i) = \sum_{x \in \mathbb{Z}} N_n(x) \xi(x)$$

with occupation times

$$N_n(x) = \sum_{i=1}^n \mathbb{1}_{\{S_i=x\}}$$

$$\Delta_t = \int_{-\infty}^{\infty} L_t(x) dZ(x)$$

with  $Z$ : two-sided  $\beta$ -stable process

$L$ : local time of an  $\alpha$ -stable process  $S^*$ , i.e.

$$\int_0^t \mathbb{1}_{[a,b]}(S_s^*) ds = \int_a^b L_t(x) dx$$

# Sequential Empirical Process

$(X_n)_{n \in \mathbb{N}}$  iid, in the normal domain of attraction of an  $\alpha$ -stable law with  $1 < \alpha \leq 2$

$$S_n := \sum_{m=1}^n X_m$$

**sequential empirical process:**

$$W_n(s, t) := \sum_{i=1}^{\lfloor nt \rfloor} (\mathbb{1}_{\{\xi(S_i) \leq s\}} - F(s))$$

no reduction principle: if  $S_n$  simple random walk, then for all  $p \in \mathbb{N}$

$$\text{Cov}(H_p(\xi(S_i)), H_p(\xi(S_{i+2k}))) \approx C_p \frac{1}{\sqrt{k}}$$

# Limit Theorem for Sequential Empirical Process

without loss of generality:  $\xi_j$  uniformly distributed on  $[0, 1]$

Theorem (W., 2016)

$$n^{-1+\frac{1}{2\alpha}} W_n \Rightarrow W$$

in the space  $D([0, 1]^2)$

with

- ▶  $W(s, t) := \int_{\mathbb{R}} L_t(x) dK(s, x)$
- ▶  $(K(s, t))_{s, t \in [0, 1]}$ : Kiefer-Müller process
- ▶ local time  $L$

# Sketch of Proof I

- ▶ occupations times

$$N_n(x) := \sum_{i=1}^n \mathbb{1}_{\{S_i=x\}}.$$

- ▶  $L$ : local time

$$\int_0^t \mathbb{1}_{[a,b)}(S_s^*) ds = \int_a^b L_t(x) dx$$

## Lemma

for  $k \in \mathbb{N}$ ,  $t_1, \dots, t_k \in [0, 1]$

$$\left( n^{-2+\frac{1}{\alpha}} \sum_{x \in \mathbb{Z}} N_{[nt_i]}(x) N_{[nt_j]}(x) \right)_{1 \leq i, j \leq k} \Rightarrow \left( \int L_{t_i}(x) L_{t_j}(x) dx \right)_{1 \leq i, j \leq k}$$

# Sketch of Proof II

- ▶ finite dimensional convergence: use characteristic function and Cramér-Wold theorem
- ▶

$$\begin{aligned} n^{-1+\frac{1}{2\alpha}} \sum_{j=1}^k \theta_j \sum_{i=1}^{\lfloor nt_j \rfloor} \left( \mathbb{1}_{\{Y_i \leq s_j\}} - s_j \right) \\ = n^{-1+\frac{1}{2\alpha}} \sum_{j=1}^k \theta_j \sum_{x \in \mathbb{Z}} N_{\lfloor nt_j \rfloor}(x) \left( \mathbb{1}_{\{\xi_x \leq s_j\}} - s_j \right) \\ = n^{-1+\frac{1}{2\alpha}} \sum_{j=1}^k \theta_j \sum_{x \in \mathbb{Z}} N_{\lfloor nt_j \rfloor}(x) \zeta_j(x) \end{aligned}$$

with  $\zeta_j(x) = \mathbb{1}_{\{\xi_x \leq s_j\}} - s_j$

# Sketch of Proof III

- ▶ condition on  $(S_n)_{n \in \mathbb{N}}$  and use conditional independence

$$\begin{aligned}\varphi_n(\lambda) &:= E\left(\exp\left(i\lambda n^{-1+\frac{1}{2\alpha}} \sum_{j=1}^k \theta_j \sum_{x \in \mathbb{Z}} N_{[nt_j]}(x) \zeta_j(x)\right)\right) \\ &= E\left(\prod_{x \in \mathbb{Z}} E\left(\exp\left(i\lambda n^{-1+\frac{1}{2\alpha}} \sum_{j=1}^k \theta_j N_{[nt_j]}(x) \zeta_j(x)\right) \middle| (X_n)_{n \in \mathbb{N}}\right)\right)\end{aligned}$$

- ▶ finite dimensional convergence: Taylor expansion and Lévy's continuity theorem
- ▶ tightness: fourth moment inequality and lemma by Bickel and Wichura (1971)

# Properties of Limit Process

- ▶ self-similar with exponent  $1 - \frac{1}{2\alpha}$
- ▶ for fixed  $s$ :  $(W(s, t))_{t \in [0,1]}$  special case of process  $\Delta$
- ▶ for fixed  $t$ : conditional on random walk  $S_n$  Brownian bridge, so  $(W(s, t))_{s \in [0,1]}$  mixture of Brownian bridges
- ▶ thus rough paths
- ▶ marginal distributions: not Gaussian (Gaussian mixtures)
- ▶ after continuous modification: for any  $\gamma < 1 - \frac{1}{2\alpha}$ ,  $\gamma' < \frac{1}{2}$  there exists almost surely finite  $C_{\gamma, \gamma'}$ , such that

$$|W(s, t) - W(s', t')| \leq C_{\gamma, \gamma'} (|s - s'|^{\gamma'} + |t - t'|^{\gamma}).$$

# Continuity of Limit Process

nonuniform Kolmogorov-Chentsov theorem

## Lemma

$(\mathbf{X}_t)_{t \in [0,1]^d}$  stochastic process, for some  $m \geq 1$ ,  $c_1, \dots, c_d, \beta_1, \dots, \beta_d$ :

$$E [|\mathbf{X}_t - \mathbf{X}_s|^m] \leq \sum_{i=1}^d c_i |t_i - s_i|^{d+\beta_i}.$$

for all  $t = (t_1, \dots, t_d)$ ,  $s = (s_1, \dots, s_d)$ , then for  $\gamma_1, \dots, \gamma_d$  with  $\gamma_i < \frac{\beta_i}{m}$  there exists a continuous modification  $\tilde{\mathbf{X}}$  with

$$|\tilde{\mathbf{X}}_t - \tilde{\mathbf{X}}_s| \leq C_{\gamma_1, \dots, \gamma_d} \sum_{i=1}^d |t_i - s_i|^{\gamma_i}.$$



# Comparison

	independent	random walk in random scenery	Ird Gaussian
exponent of self similarity	$1/2$	$1 - \frac{1}{2\alpha} > 1/2$	$\frac{2-mD}{2} > 1/2$
marginal distr.	Gaussian	not Gaussian: Gaussian mixture	not Gaussian if $m > 1$
$\gamma_t$ -Hölder-cont. $t$ direction	$\gamma_t < 1/2$	$\gamma_t > 1/2$	$\gamma_t > 1/2$
$\gamma_s$ -Hölder-cont. $s$ direction	$\gamma_s < 1/2$	$\gamma_s < 1/2$	$\gamma_s = 1$

# Definition

- ▶  $(X_n)_{n \in \mathbb{N}}$  stationary sequence of random variables
- ▶ kernel:  $h : \mathbb{R}^2 \rightarrow \mathbb{R}$  measurable and symmetric

## Definition

$U$ -statistic:

$$U_n(h) := \sum_{1 \leq i < j \leq n} h(X_i, X_j)$$

von Mises-statistic:

$$V_n(h) := \sum_{i,j=1}^n h(X_i, X_j)$$

# Relation to Empirical Process

- ▶ empirical distribution function:  $F_n(s) := \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{X_i \leq t}$
- ▶ without loss of generality: distribution function  $F(s) = s$
- ▶ under independence:  $E[h(X_i, X_j)] = \iint h(x, y) dF(x) dF(y)$ , so  $E[V_n] \approx n^2 \iint h(x, y) dF(x) dF(y)$

$$\begin{aligned} V_n - n^2 \iint h(x, y) dF(x) dF(y) &= n^2 \iint h(x, y) dF_n(x) dF_n(y) - n^2 \iint h(x, y) dF(x) dF(y) \\ &= 2n \iint h(x, y) dF(x) dW_n(y, 1) + \iint h(x, y) dW_n(x, 1) dW_n(y, 1) \end{aligned}$$

# Linear Part

- ▶ set  $h_1(x) := \int h(x, y) dF(y) = E[h(x, X_1)]$
- ▶ assume:  $h_1$  of bounded variation

$$\begin{aligned} 2n \iint h(x, y) dF(x) dW_n(y, 1) &= 2n \int h_1(y) dW_n(y, 1) \\ &= 2n \int W_n(s, 1) dh_1(s) \end{aligned}$$

- ▶ by continuous mapping theorem

$$\begin{aligned} n^{-2+\frac{1}{2\alpha}} 2n \iint h(x, y) dF(x) dW_n(y, 1) \\ = 2 \int n^{-1+\frac{1}{2\alpha}} W_n(s, 1) dh_1(s) \Rightarrow 2 \int W(s, 1) dh_1(s) \end{aligned}$$

# Degenerate Part

- ▶ note that  $\|W_n\|_\infty = O_p(n^{1-\frac{1}{2\alpha}})$
- ▶ assumption: signed measure induced by  $h$  of bounded total variation

$$\begin{aligned}\iint h(x, y) dW_n(x, 1) dW_n(y, 1) &= O(\|W_n\|_\infty^2) = O_p(n^{2-\frac{1}{\alpha}}) \\ &= o_p(n^{2-\frac{1}{\alpha}})\end{aligned}$$

- ▶ by Slutsky's theorem

$$\begin{aligned}&n^{-2+\frac{1}{2\alpha}} \left( V_n - n^2 \iint h(x, y) dF(x) dF(y) \right) \\ &= n^{-1+\frac{1}{2\alpha}} 2 \int W_n(s, 1) dh_1(s) + n^{-2+\frac{1}{2\alpha}} \iint h(x, y) dW_n(x, 1) dW_n(y, 1) \\ &\Rightarrow 2 \int W(s, 1) dh_1(s)\end{aligned}$$

# Examples

▶  $h(x, y) = |x - y|$

$$\frac{2}{n(n-1)} U_n(h) = \frac{2}{n(n-1)} \sum_{1 \leq i < j \leq n} |X_i - X_j|,$$

Gini's mean difference

▶  $h(x, y) = \frac{1}{2}(x - y)^2$

$$\frac{2}{n(n-1)} U_n(h) = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2.$$

sample variance

# Conditions on kernel

- ▶ conditions on total variation: imply boundedness of  $h$
- ▶ examples:  $h$  not bounded
- ▶ Guillotin-Plantard, Ladret (2005): fourth moments
- ▶ Franke, Pène, Wendler (2016+): domain of  $\beta$ -stable law for  $\beta \in (1, 2]$
- ▶ Franke, Pène, Wendler (2017): domain of  $\beta$ -stable for  $\beta \in (0, 2]$

## Case $\beta \in (1, 2]$

### Assumptions:

- ▶  $h_1(\xi(1))$  in normal domain of attraction of  $\beta$ -stable law,  $1 < \beta \leq 2$
- ▶  $E|h(\xi(1), \xi(2))|^\eta < \infty$  with  $\eta = \frac{2\beta'}{1+\beta'}$  for a  $\beta' > \beta$
- ▶  $E[h(\xi(1), \xi(2))] = 0$

### Theorem (Franke, Pène, W., 2016+)

If  $1 < \alpha \leq 2$ , then in  $C[0, 1]$

$$(n^{-2+\frac{1}{\alpha}-\frac{1}{\alpha\beta}} U_n(t))_{t \in [0,1]} \Rightarrow (\Delta_t)_{t \in [0,1]},$$

- ▶  $U_n(t) = U_k$  if  $nt = k$ , linear interpolated in between
- ▶  $\Delta_t = \int L_t(x) dZ(x)$



# Hoeffding decomposition

$$U_n = (n-1) \sum_{i=1}^n h_1(\xi(S_i)) + \sum_{1 \leq i < j \leq n} h_2(\xi(S_i), \xi(S_j))$$

with  $h_1(x) := E(h(x, \xi(1)))$

$h_2(x, y) := h(x, y) - h_1(x) - h_1(y)$ .

## Lemma

$$\max_{k \leq n} \sum_{1 \leq i < j \leq k} h_2(\xi(S_i), \xi(S_j)) = o(n^{2 - \frac{1}{\alpha} + \frac{1}{\alpha\beta}})$$

*almost surely*

## Case $\beta \in (0, 2)$

### Assumptions:

- ▶  $h(\xi_1, \xi_2)$  in domain of  $\beta$ -stable law with  $\beta \in (0, 2)$
- ▶ there exist  $C_0 > 0$  and  $\gamma > \frac{3\beta}{4}$  such that for all  $z, z' \in (1, +\infty)$

$$P(|h(\xi_1, \xi_2)| \geq z \text{ and } |h(\xi_1, \xi_3)| \geq z') \leq C_0 (zz')^{-\gamma}$$

- ▶ if  $\beta > 1$ , then  $\mathbb{E}[h(\xi_1, \xi_2)] = 0$
- ▶ if  $\beta \geq 4/3$ , there exists  $C'_0 > 0$  and  $\theta' > \frac{3\beta}{4} - 1$  such that

$$\forall M, M' \in (0, +\infty), \quad |\mathbb{E}[\mathbf{h}_M(\xi_1, \xi_2)\mathbf{h}_{M'}(\xi_1, \xi_3)]| \leq C'_0 (MM')^{-\theta'},$$

where  $\mathbf{h}_M(x, y) := h(x, y)\mathbf{1}_{\{|h(x, y)| \leq M\}} + \frac{\beta}{\beta-1}(c_0 - c_1)M^{1-\beta}$

- ▶ if  $\beta = 1$ , then  $\lim_{M \rightarrow +\infty} \mathbb{E}[h(\xi_1, \xi_2)\mathbf{1}_{\{|h(\xi_1, \xi_2)| \leq M\}}] = 0$

# Weak Convergence

Theorem (Franke, Pène, W., 2017)

$$\left( n^{-2+\frac{2}{\alpha}-\frac{2}{\alpha\beta}} U_{[nt]} \right)_{t \in [0, T]} \Rightarrow \left( \int_{\mathbb{R}^2} L_t(x) L_t(y) dZ_{x,y} \right)_{t \in [0, T]}$$

*in the Skorokhod space  $D([0, T])$  endowed with the  $J_1$ -metric*

- ▶  $(Z_{x,y})_{x,y \in \mathbb{R}}$ :  $\beta$ -stable Lévy-sheet
- ▶ method of proof: point processes
- ▶ for  $\beta \in (1, 2]$ : rate faster than in previous theorem
- ▶ conditions imply:  $h_1 = 0$ , thus linear part vanishes

# Conclusion

- ▶ functional non-central limit theorem for sequential empirical process
- ▶ some properties like in independent case (roughness of the paths), some properties like in long memory case (not Gaussian, self-similarity)
- ▶ application:  $U$ -statistics (restrictive conditions)
- ▶ less restrictive conditions: other methods like Hoeffding-decomposition or point processes

Thank you for your attention!

# References

- D.W. MÜLLER (1970): On Glivenko-Cantelli convergence, *Probab. Theory Related Fields* **16** 195-210.
- H. KESTEN, F. SPITZER (1979): A limit theorem related to an new class of self similar processes, *Probab. Theory Related Fields* **50** 5-25.
- H. DEHLING, M.S. TAQUU (1989): The empirical process of some long-range dependent sequences with an application to U-statistics, *Ann. Statist.* **17** 1767-1783.
- N. GUILLOTIN-PLANTARD, V. LADRET (2005): Limit theorems for U-statistics indexed by a one dimensional random walk, *ESAIM* **9** 95-115.
- M. WENDLER (2016): The sequential empirical process of a random walk in random scenery, *Stochastic Process. Appl.* **126** 2787-2799.
- B. FRANKE, F. PÈNE, M. WENDLER (2017): Convergence of U-statistics indexed by a random walk to stochastic integrals of a Levy sheet, *Bernoulli* **23**, 329-378.
- B. FRANKE, F. PÈNE, M. WENDLER (2016+): Stable limit theorem for U-Statistic processes indexed by a random walk, *Electronic Communications in Probability*.