Cylindrical Lévy processes

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Why do we need a model of random perturbations in infinite dimension?

Let
$$\mathscr{O} \subseteq \mathbb{R}$$

$$\frac{\partial X}{\partial t}(t,r) = \frac{\partial^2 X}{\partial r^2}(t,r)$$

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$$\frac{\partial X}{\partial t}(t,r) = \frac{\partial^2 X}{\partial r^2}(t,r) + f(X(t,r))\underbrace{\frac{\partial N}{\partial t}(t,r)}_{\text{noise in } t \text{ and } r} \text{ for all } r \in \mathscr{O}, \ t \in [0,T].$$

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Search solution $X:=(X(t,\cdot):t\in[0,T])$ in $L^2(\mathscr{O})$:

$$\frac{dX}{dt}(t,\cdot) = AX(t,\cdot) + f(X(t,\cdot)) \underbrace{\frac{dN}{dt}(t,\cdot)}_{\text{noise in } L^2(\mathscr{O})} \qquad \text{for all } t \in [0,T],$$

where $A: \operatorname{dom}(A) \subseteq L^2(\mathscr{O}) \to L^2(\mathscr{O})$ with $Af = \frac{d^2f}{dr^2}$.

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where $A: \text{dom}(A) \subseteq L^2(\mathscr{O}) \to L^2(\mathscr{O})$ with $Af = \frac{d^2f}{dr^2}$. As integral equation:

$$X(t,\cdot) = X(0,\cdot) + \int_0^t AX(s,\cdot)ds + \underbrace{\int_0^t f(X(s,\cdot))\,N(ds,\cdot)}_{\text{stochastic integral}} \quad \text{for all } t \in [0,T].$$

Why cannot we use a standard Brownian motion in infinite dimensions?

Brownian motion

Definition. Let U be a Hilbert space. A stochastic process $(W(t): t \ge 0)$ with values in U is called a **Brownian motion**, if

- (1) W(0) = 0;
- (2) W has independent, stationary increments;
- (3) $W(t) W(s) \stackrel{\mathscr{D}}{=} N(0, (t-s)Q)$ for all $0 \leqslant s \leqslant t$,

where $Q: U \to U$ is a linear operator with the following properties:

symmetric: $\langle Qu, v \rangle_U = \langle u, Qv \rangle_U$ for all $u, v \in U$;

non-negative: $\langle Qu, u \rangle_U \geqslant 0$ for all $u \in U$;

nuclear: $\sum_{k=1}^{\infty} \langle Qe_k, e_k \rangle_U < \infty$ for an orthonormal basis $\{e_k\}_{k \in \mathbb{N}}$.

Why are Brownian motions not sufficient?

There does not exist a Brownian motion with independent components in an infinite dimensional Hilbert space:

Let U be a Hilbert space with orthonormal basis $\{e_k\}_{k\in\mathbb{N}}$ and $W(t)\stackrel{\mathscr{D}}{=} N(0,tQ)$ with independent components. Then we have

$$t\langle Qe_k, e_l\rangle_U = E\Big[\langle W(t), e_k\rangle_U \langle W(t), e_l\rangle_U\Big] = \begin{cases} t, & \text{if } k = l, \\ 0, & \text{if } k \neq l, \end{cases}$$

which implies $Q = \operatorname{Id}$. However, $Q = \operatorname{Id}$ is not a nuclear operator:

$$\sum_{k=1}^{\infty} \langle Qe_k, e_k \rangle_U = \sum_{k=1}^{\infty} \|e_k\|_U^2 = \infty.$$

What is a cylindrical Brownian motion?

Common definition

Working definition: Let H be a Hilbert space with orthonormal basis $\{e_k\}_{k\in\mathbb{N}}$ and let $\{b_k\}_{k\in\mathbb{N}}$ be independent real valued Brownian motions.

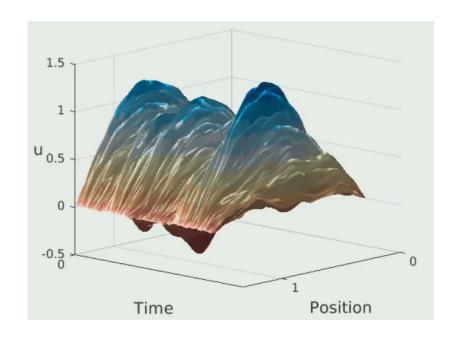
A cylindrical Brownian motion in H is a family $(W(t): t \ge 0)$ such that

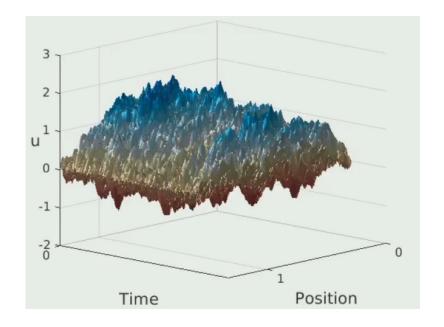
$$W(t) = \sum_{k=1}^{\infty} e_k b_k(t), \qquad t \geqslant 0,$$

converges in square mean in a larger Hilbert space H_1 containing H.

Genuine vs. cylindrical

Solution of
$$X(t,\cdot) = \int_0^t \Delta X(s,\cdot) \, ds + W(t)$$
:





genuine Brownian motion W

cylindrical Brownian motion W

Code & graphics by David Cohen (University of Gothenburg)

Cylindrical random variables

and

cylindrical measures

Cylindrical measures

Let U be a Banach space with dual space U^* and dual pairing $\langle \cdot, \cdot \rangle$ and let (Ω, \mathscr{A}, P) denote a probability space.

The cylindrical algebra $\mathfrak{Z}(U,\Gamma)$ for some $\Gamma\subseteq U^*$ is defined by

$$\mathfrak{Z}(U,\Gamma):=\Big\{\left\{u\in U:\left(\langle u,u_1^*\rangle,\ldots,\langle u,u_n^*\rangle\right)\in B\right\}:u_i^*\in\Gamma,B\in\mathfrak{B}(\mathbb{R}^n),n\in\mathbb{N}\Big\}$$

If Γ is finite, then $\mathfrak{Z}(U,\Gamma)$ is a σ -algebra.

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Definition: A map $\mu \colon \mathfrak{Z}(U,U^*) \to [0,1]$ is called a cylindrical (probability) measure if for each finite $\Gamma \subseteq U^*$, the restriction $\mu|_{\mathfrak{Z}(U,\Gamma)}$ is a probability measure.

Operations for cylindrical measures

Image of a cylindrical measure:

If $\mu \colon \mathfrak{Z}(U,U^*) \to [0,1]$ and $F \colon U \to V$ linear and continuous, then

$$F(\mu) := \mu \circ F^{-1} \colon \mathfrak{Z}(V, V^*) \to [0, 1]$$

is a cylindrical measure defined by

$$F(\mu)\Big(\left\{v \in V : (\langle v, v_1^* \rangle, \dots, \langle v, v_n^* \rangle) \in B\right\}\Big)$$
$$:= \mu\Big(\left\{u \in U : (\langle u, F^* v_1^* \rangle, \dots, \langle u, F^* v_n^* \rangle) \in B\right\}\Big)$$

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Convolution of cylindrical measures:

If μ , $\nu \colon \mathfrak{Z}(U,U^*) \to [0,1]$ then the convolution

$$(\mu * \nu) : \mathfrak{Z}(U, U^*) \to [0, 1], \qquad (\mu * \nu)(C) := \int_U \mu(C - u) \, \nu(du).$$

Finite-dimensional projections

For $\mu \colon \mathfrak{Z}(U,U^*) \to [0,1]$ and $u_1^*,\ldots,u_n^* \in U^*$ define

$$\pi_{u_1^*,\ldots,u_n^*}\colon U\to\mathbb{R}^n, \qquad \pi_{u_1^*,\ldots,u_n^*}(u)=\left(\langle u,u_1^*\rangle,\ldots,\langle u,u_n^*\rangle\right).$$

Then the image of μ under $\pi_{u_1^*,...,u_n^*}$ defines a probability measure

$$\mu \circ \pi_{u_1^*,...,u_n^*}^{-1} \colon \mathfrak{B}(\mathbb{R}^n) \to [0,1].$$

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The family $\{\mu \circ \pi_{u_1^*,\dots,u_n^*}^{-1}: u_1^*,\dots,u_n^* \in U^*, n \in \mathbb{N}\}$ satisfies the consistency condition:

$$\mu \circ \pi_{u_1^*,...,u_n^*}^{-1} \circ A^{-1} = \mu \circ \pi_{A(u_1^*,...,u_n^*)}^{-1}$$
 for all $A \in \mathbb{R}^{m,n}$.

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 for all $A \in \mathbb{R}^{m,n}$.

Lemma. If a family $\{\mu_{u_1^*,...,u_n^*}: u_1^*,...,u_n^* \in U^*, n \in \mathbb{N}\}$ of Borel measures $\mu_{u_1^*,...,u_n^*}$ on $\mathfrak{B}(\mathbb{R}^n)$ satisfies the consistency condition

$$\mu_{u_1^*,...,u_n^*} \circ A^{-1} = \mu_{A(u_1^*,...,u_n^*)}$$
 for all $A \in \mathbb{R}^{m,n}, u_i^* \in U^*, n \in \mathbb{N},$

then it defines a cylindrical measure on $\mathfrak{Z}(U,U^*)$.

Characteristic function

For a cylindrical measure μ the mapping

$$\varphi_{\mu}: U^* \to \mathbb{C}, \qquad \varphi_{\mu}(u^*) := \int_U e^{i\langle u, u^* \rangle} \, \mu(du)$$

is called characteristic function of μ .

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Theorem. (Kolmogorov 1935)

For cylindrical measures μ and ν the following are equivalent:

- (1) $\mu = \nu$;
- (2) $\varphi_{\mu} = \varphi_{\nu}$

Bochner's theorem

Bochner's Theorem. (finite dimensions)

Let $\varphi\colon \mathbb{R}^d \to \mathbb{C}$ be a function. Then φ is the characteristic function of a probability measure on $\mathfrak{B}(\mathbb{R}^d)$ if and only if φ is continuous with $\varphi(0)=1$ and positive-definite.

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Bochner's Theorem. (infinite dimensions) (Bochner 1955)

Let $\varphi\colon U^*\to \mathbb{C}$ be a function. Then φ is the characteristic function of a cylindrical probability measure if and only if φ is continuous with $\varphi(0)=1$ and positive-definite.

Genuineness test

Lemma. Let $\mu \colon \mathfrak{B}(U) \to [0,1]$ be a genuine Radon measure with characteristic function

$$\varphi_{\mu} \colon U^* \to \mathbb{C}, \qquad \varphi_{\mu}(u^*) := \int_U e^{i\langle u, u^* \rangle} \, \mu(du).$$

Then φ_{μ} is weak* sequentially continuous.

Example. The function $h \mapsto e^{-\frac{1}{2}\|h\|^2}$ is not sequentially weak* continuous.

Cylindrical random variables

Definition: A cylindrical random variable Z in U is a mapping

 $Z:U^* o L^0_P(\Omega;\mathbb{R})$ linear and continuous.

A cylindrical process in U is a family $(Z(t):t\geqslant 0)$ of cylindrical random variables.

- I. E. Segal, 1954
- I. M. Gel'fand 1956: Generalized Functions
- L. Schwartz 1969: seminaire rouge,
 radonifying operators



Cylindrical measures and cylindrical random variables

Theorem.

(a) Let $Z\colon U^* o L^P_0(\Omega;\mathbb{R})$ be a cylindrical random variable. By defining

$$\mu(\lbrace u \in U : (\langle u, u_1^* \rangle, \dots, \langle u, u_n^* \rangle) \in B \rbrace) := P((Zu_1^*, \dots, Zu_n^*) \in B)$$

for all $u_i^* \in U^*$, $B \in \mathfrak{B}(\mathbb{R}^n)$ we obtain a cylindrical measure on $\mathfrak{Z}(U,U^*)$.

Cylindrical measures and cylindrical random variables

Theorem.

(a) Let $Z:U^* \to L_0^P(\Omega;\mathbb{R})$ be a cylindrical random variable. By defining

$$\mu(\lbrace u \in U : (\langle u, u_1^* \rangle, \dots, \langle u, u_n^* \rangle) \in B \rbrace) := P((Zu_1^*, \dots, Zu_n^*) \in B)$$

for all $u_i^* \in U^*$, $B \in \mathfrak{B}(\mathbb{R}^n)$ we obtain a cylindrical measure on $\mathfrak{Z}(U,U^*)$.

(b) Let μ be a cylindrical measure on $\mathfrak{Z}(U,U^*)$. Then there exists a probability space $(\Omega',\mathscr{A}',P')$ and a cylindrical random variable $Z\colon U^*\to L^0_P(\Omega;\mathbb{R})$ such that

$$\mu(\lbrace u \in U : (\langle u, u_1^* \rangle, \dots, \langle u, u_n^* \rangle) \in B \rbrace) = P'((Zu_1^*, \dots, Zu_n^*) \in B)$$

for all $u_i^* \in U^*$, $B \in \mathfrak{B}(\mathbb{R}^n)$.

Cylindrical measures and cylindrical random variables

Definition. Let $Z: U^* \to L_0^P(\Omega; \mathbb{R})$ be a cylindrical random variable.

- (a) The cylindrical measure μ defined previously is called the (cylindrical) distribution of Z.
- **(b)** The function

$$\varphi_Z \colon U^* \to \mathbb{C}, \qquad \varphi_Z(u^*) := E\left[e^{iZu^*}\right].$$

is called characteristic function of Z.

It follows: $\varphi_{\mu} = \varphi_{Z}$.

Example: induced cylindrical random variable

Example: Let $X:\Omega \to U$ be a (classical) random variable. Then

$$Z: U^* \to L_P^0(\Omega; \mathbb{R}), \qquad Zu^* := \langle X, u^* \rangle$$

defines a cylindrical random variable.

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defines a cylindrical random variable.

But: not for every cylindrical random variable $Z:U^*\to L^0_P(\Omega;\mathbb{R})$ there exists a classical random variable $X:\Omega\to U$ satisfying

$$Zu^* = \langle X, u^* \rangle$$
 for all $u^* \in U^*$.

Cylindrical Lévy processes

Definition: cylindrical Lévy process

Definition. (Applebaum, Riedle (2010))

A cylindrical process $(L(t): t \ge 0)$ is called a *cylindrical Lévy process*, if for all $u_1^*, \ldots, u_n^* \in U^*$ and $n \in \mathbb{N}$ the stochastic process :

$$\left((L(t)u_1^*, \dots, L(t)u_n^*) : t \geqslant 0 \right)$$

is a Lévy process in \mathbb{R}^n .

A stochastic process $(\ell(t): t \ge 0)$ with values in \mathbb{R}^n is called Lévy process, if:

- $(1) \ \ell(0) = 0;$
- (2) ℓ has stationary, independent increments;
- (3) ℓ has càdlàg paths and jumps only at random times.

Verifying a cylindrical Lévy process

Lemma. A cylindrical process $(L(t): t \ge 0)$ in U is a cylindrical Lévy process if and only if the following two conditions are satisfied:

(i) for each $u_1^*, \ldots, u_n^* \in U^*$, $t_0 \leqslant t_1 \leqslant \cdots \leqslant t_n$ and $n \in \mathbb{N}$ the random variables

$$(L(t_1) - L(t_0))u_1^*, \dots, (L(t_n) - L(t_{n-1}))u_n^*$$

are independent;

(ii) $(L(t)u^*: t \ge 0)$ is a Lévy process for all $u^* \in U^*$.

Example: genuine Lévy process

If $(Y(t):t\geqslant 0)$ is a genuine Lévy process in U then

$$L(t): U^* \to L_P^0(\Omega; \mathbb{R}), \qquad L(t)u^* := \langle Y(t), u^* \rangle$$

defines a cylindrical Lévy process $(L(t): t \ge 0)$.

Example: cylindrical compound Poisson process

Let $(Y_k:k\in\mathbb{N})$ be a sequence of independent cylindrical random variables in U with identical cylindrical distribution. If $(n(t):t\geqslant 0)$ is a real valued Poisson process which is independent of $\{Y_ku^*:k\in\mathbb{N},u^*\in U^*\}$ then the *cylindrical compound Poisson process* $(L(t):t\geqslant 0)$ is defined for each $u^*\in U^*$ by

$$L(t)u^* := \begin{cases} 0, & \text{if } n(t) = 0, \\ Y_1u^* + \dots + Y_{n(t)}u^*, & \text{else.} \end{cases}$$

Example:

Hedgehog cylindrical Lévy processes

Theorem. Let U be a Hilbert space with ONB $(e_k)_{k\in\mathbb{N}}$ and $(\sigma_k)_{k\in\mathbb{N}}\subseteq\mathbb{R}$;

 $(h_k)_{k\in\mathbb{N}}$ be a sequence of independent, real-valued Lévy processes.

1) (weak convergence) If for all $u^* \in U$ and $t \ge 0$ the sum

$$L(t)u^* := \sum_{k=1}^{\infty} \langle e_k, u^* \rangle \sigma_k h_k(t)$$

converges P-a.s. then it defines a cylindrical Lévy process $(L(t): t \ge 0)$.

2) (strong convergence) If for all $t \ge 0$ the sum

$$L(t) := \sum_{k=1}^{\infty} e_k \, \sigma_k h_k(t)$$

converges P-a.s. then it defines an genuine Lévy process $(L(t): t \ge 0)$.

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Example 0: for h_k standard, real-valued Brownian motion:

 $(\sigma_k)_{k\in\mathbb{N}}\in\ell^\infty\iff \text{cylindrical (Brownian) Lévy process}$

 $(\sigma_k)_{k\in\mathbb{N}}\in\ell^2\iff$ genuine (Brownian) Lévy process

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Example 1: for h_k Poisson process with intensity 1:

$$(\sigma_k)_{k\in\mathbb{N}}\in\ell^2\iff \text{cylindrical L\'evy process}$$

$$(\sigma_k)_{k\in\mathbb{N}}\in\ell^1\iff ext{genuine L\'evy process}$$

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Example 2: for h_k symmetric, standardised, α -stable:

$$(\sigma_k)_{k\in\mathbb{N}}\in\ell^{(2lpha)/(2-lpha)}\iff ext{cylindrical L\'evy process}$$
 $(\sigma_k)_{k\in\mathbb{N}}\in\ell^lpha \iff ext{genuine L\'evy process}$

Example:

Subordination

Example: subordination

Theorem.

Let W be a cylindrical Brownian motion in a Banach space U,

 ℓ be a real-valued Lévy subordinator, independent of W.

Then, for each $t \geqslant 0$,

$$L(t): U^* \to L_P^0(\Omega; \mathbb{R}), \qquad L(t)u^* = W(\ell(t))u^*$$

defines a cylindrical Lévy process $(L(t): t \ge 0)$ in U.

Example. If ℓ is an $\alpha/2$ stable process, then $\varphi_{L(t)}(u^*) = \exp(-t \|u^*\|^{\alpha})$ for all $u^* \in U^*$.

Example:

Lévy basis

Independently scattered random measures

For $\mathscr{O} \subseteq \mathbb{R}^d$ define $\mathfrak{B}_b(\mathscr{O}) := \{A \subseteq \mathscr{O} : A \text{ relatively compact}\}.$

Definition (Rajput and Rosinski (1989)).

An infinitely divisible random measure is a map

$$M: \mathfrak{B}_b(\mathscr{O}) \to L^0(\Omega, P)$$

satisfying for each collection of disjoint sets $A_1, A_2, \ldots \in \mathfrak{B}_b(\mathscr{O})$:

- (a) the random variables $M(A_1), M(A_2), \ldots$ are independent;
- (b) if $\bigcup_{k\in\mathbb{N}}A_k\in\mathfrak{B}_b(\mathscr{O})$ then $M\left(\bigcup_{k\in\mathbb{N}}A_k\right)=\sum_{k\in\mathbb{N}}M(A_k)$ P-a.s.
- (c) the random variable M(A) is infinitely divisible for each $A \in \mathfrak{B}_b(\mathscr{O})$.

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(c) the random variable M(A) is infinitely divisible for each $A \in \mathfrak{B}_b(\mathscr{O})$.

$$M(A) \stackrel{\mathscr{D}}{=} (\gamma(A), \Sigma(A), \nu_A)$$
 characteristics of M

$$\lambda(A) = \|\gamma\|_{TV} \, (A) + \Sigma(A) + \int_{\mathbb{R}} \left(\beta^2 \wedge 1\right) \, \nu_A(d\beta) \text{ control measure of } M$$

Lévy-valued random measure

Definition. A family $(M(t):t\geq 0)$ of infinitely divisible random measures $M(t)\colon \mathfrak{B}_b(\mathscr{O})\to L^0_R(\Omega,\mathbb{R})$ is called a Lévy-valued random measure if, for every $A_1,\ldots,A_n\in\mathfrak{B}_b(\mathscr{O})$, $n\in\mathbb{N}$, the stochastic process

$$((M(t)(A_1),\ldots,M(t)(A_n)): t \geqslant 0)$$

is a Lévy process in \mathbb{R}^n . We shall write M(t,A) := M(t)(A).

Example: stable noise (Balan (2014))

Define for $B \in \mathfrak{B}_b\left([0,\infty) \times \mathbb{R}^d\right)$:

$$\widetilde{M}(B) := \begin{cases} \int_{B \times \mathbb{R}} y \, N(\mathrm{d}s, \mathrm{d}x, \mathrm{d}y), & \text{if } \alpha \in (0, 1], \\ \int_{B \times \mathbb{R}} y \, \widetilde{N}(\mathrm{d}s, \mathrm{d}x, \mathrm{d}y), & \text{if } \alpha \in (1, 2), \end{cases}$$

where N is a Poisson random measure on $[0, \infty) \times \mathbb{R}^d \times \mathbb{R}$ with intensity $leb \otimes leb \otimes \nu_{\alpha}$ for $\nu_{\alpha}(dy) = \frac{\alpha}{2} \frac{1}{|y|^{1+\alpha}} dy$.

Then

$$M(t,A) := \widetilde{M}((0,t] \times A)$$
 for $A \in \mathfrak{B}_b(\mathbb{R}^d), t \geqslant 0$,

defines a Lévy-valued random measure on \mathbb{R}^d with control measure

$$\lambda(A) = \frac{2}{2-\alpha} \operatorname{leb}(A).$$

Integration (Rajput and Rosinski (1989))

Let M be a Lévy-valued random measure. For a simple function

$$f \colon \mathscr{O} \to \mathbb{R}, \qquad f(x) = \sum_{k=1}^{n} \alpha_k \mathbb{1}_{A_k}(x),$$

for $\alpha_k \in \mathbb{R}$ and pairwise disjoint sets $A_1, \ldots, A_n \in \mathfrak{B}_b(\mathcal{O})$, define

$$\int_{\mathscr{O}} f(x) M(t, \mathrm{d}x) := \sum_{k=1}^{n} \alpha_k M(t, A_k) \qquad \text{for all } t \geqslant 0.$$

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A measurable function $f \colon \mathscr{O} \to \mathbb{R}$ is said to be M-integrable if

- (1) there exists a sequence of simple functions $(f_n)_{n\in\mathbb{N}}$ such that f_n converges pointwise to f λ -a.e., where λ is the control measure of M;
- (2) for each $t \geq 0$, the sequence $\left(\int_{\mathscr{O}} f_n(x) \, M(t, \mathrm{d}x)\right)_{n \in \mathbb{N}}$ converges in probability.

In this case:
$$\int_A f(x)\,M(t,\mathrm{d} x):=P-\lim_{n\to\infty}\int_A f_n(x)\,M(t,\mathrm{d} x).$$

Integration (Rajput and Rosinski (1989))

Let M be a Lévy-valued random measure with control measure λ .

The space of M-integrable functions is given by the Musielak-Orlicz space

$$L_{M}(\mathscr{O},\lambda) := \left\{ f \in L^{0}(\mathscr{O},\lambda) : \int_{\mathscr{O}} \Phi_{M}(|f(x)|,x) \lambda(\mathrm{d}x) < \infty \right\},\,$$

where $\Phi_M \colon \mathbb{R} \times \mathscr{O} \to \mathbb{R}$ is a function depending on the distribution of M.

From random measure to cylindrical

Theorem. Let M be a Lévy-valued random measure on $\mathfrak{B}_b(\mathscr{O})$ with control measure λ . If U is a Banach space for which U^* is continuously embedded into $L_M(\mathscr{O}, \lambda)$, then

$$L(t)f := \int_{\mathscr{O}} f(x) \, M(t, dx)$$
 for all $f \in U^*$,

defines a cylindrical Lévy processes L in U.

Example: stable noise

Define for $B \in \mathfrak{B}_b\left([0,\infty) \times \mathbb{R}^d\right)$:

$$\widetilde{M}(B) := \begin{cases} \int_{B \times \mathbb{R}} y \, N(\mathrm{d}s, \mathrm{d}x, \mathrm{d}y), & \text{if } \alpha \in (0, 1], \\ \int_{B \times \mathbb{R}} y \, \widetilde{N}(\mathrm{d}s, \mathrm{d}x, \mathrm{d}y), & \text{if } \alpha \in (1, 2), \end{cases}$$

where N is a Poisson random measure on $[0, \infty) \times \mathbb{R}^d \times \mathbb{R}$ with intensity $\operatorname{leb} \otimes \operatorname{leb} \otimes \nu_{\alpha}$ for $\nu_{\alpha}(\mathrm{d}y) = \frac{\alpha}{2} \frac{1}{|y|^{1+\alpha}} \mathrm{d}y$.

Then

$$M(t,A) := \widetilde{M}((0,t] \times A)$$
 for $A \in \mathfrak{B}_b(\mathbb{R}^d), t \geqslant 0$,

defines a Lévy-valued random measure on \mathbb{R}^d with control measure

$$\lambda(A) = \frac{2}{2-\alpha} \operatorname{leb}(A).$$

Example: stable noise

For each $\alpha \in (0,2)$ we have

$$L_M(\mathcal{O}, \lambda) = L^{\alpha}(\mathcal{O}, \text{leb}).$$

Thus, M defines a cylindrical Levy process L on

$$\begin{cases} U = L^{\alpha'}(\mathscr{O}, \mathrm{leb}), & \text{if } \alpha \in (1, 2), \\ U = L^p(\mathscr{O}, \mathrm{leb}), & \text{if } \alpha \in (0, 1), \ \mathscr{O} \text{ bounded, any } p > 1. \end{cases}$$

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In this case, we have for $f \in U^*$:

$$\varphi_{L(t)}(f) = E \left[\exp \left(i \int_{\mathscr{O}} f(x) M(t, dx) \right) \right]$$
$$= e^{-c_{\alpha} t \|f\|^{\alpha}}.$$

for a constant $c_{\alpha} > 0$, i.e. L is the canonical α -stable cylindrical process.

From cylindrical to random measure

Definition. A cylindrical Lévy process $(L(t):t\geqslant 0)$ in $L^p(\mathcal{O},\zeta)$ for some $p\geqslant 1$ is called independently scattered if

$$L(t)\mathbb{1}_{A_1},\ldots,L(t)\mathbb{1}_{A_n}$$
 are independent

for any disjoint sets $A_1, \ldots, A_n \in \mathfrak{B}_b(\mathscr{O})$ and $n \in \mathbb{N}$.

From cylindrical to random measure

Definition. A cylindrical Lévy process $(L(t): t \ge 0)$ in $L^p(\mathcal{O}, \zeta)$ for some $p \ge 1$ is called independently scattered if

$$L(t)\mathbb{1}_{A_1},\ldots,L(t)\mathbb{1}_{A_n}$$
 are independent

for any disjoint sets $A_1, \ldots, A_n \in \mathfrak{B}_b(\mathscr{O})$ and $n \in \mathbb{N}$.

Theorem An independently scattered cylindrical Lévy process $(L(t): t \geq 0)$ in $L^p(\mathcal{O}, \zeta)$ for some $p \geqslant 1$ defines by

$$M(t,A) := L(t)\mathbb{1}_A$$
 for all $A \in \mathfrak{B}_b(\mathscr{O})$,

a Lévy-valued random measure M on $(\mathcal{O}, \mathfrak{B}_b(\mathcal{O}))$.

Counterexample

Let (h_k) be independent, identically distributed real-valued Lévy processes with characteristics $(0,0,\varrho)$. Every cylindrical Lévy process L of the form

$$L(t)u^* := \sum_{k=1}^{\infty} \langle e_k, u^* \rangle h_k(t)$$

for an ONB (e_k) of U is **not independently scattered**.