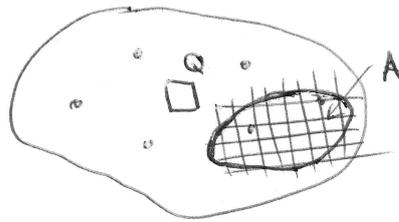


# Max-stable random fields: Theory and examples.

## Poisson processes.



Stars in the sky.

Cube  $Q$ . Volume  $\varepsilon \times 0$ .

$P[\text{Star in } Q] \approx \lambda \varepsilon, \lambda > 0$

Consider set  $A$ . Vol of  $A$ :  $|A|$ .  $N(A)$  = number of stars in  $A$ .

Distribution of  $N(A)$ ? Cover  $A$  by  $\approx \frac{|A|}{\varepsilon}$  cubes.

$$N(A) \sim \text{Bin}\left(\frac{|A|}{\varepsilon}, \lambda \varepsilon\right) \underset{\varepsilon \rightarrow 0}{\approx} \text{Poi}(\lambda |A|).$$

ZAKHAR KABLUCHKO, MAY 2013,  
LECTURES AT THE PHD COURSE ON  
EXTREMES IN SPACE AND TIME, COPENHAGEN

Def. Homogeneous PPP with intensity  $\lambda > 0$  is a random collection of points in  $\mathbb{R}^d$  s.t.

① If  $A_1, \dots, A_n \subset \mathbb{R}^d$  (Borel) are disjoint  $\Rightarrow N(A_1), \dots, N(A_n)$  are independent r.v.

②  $N(A) \sim \text{Poi}(\lambda |A|)$ .

Def. Inhomogeneous PPP. Let  $(E, \mathcal{A}, \lambda)$  be a measure space.  $\lambda$   $\sigma$ -finite measure.

PPP( $\lambda$ ) is a random point configuration  $\{X_i\}$  s.t.

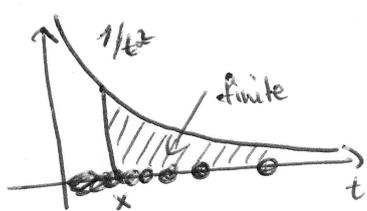
① If  $A_1, \dots, A_n \in \mathcal{A}$  are disjoint  $\Rightarrow N(A_1), \dots, N(A_n)$  are indep. r.v.

②  $N(A) \sim \text{Poi}(\underbrace{\lambda(A)}_{\text{meas of } A})$  for  $\forall A \in \mathcal{A}$ . Rem.  $\text{Poi}(\infty)$  takes value  $+\infty$  with probab 1.

Here,  $N(A) = \sum_i \mathbb{1}_{X_i \in A}$  is the number of points in  $A$ .

Rem.  $\mathbb{E}N(A) = \lambda(A)$

Example.  $E = \mathbb{R}_+$ ,  $\mathcal{A} = \text{Borel } \sigma\text{-Algebra}$ ,  $\lambda(dt) = \frac{dt}{t^2}$ , that is  $\lambda(A) = \int_A \frac{dt}{t^2}$ .



①  $\lambda((x, +\infty)) = \int_x^\infty \frac{dt}{t^2} = \frac{1}{x} < \infty, x > 0$

$N((x, +\infty)) \sim \text{Poi}\left(\frac{1}{x}\right)$

$\mathbb{E}N((x, +\infty)) = \frac{1}{x}$

②  $\lambda((0, x)) = \int_0^x \frac{dt}{t^2} = \infty$

$N((0, x)) = +\infty$  a.s.

# Extreme-value theory

$X_1, X_2, X_3, \dots$  iid r.v.

Sums. CLT:  $\frac{X_1 + \dots + X_n - EX_1 \cdot n}{\sqrt{n \text{Var } X_1}} \xrightarrow[n \rightarrow \infty]{d} N(0, 1)$  if  $\text{Var } X_1 < \infty$

If  $\text{Var } X_1 = \infty \Rightarrow$  stable:  $\frac{X_1 + \dots + X_n - a_n}{b_n} \xrightarrow[n \rightarrow \infty]{d}$  stable laws.

Maxima.  $M_n = \max\{X_1, \dots, X_n\} = X_1 \vee \dots \vee X_n$ .

Question:  $\exists a_n, b_n$  s.t.  $\frac{M_n - a_n}{b_n} \xrightarrow[n \rightarrow \infty]{d} G(x)$  (non-degenerate)?

Fisher-Tippett - Gnedenko: Possible limits (called extreme-value distributions)

$$\Lambda(x) = e^{-e^{-x}}, x \in \mathbb{R} \quad \text{Gumbel}$$

$$\Phi_d(x) = e^{-1/x^d}, x > 0, d > 0 \quad \text{Fréchet}$$

$$\Psi_d(x) = e^{-(|x|)^d}, x < 0, d > 0 \quad \text{Weibull}$$

or linear transformation of one of these laws.

Def. A r.v.  $X$  is max-stable if  $\forall n \exists a_n, b_n$  s.t.  $\frac{X_1 \vee \dots \vee X_n - a_n}{b_n} \stackrel{d}{=} X$

Max-stable  $\Leftrightarrow$  extreme-value distribution  $\Leftrightarrow \Lambda, \Phi_d, \Psi_d$  or linear transformation.

Let  $\{X(t), t \in T\}$  be a random field. Let  $X_1, X_2, \dots$  be iid copies of  $X$ .

Def.  $X$  is called max-stable (with  $\mathbb{I}$ -Fréchet margins) if

$$\frac{X_1 \vee \dots \vee X_n}{n} \stackrel{d}{=} X \quad \forall n \in \mathbb{N}.$$

Here,  $(X_1 \vee \dots \vee X_n)(t) = X_1(t) \vee \dots \vee X_n(t)$ , pointwise maximum.

Rem.  $\forall t \in T$ :  $X(t)$  has distr. func.  $e^{-c(t)/x}, x > 0$ , for some  $c(t) > 0$ .

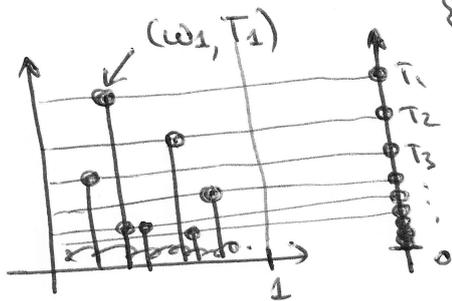
# De Haan Representation of max-stable processes.

Fréchet noise  $(E, \mathcal{A}, \lambda)$   $\sigma$ -finite measure space. Main example:  $E=[0,1], \lambda=\text{Leb}$ .

Def. Fréchet noise is a PPP on  $E \times \mathbb{R}_+$  with intensity  $\lambda \times \frac{dt}{t^2}$ .

Points are denoted by  $\{(\omega_i, T_i)\}_{i \in \mathbb{N}}$ .

For  $E=[0,1], \lambda=\text{Leb}$ : let  $\{T_i\}$  be PPP  $(\frac{dt}{t^2})$  on  $\mathbb{R}_+$   
 $\{\omega_i\}_{i \in \mathbb{N}}$  be i.i.d uniform on  $[0,1]$  } indep



Def (Stochastic integral) Let  $f \in L^1_+(E)$ , that is  $f \geq 0, \int_E f < \infty$ .

$$\int^v f \stackrel{\text{def}}{=} \sup_{i \in \mathbb{N}} (f(\omega_i) \cdot T_i).$$

Properties:

- ① Max-linearity:  $\int^v cf = c \int^v f, \int^v (f \vee g) = (\int^v f) \vee (\int^v g)$ .
- ② Independence: if  $\text{supp } f \cap \text{supp } g = \emptyset \Rightarrow \int^v f$  is indep of  $\int^v g$ .
- ③  $\int^v f$  is 1-Fréchet:  $\mathbb{P}[\int^v f \leq x] = \exp\left\{-\int_E f(t) \lambda(dt) \cdot \frac{1}{x}\right\}, x > 0$ .

Proof.  $\mathbb{P}[\int^v f \leq x] = \mathbb{P}[\forall i: T_i \leq \frac{x}{f(\omega_i)}]$

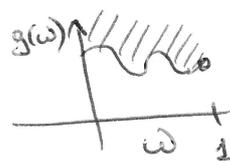
$$= \mathbb{P}[\text{no point above } g]$$

$$= \exp\left\{-\int_0^1 \int_{g(\omega)}^{\infty} \frac{1}{t^2} dt d\omega\right\}$$

$$= \exp\left\{-\int_0^1 \frac{d\omega}{g(\omega)}\right\}$$

$$= \exp\left\{-\int_0^1 f(\omega) d\omega \cdot x^{-1}\right\}.$$

Let  $g(\omega) = \frac{x}{f(\omega)}$



□

④ T any set,  $\{f_t, t \in T\} \subset L^1_+$ .

Then  $\{\int^v f_t : t \in T\}$  is a max-stable process (with 1-Fréchet margins).

Theorem (De Haan, 1984). Let  $\{X(t), t \in T\}$  be a max-stable process (with 1-Fréchet margins). Assume that

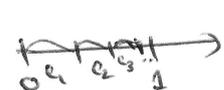
$T$  is countable

or  $T = \mathbb{R}^d$  and  $X$  is continuous in probability.

Then,  $\exists \{f_t : t \in T\} \subset L_1^+ [0, 1]$  s.t.

$$\{X(t) : t \in T\} \stackrel{\text{f.d.d.}}{=} \{S^{\vee} f_t : t \in T\}.$$

Example. Let  $\{X(t), t \in \mathbb{N}\}$  be iid with d.f.  $e^{-1/x}, x > 0$ .

Representation: Let  $\sum \alpha_i = 1, \alpha_i > 0$    $I_t := [c_{t-1} + c_t, c_t + c_{t+1}]$

$$\text{Let } f_t = \frac{1}{c_t} \mathbb{1}_{I_t}$$

$\Rightarrow \{S^{\vee} f_t : t \in T\}$  are iid Fréchet with d.f.  $e^{-1/x}$ .

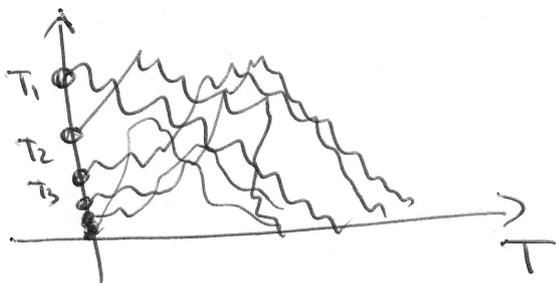
View  $[0, 1]$  as a probability space and  $\{f_t, t \in T\}$  as a stochastic process.

If  $\omega \sim \mathcal{U}[0, 1] \Rightarrow F(t; \omega) = f_t(\omega)$  is a stoch. process.

$F_1, F_2, \dots, F_i(t; \omega) = f_t(\omega_i)$  are iid copies of  $F$  ( $\omega_i \sim \mathcal{U}[0, 1]$  iid).

Then,

$$\{X(t) : t \in T\} \stackrel{\text{f.d.d.}}{=} \left\{ \sup_{i \in \mathbb{N}} (\pi_i \cdot F_i(t)) : t \in T \right\}.$$



# Hüsler-Reiss distributions and Brown-Resnick processes

First we recall de Haan's representation in the setting of Gumbel margins.

$\{X(t), t \in T\}$  random field.  $X_1, X_2, \dots$  copies of  $X$ .

Def.  $X$  is called max-stable (with Gumbel margins) if  $\{X_1 \vee \dots \vee X_n(t) - \log n, t \in T\} \stackrel{\text{fold}}{=} \{X(t), t \in T\}$ .

Rem.  $\forall t \in T$   $X(t)$  has distr. function  $e^{-e^{-(x-\mu(t))}}$ ,  $\mu(t) \in \mathbb{R}$ .

Rem.  $X(t)$  max-stable Gumbel  $\Leftrightarrow e^{X(t)}$  max-stable Fréchet.

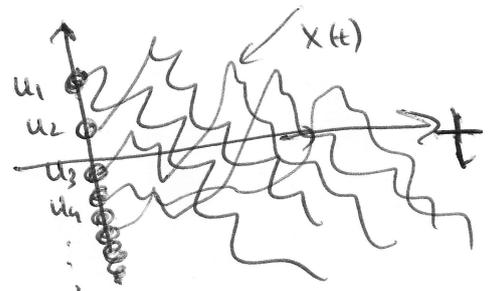
De Haan Representation:

$\exists$  process  $\{F(t), t \in T\}$  with values  $[-\infty, \infty)$  s.t.  $\mathbb{E} e^{F(t)} < \infty \forall t \in T$ .

$F_1, F_2, \dots$  iid copies of  $F$

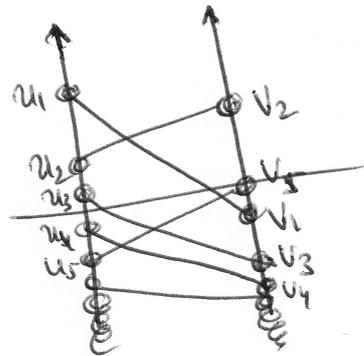
$\{u_i\} \sim \text{PPP}(e^{-t} dt)$  on  $\mathbb{R}$

$\{X(t), t \in T\} \stackrel{\text{fold}}{=} \left\{ \sup_{i \in \mathbb{N}} (u_i + F_i(t)), t \in T \right\}$



## 2Dim Hüsler-Reiss distr.

Example  $\{u_i\} \sim \text{PPP}(e^{-t} dt)$  } indep.  
 $\xi_i \sim N(-\frac{\delta^2}{2}, \delta^2)$  iid  
 negative drift  
 $v_i = u_i + \xi_i$



Claim:  $\{v_i\} \sim \text{PPP}(e^{-t} dt)$

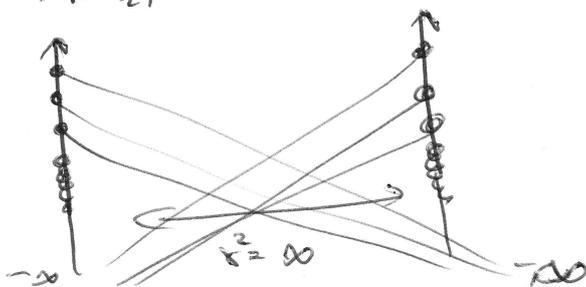
Proof Intensity of  $v_i$  at  $v = \int_{\mathbb{R}} du e^{-u} \mathbb{P}[\xi = v-u] = \int_{\mathbb{R}} dz e^z \mathbb{P}[\xi = z] \cdot e^{-v}$   
 $= e^{-v} \cdot \mathbb{E} e^{\xi} = 1$  since  $\mathbb{E} e^{\xi} = \mathbb{E} e^{\delta N - \delta^2/2} = e^{\delta^2/2 - \delta^2/2} = 1$ .  $\square$

Special cases:

$\delta = 0 \Rightarrow$  complete dependence

$\delta^2 = +\infty \Rightarrow N(\frac{\delta^2}{2}, \delta^2) = -\infty$  a.s.

complete independence.



Def. The vector  $(\max u_i, \max v_i)$  has the two-dim Hüsler-Reiss distr. with parameter  $\delta^2$ .

## 2Dim Hüsler-Reiss distr. as a limit

1 Station: Measurements  $X_1, \dots, X_n \sim N(0, 1)$  iid.

$$M_n^X = \max\{X_1, \dots, X_n\}$$

$$\exists b_n \sim \sqrt{2 \log n} : b_n (M_n^X - b_n) \xrightarrow[n \rightarrow \infty]{d} e^{-e^{-x}}$$

$$\{b_n (X_i - b_n)\}_{i=1}^n \xrightarrow[n \rightarrow \infty]{d} \text{PPP}(e^{-t} dt) \text{ on } \mathbb{R}.$$

2 Stations Measurements  $X_1, \dots, X_n$   
 $Y_1, \dots, Y_n$

On day  $i$ :  $(X_i, Y_i)$ .

Assumptions:  $(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)$  are indep. bivariate Gaussian

$$X_1, \dots, X_n \sim N(0, 1), \quad Y_1, \dots, Y_n \sim N(0, 1)$$

$$\text{corr}(X_i, Y_i) = \rho < 1.$$

$$M_n^X = \max_{i=1, \dots, n} X_i$$

$$M_n^Y = \max_{i=1, \dots, n} Y_i$$

$$\text{Sibuya: } (b_n (M_n^X - b_n), b_n (M_n^Y - b_n)) \xrightarrow[n \rightarrow \infty]{d} (e^{-e^{-x}}, e^{-e^{-y}})$$

$\uparrow \quad \quad \uparrow$   
 dependent                      independent!

Asymptotic independence of  $M_n^X$  and  $M_n^Y$  for  $\forall \rho < 1$ .

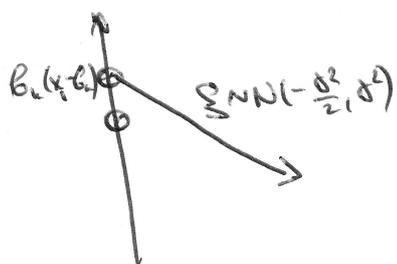
$$\text{Hüsler-Reiss suggested: } \rho = \rho_n = 1 - \frac{\delta^2}{4 \log n} + o\left(\frac{1}{\log n}\right) \xrightarrow[n \rightarrow \infty]{} 1.$$

We compute the limiting distr. of  $(b_n (M_n^X - b_n), b_n (M_n^Y - b_n))$ .

Condition on  $X_1 = b_n + \frac{x}{b_n}$ ,  $x \in \mathbb{R}$  fixed

$$\mathbb{E}[b_n (Y_1 - b_n) \mid X_1 = b_n + \frac{x}{b_n}] = \rho_n \cdot b_n (b_n + \frac{x}{b_n}) - b_n^2 = \dots = -\frac{\delta^2}{2} + o(1)$$

$$\text{Var}[b_n (Y_1 - b_n) \mid X_1 = b_n + \frac{x}{b_n}] = (1 - \rho_n^2) b_n^2 = \delta^2 + o(1).$$



$$\Rightarrow (b_n (M_n^X - b_n), b_n (M_n^Y - b_n)) \xrightarrow[n \rightarrow \infty]{d} \overbrace{(\max U_i, \max V_i)}^{\text{Hüsler-Reiss distr.}}$$

## Brown-Resnick processes.

Let  $\{\xi(t), t \in T\}$  be a stock process,  $\xi(t) \in L^2$ ,  $\mathbb{E}\xi(t) = 0$ .

The incremental variance of  $\xi$  is

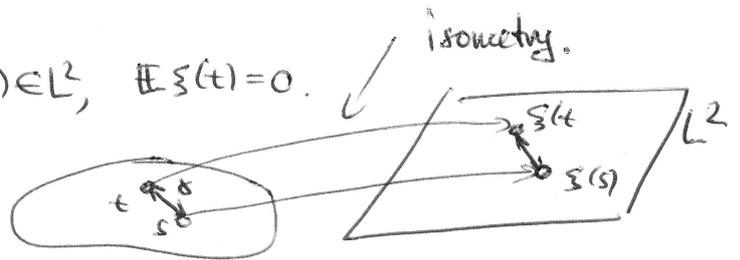
$$\delta^2(t,s) := \text{Var}[\xi(t) - \xi(s)]$$

Note:  $\delta = \sqrt{\delta^2}$  is a pseudometric on  $T$  which is isometrically embeddable in  $L^2$ .

$\delta^2$  is a negative definite kernel on  $T$  meaning that  $\forall t_1, \dots, t_n \in T, \forall a_1, \dots, a_n \in \mathbb{R}$

s.t.  $\sum a_i = 0$  we have  $\sum_{i,j} a_i a_j \delta^2(t_i, t_j) \leq 0$ .

Incremental variance  $(\Leftrightarrow)$  pseudometric embeddable  $(\Leftrightarrow)$  negative definite kernel into Hilbert space



## Construction of Brown-Resnick processes.

1) Let  $T$  be a set

2) Let  $\delta^2(\cdot, \cdot)$  be negative definite kernel on  $T$

3) Let  $\{\xi(t), t \in T\}$  be a Gauss process s.t.  $\mathbb{E}\xi(t) = 0$ ,  $\text{Var}[\xi(t) - \xi(s)] = \delta^2(t,s)$ .

Let  $\sigma^2(t) = \text{Var} \xi(t)$ .

Rem.  $\xi(t)$  is non-unique.  $\forall t_0 \in T \exists \xi$  such that  $\xi(t_0) = 0$ .

4) Let  $\xi_1, \xi_2, \dots$  be iid copies of  $\xi$ .

5) Let  $\{\mathcal{U}_i\}$  be PPP ( $e^{-t} dt$ ) on  $\mathbb{R}$ .

Thm. The process  $X(t) = \max \{ \mathcal{U}_i + \xi_i(t) - \frac{\sigma^2(t)}{2} \}$ ,  $t \in T$  is

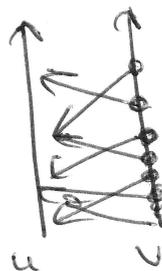
max-stable (follows from de Haan's repr.) and its f.d.d. depend on the

$\delta^2$  only (and not on the choice of  $\xi$ ).

## Example



gives the same as

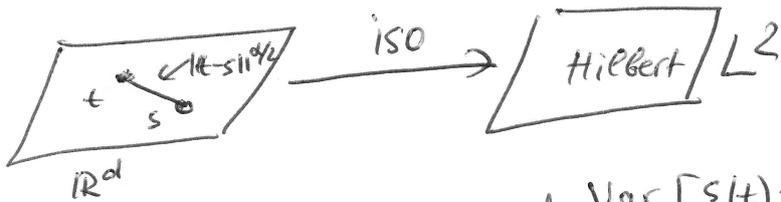


We call  $X(t)$  the Brown-Resnick process associated to  $\delta^2$ .

Stationary Brown-Riesz processes. Let  $T = \mathbb{R}^d$

Consider  $\delta^2(t, s) = \delta^2(t-s)$  depending only on  $t-s$ .

~~Example~~ Example:  $\delta^2(t) = \|t\|_2^\alpha, \alpha \in (0, 2]$ .



Gaussian process with  $\mathbb{E}\xi(t) = 0$  and  $\text{Var}[\xi(t) - \xi(s)] = \|t-s\|_2^\alpha$  is called (Lévy) fractional Brownian Motion (fBM).

1) Let  $\{\xi(t), t \in \mathbb{R}^d\}$  be a Gaussian process with  $\mathbb{E}\xi(t) = 0, \text{Var}[\xi(t) - \xi(s)] = \delta^2(t-s)$ . Note:  $\xi$  has stationary increments. Let  $\text{Var} \xi(t) = \sigma^2(t)$ .

2) Let  $\xi_1, \xi_2, \dots$  be iid copies of  $\xi$

3) Let  $\{u_i\} \sim \text{PPP}(e^{-t} dt)$  on  $\mathbb{R}$ .

Thm. The process  $X(t) = \max_{i \in \mathbb{N}} \{u_i + \xi_i(t) - \frac{\sigma^2(t)}{2}\}$  is max-stable and stationary.

Proof.  $\delta^2(t+h, s+h) = \delta^2(t, s)$ .  $\square$

Ex 1.  $\delta^2(t) = |t|, T = \mathbb{R}$ .

$\xi(t)$  is Brownian Motion on  $\mathbb{R}$ .

$$X(t) = \max_{i \in \mathbb{N}} \left\{ u_i + \xi_i(t) - \frac{|t|}{2} \right\}$$

(Original Brown-Riesz process, 1977)

Explanation of stationarity:

$e^{-t} dt$  is invariant measure for  $B(t) - \frac{t}{2}$ .

Ex 2.  $\xi(t) = Nt, N \sim N(0, 1)$

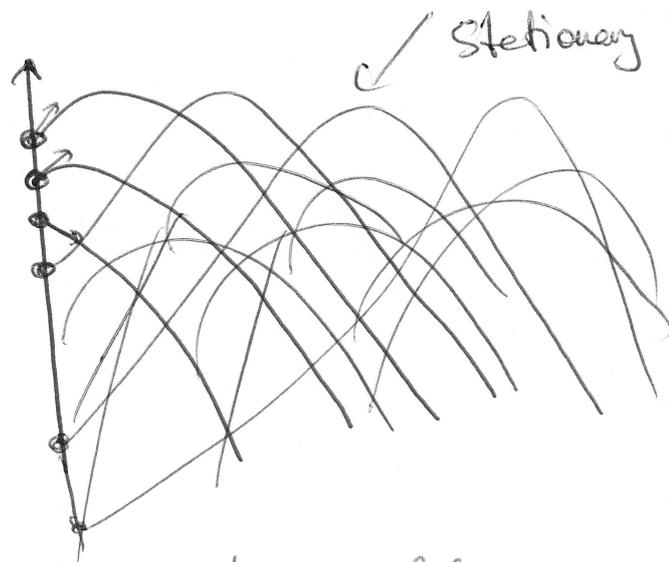
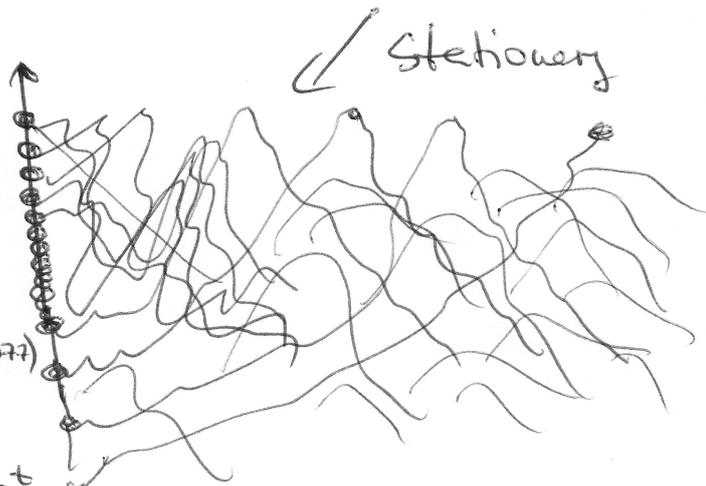
$$\delta^2(t) = t^2$$

$$\xi(t) = \max_{i \in \mathbb{N}} \left\{ u_i + Nt - \frac{t^2}{2} \right\}$$

Ex 3.  $\delta(t) = |t|^\alpha$ . Systems of fBM's.

$$\alpha = 1 \Rightarrow \text{Ex 1.}$$

$$\alpha = 2 \Rightarrow \text{Ex 2.}$$



Random parabolas.  
= Smith process.