

M800 Roger Temam 4/15 Report

1 Infinite Dimensional Stochastic Processes

Definition 1.1. Let (Z, \mathcal{Z}) be a measurable space. A family $\{X_i\}_{i \in I}$ of Z -valued r.v.'s on $(\Omega, \mathcal{F}, \mathbb{P})$ is called a **stochastic process**. For $\{i_1, \dots, i_m\} \subset I$, the measures defined on the product space Z^m given by

$$\mu(X_{i_1}, \dots, X_{i_m})(S) = \mathbb{P}[(X_{i_1}, \dots, X_{i_m}) \in S]$$

are called the **finite dimensional distributions (f.d.d.'s)** of $\{X_i\}_{i \in I}$ (also called the **marginals**).

Source: M647 Lecture 1 (revised), Definition 1.1.5

Remark: In the SPDE context, we look at stochastic processes $\{X(t)\}_{t \geq 0}$ with values in Banach/Hilbert spaces.

Definition 1.2. Let \mathcal{U} be a Hilbert space. A \mathcal{U} -valued stochastic process $(L(t))_{t \geq 0}$ is called a **Levy process** if,

(i) $L(0) = 0$

(ii) L has independent increments: $\forall 0 \leq t_1 < t_2 < \dots < t_k$ the r.v.'s $L(t_k) - L(t_1), \dots, L(t_k) - L(t_{k-1})$ are independent.

(iii) L has stationary increments: $L(t) - L(s) \sim L(t - s)$, $\forall t \geq s \geq 0$.

(iv) *Stochastic continuity:* $\forall t_0 \geq 0$, $L(t) \rightarrow L(t_0)$ in probability as $t \rightarrow t_0$, i.e. $\forall \epsilon > 0$,

$$\lim_{t \rightarrow t_0} \mathbb{P}[||L(t) - L(t_0)||_{\mathcal{U}} > \epsilon] = 0.$$

Source: M647 Lecture 2, Definition 2.2.1

Theorem 1.3. Every Levy process L has a cadlag modification, i.e. there is a \mathcal{U} -valued Levy process \tilde{L} such that

(i) \tilde{L} has cadlag sample paths a.s.

(ii) $\forall t \geq 0 \mathbb{P}[\tilde{L}(t) = L(t)] = 1$.

Source: M647 Lecture 2 (revised), Theorem 2.2.3

Proof. For the sequence $\{t + n^{-1}\}_{n \in \mathbb{N}}$, we find that $L(t + n^{-1}) \xrightarrow{\mathbb{P}} L(t)$, and it follows that $L(t + n^{-1}) \xrightarrow{\text{a.s.}} L(t)$, since we find that the series

$$\bar{L}(t) := L(t + 1) + \sum_{n=1}^{\infty} [L(t + (n + 1)^{-1}) - L(t + n^{-1})] \quad (1.1)$$

converges in \mathbb{P} , so $\bar{L}(t)$ exists a.s., since $\{L(t + (n + 1)^{-1}) - L(t + n^{-1})\}_{n \in \mathbb{N}}$ is a sequence of independent random variables. Note moreover, that almost surely we have

$$(\forall t \in \mathbb{Q}_+) (\bar{L}(t) \text{ exists})$$

Define

$$\tilde{L}(t) := \begin{cases} 0 & \text{if } t = 0, \\ \bar{L}(t) & \text{if } t \in \mathbb{Q}_+ \setminus \{0\} \text{ and } \bar{L}(t) \text{ exists,} \\ L^*(t) \in \bigcap_{t' \in \mathbb{Q}_+, t < t'} \overline{\bar{L}([t, t'])} & \text{if } t \in \mathbb{R}_+ \setminus \mathbb{Q}_+ \text{ and such an } L^*(t) \text{ exists.} \\ L(t) & \text{otherwise.} \end{cases} \quad (1.2)$$

It shall then suffice to verify (i) and (ii) of the theorem, since the fact that \tilde{L} is a Levy process follows immediately by property (ii).

(i) To show that \tilde{L} has cadlag sample paths a.s., we want to show that for all $t \geq 0$, we have

$$\lim_{s \rightarrow t^+} \tilde{L}(s) = \tilde{L}(t).$$

First, note that almost surely $\bar{L}(t)$ exists for all $t \in \mathbb{Q}_+ \setminus \{0\}$. Next, we want to verify the following claim:

Claim. $\tilde{L}|(\mathbb{Q}_+ \setminus \{0\})$ is cadlag a.s.

Given a decreasing sequence $\{q_k\}_{k \in \mathbb{N}} \subset \mathbb{Q}_+ \setminus \{0\}$ such that $q_k \searrow q$, for $q \in \mathbb{Q}_+ \setminus \{0\}$, we

want to show that

$$\lim_{k \rightarrow +\infty} \tilde{L}(q_k) = \tilde{L}(q) \text{ a.s. (1.3)}$$

First, note that q is of the form

$$q = \sum_{j=1}^N n_j^{-1}$$

for $n_1 \leq n_2 \leq \dots \leq n_N$ and all q_k is of the form

$$q_k = \sum_{j=1}^{N_k} n_{j,k}^{-1},$$

for $n_{1,k} \leq n_{2,k} \leq \dots \leq n_{N_k,k}$. As $q_k \searrow q$, we find $n_{j,k} = n_j$ eventually for $1 \leq j \leq N$ as $k \rightarrow +\infty$ and $n_{j,k} \rightarrow +\infty$ for all $j > N$ (for whichever j subindex exists for each k). As a result, for each $l \geq 1$, we find by recursive diagonalization of the sequences

$$\left\{ L \left(\sum_{j=1}^{\min(N_k, l)} n_{j,k}^{-1} \right) \right\}_{k \in \mathbb{N}}$$

that we have

$$\lim_{k \rightarrow +\infty} \bar{L} \left(\sum_{j=1}^{\min(N_k, l)} n_{j,k}^{-1} \right) = \bar{L} \left(\sum_{j=1}^{\min(N, l)} n_j^{-1} \right),$$

almost surely and it follows taking $l \rightarrow +\infty$ and applying further diagonalization that

$$\lim_{k \rightarrow +\infty} \tilde{L}(q_k) = \lim_{k \rightarrow +\infty} \bar{L}(q_k) = \bar{L}(q) = \tilde{L}(q)$$

almost surely, and (1.3) is reached.

Now that we have proved the claim, we then want to verify that a cadlag restriction

$\tilde{L}|(\mathbb{Q}_+ \setminus \{0\})$ on the dense subset $\mathbb{Q}_+ \setminus \{0\} \subset \mathbb{R}_+$ has a Cadlag extension L^* that almost

surely agrees with \tilde{L} . It can be shown (using a similar argument to the argument that a continuous function on a dense subset of a metric space extends to a continuous extension on the metric space) that the cadlag property of $\tilde{L}|(\mathbb{Q}_+ \setminus \{0\})$ implies preservation of Cauchy decreasing sequences $\{q_k\}_{k \in \mathbb{N}} \subset \mathbb{Q}_+ \setminus \{0\}$, to the image, and hence for every $t \in \mathbb{R}_+$, we find that every decreasing sequence $\{q_k\}_{k \in \mathbb{N}} \subset \mathbb{Q}_+ \setminus \{0\}$ such that $q_k \searrow t$, we find $\left\{ \tilde{L}(q_k) \right\}_{k \in \mathbb{N}}$ is Cauchy and hence converges to some uniquely determined limit $L^*(t)$.

To show that L^* (in the almost sure scenario that $\tilde{L}|(\mathbb{Q}_+ \setminus \{0\})$ is Cadlag where L^* exists on all \mathbb{R}_+) agrees almost surely with \tilde{L} . We find that the case where $t > 0$ is immediate, since almost surely $\bar{L}(t) = \tilde{L}|(\mathbb{Q}_+ \setminus \{0\}) = L^*(t)$ exists if $t \in \mathbb{Q}_+ \setminus \{0\}$ and $\tilde{L}(t) = L^*(t)$ by construction of \tilde{L} if $t \in \mathbb{R}_+ \setminus \mathbb{Q}_+$. We are then left with the case where $t = 0$, which is a more special case of part (ii) (which we prove next).

(ii) Let $t \geq 0$. To show that $\mathbb{P}[\tilde{L}(t) = L(t)] = 1$, note first by stochastic continuity that $L(s) \xrightarrow{\mathbb{P}} L(t)$ as $s \rightarrow t^+$. In the case where $t \in \mathbb{Q}_+$, we find by (1.1) and (1.2) that almost surely we have $L(t) = \bar{L}(t) = \tilde{L}(t)$, since $L(t)$ and $\bar{L}(t)$ are both \mathbb{P} -limits of the sequence $\left\{ L(t + n^{-1}) \right\}_{n \in \mathbb{N}}$. Next, in the case where $t \in \mathbb{R}_+ \setminus \mathbb{Q}_+$, we can choose $q_k \searrow t$ and note that since almost surely we have $\tilde{L}(q_k) = L(q_k)$, for each $k \in \mathbb{N}$, and it follows from the fact that $\tilde{L}(q_k) \xrightarrow{\text{a.s.}} \tilde{L}(t)$ and $L(q_k) \xrightarrow{\mathbb{P}} L(t)$ that $\tilde{L}(t)$ and $L(t)$ are both \mathbb{P} -limits of the sequence $\{L(q_k)\}$, and hence agree almost surely. \square

Proposition 1.4. Let L a Levy process

(i) $\mathbb{E}[|L_t|]_{\mathcal{H}} < +\infty \quad \forall t \geq 0$

(ii) If L is a mean-zero Levy process, then L is a martingale with respect to its natural filtration $\{\sigma(X_t)\}_{t \geq 0}$.

Source: M647 Lecture 2 (revised), Proposition 2.5.2

Remark 1.1: This proposition is a more general claim than that of the cited proposition. A mean-zero Levy Processes are $\mathcal{L}^1(\mathbb{P}; \mathcal{U})$ by definition, while part (i) claims that all Levy processes are $\mathcal{L}^1(\mathbb{P}; \mathcal{U})$.

Proof.

(i) In the case that $t = 0$, we have $L_t = 0$ and we are done. Suppose $t > 0$, and suppose towards contradiction otherwise, i.e., that

$$\mathbb{E}||L_t||_{\mathfrak{U}} = +\infty.$$

Observe that for all $k \geq 1$, and $1 \leq l \leq k$ we have

$$L(t) = \sum_{l=1}^k L\left(\frac{lt}{k}\right) - L\left(\frac{(l-1)t}{k}\right),$$

and the random variables

$$L\left(\frac{lt}{k}\right) - L\left(\frac{(l-1)t}{k}\right) \sim L\left(\frac{t}{k}\right) \quad (1.4)$$

are i.i.d. for $1 \leq l \leq k$. Then for all $k \geq 1$, and $1 \leq l \leq k$, we have

$$\begin{aligned} k\mathbb{E}\left\|L\left(\frac{t}{k}\right)\right\|_{\mathfrak{U}} &= \sum_{l=1}^k \mathbb{E}\left\|L\left(\frac{lt}{k}\right) - L\left(\frac{(l-1)t}{k}\right)\right\|_{\mathfrak{U}} \geq \mathbb{E}\left\|\sum_{l=1}^k L\left(\frac{lt}{k}\right) - L\left(\frac{(l-1)t}{k}\right)\right\|_{\mathfrak{U}} \\ &= \mathbb{E}||L(t)||_{\mathfrak{U}} = +\infty \\ \Rightarrow \mathbb{E}\left\|L\left(\frac{t}{k}\right)\right\|_{\mathfrak{U}} &= +\infty. \end{aligned}$$

We find that for all $k \geq 1$, we have for each $1 \leq l \leq k$

$$\mathbb{E}\left\|L\left(\frac{t}{k}\right)\right\|_{\mathfrak{U}} = +\infty,$$

and it follows by (1.4) that for each $j, k \geq 1$, we find that for $1 \leq l \leq j$

$$\mathbb{E}\left\|L\left(\frac{lt}{jk}\right) - L\left(\frac{(l-1)t}{jk}\right)\right\|_{\mathfrak{U}} = \mathbb{E}\left\|L\left(\frac{t}{jk}\right)\right\|_{\mathfrak{U}} = +\infty,$$

hence as $j \rightarrow +\infty$ we find by a corollary of the *Strong Law of Large Numbers Billingsley*,

page 284 that

$$j^{-1} \sum_{l=1}^j \left\| L\left(\frac{lt}{jk}\right) - L\left(\frac{(l-1)t}{jk}\right) \right\|_{\mathcal{U}} \xrightarrow{\text{a.s.}} \mathbb{E} \left\| L\left(\frac{t}{jk}\right) \right\|_{\mathcal{U}} = +\infty.$$

Then almost surely for each $k \geq 1$, we have some $1 \leq l_k \leq j_k$ such that

$$\left\| L\left(\frac{l_k t}{j_k k}\right) - L\left(\frac{(l_k - 1)t}{j_k k}\right) \right\|_{\mathcal{U}} \geq 1. \quad (1.5)$$

We then conclude that almost surely there exists $\frac{r_k t}{j_k k} \leq \frac{t}{k}$ such that $\frac{r_k t}{j_k k} \rightarrow 0$ as $k \rightarrow +\infty$, but the sequence

$$\left\{ \left\| L\left(\frac{l_k t}{j_k k}\right) - L\left(\frac{(l_k - 1)t}{j_k k}\right) \right\|_{\mathcal{U}} \right\}_{k \in \mathbb{N}}$$

isn't Cauchy by (1.5), which contradicts the fact that $L\left(\frac{r_k t}{j_k k}\right) \xrightarrow{\mathbb{P}} L(0) = 0$ as $k \rightarrow +\infty$.

(ii) Note that we proved in part (i) that L_t is $\mathcal{L}^1(\mathbb{P}; \mathcal{U})$, for all $t \geq 0$ and we use the mean-zero hypothesis to prove the remaining condition that $\mathbb{E}[L_t | \sigma(L_s)] = L_s$. Note that since

$$\mathbb{E}[L_t | \sigma(L_s)] = \mathbb{E}[L_t - L_s | \sigma(L_s)] + \mathbb{E}[L_s | \sigma(L_s)] = \mathbb{E}[L_t - L_s | \sigma(L_s)] + L_s$$

we find the desired condition to be equivalent to the condition that

$$\mathbb{E}[L_t - L_s | \sigma(L_s)] = 0, \quad (1.6)$$

and so it shall suffice to prove that. $\sigma(L_s)$ -measurability 0 is immediate. Observe that $L_t - L_s$ and $\mathbb{1}_G$, for $G \in \sigma(L_s)$ are independent. It follows that

$$\mathbb{E}[(L_t - L_s)\mathbb{1}_G] = \mathbb{E}[L_t - L_s] \cdot \mathbb{E}[\mathbb{1}_G] = 0 = \mathbb{E}[0 \cdot \mathbb{1}_G],$$

since

$$\mathbb{E}[L_t - L_s] = \mathbb{E}[L_{t-s}] = 0.$$

and (1.6) is satisfied. \square

Examples 1.5.

1. A Wiener process is a \mathcal{U} -valued, integrable, mean-zero Levy process with a.s. continuous paths.

Source: M647 Lecture 2 (revised), Definition 2.2.2

2. Let μ be a finite Borel measure on \mathcal{U} (Hilbert space) such that $\mu(\{0\}) = 0$. A compound Poisson process (CPP) with intensity measure μ is a Levy process P with cadlag \mathcal{U} -value sample paths s.t.

$$\mathbb{P}[P(t) \in \Gamma] = e^{-\mu(\mathcal{U})t} \sum_{k=0}^{\infty} \frac{t^k}{k!} \mu^{*k}(\Gamma), \quad \forall t \geq 0, \Gamma \in \mathcal{B}(\mathcal{U}).$$

Here, $\mu^{*j} = \mu * \mu * \dots * \mu$, $\mu^{*0} := \delta_0 =$ probability measure concentrated at the point $0 \in \mathcal{U}$.

Hence, the only difference between a Levy process and a Wiener process is the possible occurrences of jumps (discontinuities).

Source: M647 Lecture 2 (revised), Definition 2.4.1

Sources:

Spring 2022-M647 Lecture 1-2 (revised)

Probability and Measures § 22

Billingsley

2 Parametrization Techniques

Notation 2.1: Given a Hilbert space \mathcal{U} , $L_2^0(\mathcal{U})$ --or simply L_2^0 when context is clear--refers to the (Hilbert) space of all Hilbert-Schmit operators.

Let $\Phi: (t, \omega, x) \mapsto \Phi(t, \omega, x)$ be a measurable mapping from

$(\Omega_T \times E, \mathcal{P}_T \times \mathcal{B}(E))$ into $(L_2^0(\mathcal{U}), \mathcal{B}(L_2^0(\mathcal{U})))$,

Thus, in particular, for arbitrary $x \in E$, $\Phi(\cdot, \cdot, x)$ is a predictable L_2^0 -valued process. Additionally, let μ be a finite positive measure on (E, \mathcal{E}) .

Theorem 2.1. (*Stochastic Fubini Theorem*) Assume that:

$$\int_E \|\Phi(\cdot, \cdot, x)\|_T \mu(dx) < +\infty.$$

Then almost surely we have

$$\int_E \left[\int_0^T \Phi(t, x) dW(t) \right] d\mu(x) = \int_0^T \left[\int_E \Phi(t, x) d\mu(x) \right] dW(t).$$

Source: Da Prato, Zabczyk, Theorem 4.18 (page 109)

We shall prove a more general analogue (at least, hopefully more general, refer to *remark 2.2 (ii)*) of this theorem (that I've formulated myself) that we shall call the "Fubini Theorem for random measures". Basically, this theorem asserts that for random measures ν and η on (E, \mathcal{E}) and (G, \mathcal{G}) , respectively on the product random measure $\xi := \nu \otimes \eta$ on $(E \times G, \mathcal{E} \otimes \mathcal{G})$ (defined analogously by the random measure generated by the premeasure $\xi(A \times B) := \nu(A)\eta(B)$, for $A \in \mathcal{E}$, $G \in \mathcal{G}$), we have that the integration done in different order almost surely agrees, for any Banach Space X -valued random ξ -measurable function Φ .

Theorem 2.2. (*Fubini Theorem for random measures*) Suppose that $\Phi \in \mathcal{L}^1(\xi; X)$, i.e., that Φ is a ξ -random measurable function such that

$$\int_{E \times G} \|\Phi\|_X d\xi < +\infty \text{ a.s.}$$

Then almost surely we have

$$\int_{E \times G} \Phi d\xi = \int_G \left[\int_E \Phi(e, g) d\nu(e) \right] d\eta(g) = \int_E \left[\int_G \Phi(e, g) d\eta(g) \right] d\nu(e). \quad (2.1)$$

Outline of the Proof. First take Φ to be a simple function of the form

$$\sum_{j=1}^N x_j \mathbb{1}_{A_j \times B_j} \quad (2.2)$$

and observe that

$$\int_{E \times G} \Phi d\xi = \sum_{j=1}^N x_j \xi(A_j \times B_j) = \sum_{j=1}^N x_j \nu(A_j) \eta(B_j) = \sum_{j=1}^N x_j \int_E \mathbb{1}_{A_j}(e) d\nu(e) \int_G \mathbb{1}_{B_j}(g) d\eta(g)$$

and (2.1) is met by linearity of (Bochner)-integration over random measures.

The next part is met by utilizing an analogous "monotone class lemma" to pass Φ over a \mathbb{P} -limit of simple functions of the form of (2.2), and then invoke **Lemma 1.6 (ii)** of my 4/8 notes to get \mathbb{P} -convergence, then choose the appropriate subsequence to get the desired almost sure result. \square

Remark 2.2.

(i) Note that the proof of **Theorem 2.2** I've outlined relies on a pretty different strategy than the one done in the proof of the previously-mentioned Stochastic Fubini Theorem in *Da Prato, Zabczyk*, where there, a Borel-Cantelli Lemma, Markov inequality, and Ito-isometry argument is used to get the result. In my argument, I relate it to the arguments done in *Folland*, and claim analogous measure theoretic constructions and principles hold for random measures. (which in the future will require a more in-depth report)

(ii) As a disclaimer, the proof of **Theorem 2.2** is not as general as I would like, i.e., it doesn't quite generalize **Theorem 2.1**, the issue being that $W(t)$ (and hence the "random measure" μ_W) in that theorem is \mathcal{H} -valued (which can be done, but I have not done so in my notes) and the kernel is L_2^0 -valued, whereas both random measures are \mathbb{R} -valued and the kernel is \mathcal{H} -valued. In either a later edit of this report or a later report, I plan to further generalize this theorem accordingly.

Sources:

Stochastic equations in infinite dimensions § 4.6
Da Prato, Zabczyk

Real Analysis, Modern Techniques § 2.5

Folland