Complex Day 2023 07/02

Stochastic models driven by a Lévy noise

Application to rods orientation in turbulence

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Brownian Motion and normal distribution

Continuous stochastic process $(W_t)_{t\geq0}$ such that :

- \blacktriangleright $W_0 = 0$.
- $\blacktriangleright \forall s, t \in \mathbb{R}_+, W_{t+s} W_s$ is independent from W_s .
- ▶ $\forall s, t \in \mathbb{R}_+, W_{t+s} W_s \sim \mathcal{N}(0, t).$

SDEs driven by Brownian Motion

A stochastic process $(X_t)_{t\geq0}$ is solution of a stochastic differential equation (SDE) if

$$
X_t = \int_0^t a(s, X_s)ds + \int_0^t b(s, X_s)dW_s,
$$
 (1)

(3)

where $a, b : \mathbb{R}_+ \times \mathbb{R} \to \mathbb{R}$ are measurable applications.

Example

In finance, the Black-Scholes formula is obtained by modeling the stock price by the equation

$$
X_0 = x_0, \quad X_t = \int_0^t r X_s ds + \int_0^t \sigma X_s dW_s, \tag{2}
$$

where r is the interest rate and σ the volatility. This particular SDE can be solved analytically :

$$
X_t = x_0 e^{(r - \frac{\sigma}{2})t + \sigma W_t}
$$

The option premium is then given by $\mathbb{E}[h(X_T)]$ where h is the payoff and T is the maturity of the option.

Euler-Maruyama scheme

▶ Quantities such as $\mathbb{E}[h(X_T)]$ can be approximated by Monte-Carlo simulation :

$$
\mathbb{E}[h(X_T)] \simeq \frac{1}{N} \sum_{i=0}^{N} h(X_T^i)
$$
\n(4)

where $(X_T^i)_{i\leq n}$ are independent copies of $X_T.$

▶ For this simulation to be possible, we can discretize the process $(X_t)_{t\in[0,T]}$ on $0 = t_0 < \ldots < t_n = T$, $t_i = i/n$, using the Euler-Maryuama scheme :

$$
\bar{X}_{t_{i+1}}^n = \bar{X}_{t_i}^n + a(t_i, \bar{X}_{t_i}^n)h + b(t_i, \bar{X}_{t_i}^n)\sqrt{h}G,
$$
\n(5)

with $h=T/n$ and $G\sim \mathcal{N}(0,1).$ This allows to generate $X_T\simeq \bar{X}^n_{t_n}$

Results about convergence of this scheme are well known in the litterature :

$$
\mathbb{E}\left[\sup_{0\leq i\leq n}|X_{t_i}-\bar{X}_{t_i}^n|^2\right]\leq \frac{C_T}{n},\quad \mathbb{E}[f(X_T)-f(\bar{X}_{t_n}^n)]=O\left(\frac{1}{n}\right)\tag{6}
$$

Lévy Processes

Càdlàg stochastic process $(L_t)_{t\geq0}$ such that :

 $\blacktriangleright \forall s, t \in \mathbb{R}_+, L_{t+s} - L_s$ is independent from W_s .

$$
\blacktriangleright \ \forall s,t\in\mathbb{R}_+, L_{t+s} - L_s \sim L_t.
$$

 \blacktriangleright Lévy-Kintchine formula : L is characterized in law by the triplet (μ, σ, ν) , since

$$
\mathbb{E}[e^{ixL_t}] = \exp\left(t\left[i\mu x - \frac{1}{2}\sigma^2 x^2 + \int_{\mathbb{R}^*} (1 - e^{ixy} + ixy1_{\{|y| < 1\}})\nu(dy)\right]\right).
$$

α-Stable symmetric distribution

Example 1 : Compound Poisson Process

Numerical simulation with $\lambda = 4$ and $Y_1 \sim Exp(3)$

- ▶ $(N_t)_{t \in \mathbb{R}_+}$ a Poisson process of intensity λ .
- \blacktriangleright $(Y_i)_{i \in \mathbb{N}^*}$ i.i.d random variables with distribution π .

$$
\blacktriangleright (\mu, \sigma, \nu) = (0, 0, \lambda \pi).
$$

Example 2 : Stable Process

Numerical simulation with $\alpha = 1.5$

•
$$
(\mu, \sigma, \nu) = (0, 0, \nu_{\alpha})
$$
, with $\nu_{\alpha}(dz) = |z|^{-1-\alpha} dz, \alpha \in (0, 2]$.

$$
\blacktriangleright X_{t+h} - X_t \sim h^{1/\alpha} X_1.
$$

Easy to generate (Box-Muller like algorithm for X_1) but infinite moments : $\mathbb{E}[|X_1|^\beta]=\infty$ for $\beta\geq \alpha.$ In particular, no variance for $\alpha < 2,$ hence not convenient to model physical phenomenon.

Example 3 : Truncated Stable Process

Numerical simulation with $\alpha = 0.5$ and $z_* = 100$

- ► $(\mu, \sigma, \nu) = (0, 0, \nu_{\alpha})$, with $\nu_{\alpha}(dz) = \mathbf{1}_{|z| \leq z_*} |z|^{-1-\alpha} dz$.
- ► $\mathbb{E}[|X_t|^2] = 2t^{\frac{2^{2-\alpha}}{2-\alpha}} < \infty.$

▶ No exact simulation algorithm known for X_1 when $\alpha \in (1, 2]$.

Lévy-Itô representation

A Lévy process L with triplet (μ, σ, ν) can be written as

$$
L_t = \mu t + \sigma W_t + J_t^s + J_t^l,\tag{7}
$$

where J^s and J^l designates the "small jumps" and "large jumps" part of $L,$ i.e

$$
J_t^l = \int_0^t \int_{|z| > 1} zN(ds, dz) \simeq \sum_{i=1}^{N_t^{\lambda_t(1, \infty)}} Y_i^{1, \infty}.
$$

$$
J_t^s = \int_0^t \int_{|z| \le 1} z(N(ds, dz) - \nu(dz)ds) \simeq \lim_{\delta \to 0} \left\{ \sum_{i=1}^{N_t^{\lambda(\delta, 1)}} Y_i^{\delta, 1} - t \int_{|z| \le 1} z\nu(dz) \right\}
$$

with $\lambda(a,b)=\int_{a\leq|z|\leq b}\nu(dz)$ and $(Y_i^{a,b})_{i\in\mathbb{N}^*}$ i.i.d $\sim \frac{\nu(dz)}{\lambda(a,b)}.$

▶ The jump measure ν verifies $\int_{-\infty}^{+\infty} min(1, z^2) \nu(dz) < \infty$.

How to simulate a Lévy process ?

We fix $\varepsilon > 0$ and consider a pure jump Lévy process $L \sim (0, 0, \nu)$.

- \blacktriangleright The jumps larger than ε corresponds to the compound Poisson process $J_t^{l,\varepsilon} = \sum_{j=1}^{N_t^{\lambda(\varepsilon,\infty)}} Y_j^{\varepsilon,\infty}$, that can be simulated exactly.
- \blacktriangleright The jumps smaller than ε are approximated by a Brownian motion with the same variance $J_t^{s,\varepsilon}\simeq \sigma_\varepsilon W_t$ where $\sigma_\varepsilon=\sqrt{\mathbb E[|J_t^{s,\varepsilon}|^2]}.$

$$
\quad \blacktriangleright \text{ Then we set } L_t=J^{s,\varepsilon}_t+J^{l,\varepsilon}_t.
$$

SDEs driven by Lévy process and Approximated EM scheme

 \blacktriangleright A stochastic process X is said to solve a SDE driven by a Lévy process if

$$
X_t = \int_0^t a(X_s)ds + \int_0^t b(X_s) \int_{-\infty}^{+\infty} \left(N(ds, dz) - \nu(dz) \mathbf{1}_{|z| \le 1} \right) ds.
$$

► For $\varepsilon > 0$, we introduce the scheme $\bar{X}^{n,\varepsilon}$:

$$
\bar{X}_{t_{i+1}}^{n,\varepsilon} = \bar{X}_{t_i}^{n,\varepsilon} + a(\bar{X}_{t_i}^{n,\varepsilon}) + \sigma_{\varepsilon} \sqrt{(h)}G + b(\bar{X}_{t_i}^{n,\varepsilon}) \sum_{j=N_{t_i}^{\lambda_{\varepsilon}}+1}^{N_{t_i+1}^{\lambda_{\varepsilon}}} Y_j^{\varepsilon},
$$

with
$$
\sigma_{\varepsilon} = \sqrt{\int_{|z| \le \varepsilon} |z|^2 \nu(dz)}
$$
 and $G \sim \mathcal{N}(0, 1)$.

 \blacktriangleright N. Fournier proved that the following L^2 strong error upper bound holds :

$$
\mathbb{E}\left[\sup_{0\leq i\leq n}|X_{t_i}-\bar{X}_{t_i}^{n,\varepsilon}|^2\right]\leq C_T\left(\frac{1}{n}+n(\varepsilon)^2\right),
$$

SDEs driven by Lévy noise and Approximated EM scheme

 \blacktriangleright A stochastic process X is said to solve a SDE driven by a time inhomogeneous Lévy noise if

$$
X_t = \int_0^t a(s,X_s)ds + \int_0^t \int_{-\infty}^{+\infty} b(s,X_s,z) \left(N(ds,dz) - \nu_s(dz)\mathbf{1}_{|z|\leq 1}ds\right).
$$

For $\varepsilon > 0$ **, we introduce the scheme** $\bar{X}^{n,\varepsilon}$ **:**

$$
\bar{X}_{t_{i+1}}^{n,\varepsilon} = \bar{X}_{t_i}^{n,\varepsilon} + a(t_i, \bar{X}_{t_i}^{n,\varepsilon}) + \sigma_{\varepsilon}(t_i, \bar{X}_{t_i}^{n,\varepsilon})G + \sum_{j=N_{t_i}^{\lambda_{\varepsilon}}+1}^{N_{t_{i+1}}^{\lambda_{\varepsilon}}} b(t_i, \bar{X}_{t_i}^{n,\varepsilon}, Y(T_j^{\varepsilon}),
$$

λε

$$
\begin{aligned} &\text{with }\sigma_\varepsilon(\tau,\theta)=\sqrt{\int_{t_i}^{t_{i+1}}\int_{|z|\leq \varepsilon}|b(\tau,\theta,z)|^2\nu_s(dz)}, G\sim \mathcal{N}(0,1),\\ &T_j^\varepsilon=\inf\{t>0:N_t^{\lambda_\varepsilon}=j\}, \mathbb{P}(Y(T_j^\varepsilon)\in dx|T_j^\varepsilon=t)=\tfrac{\nu_t(dz)}{\lambda_\varepsilon}. \end{aligned}
$$

Theorem

If b *satisfies* $|b(t, x, z)| \le \overline{b}(\varepsilon)$ *for* $t \in [0, T]$ *,* $x \in \mathbb{R}$ *and* $z \in [-\varepsilon, \varepsilon]$ *, then*

$$
\mathbb{E}\left[\sup_{0\leq i\leq n}|X_{t_i}-\bar{X}_{t_i}^{n,\varepsilon}|^2\right]\leq C_T\left(\frac{1}{n}+n\bar{b}(\varepsilon)^2\right).
$$

Application to the orientation of rods in turbulence

Vorticity field ω of the turbulent flow for two different values of the shear σ^* . Blue corresponds to positive values (cyclonic eddies) and red to negative values (anticyclonic). The orientation of the rods are shown as black segments.

Figures provided courtesy of [\[Campana et al., 2022\]](#page-12-0)

 \blacktriangleright We consider intertialless rods in a turbulent flow with position equation $dX(t)/dt = v(X(t), t)$, coupled with a unit orientation vector p following Jeffery's equation :

$$
\frac{d}{dt}p = \mathbb{A}p - (p^T \mathbb{A}p)p.
$$
 (8)

 \triangleright After approximations on the gradient tensor $\mathbb A$ at the equilibrium regime, the SDE followed by the unfolded angle $\theta_t = \arctan(p_2/p_1)$ is derived

$$
\theta_t = \theta_0 + \int_0^t a(\theta_s)ds + \int_0^t b(\theta_s)dW_s,
$$
\n(9)

with $a(x)$ and $b(x)$ being linear combining of $cos(x)$ and $sin(x)$. Lorenzo Campana, Mireille Bossy, and Jérémie Bec.

Stochastic model for the alignment and tumbling of rigid fibres in two-dimensional turbulent shear flow, 2022.

The Levy noise model

This Gaussian model however fail to reproduce some of the characteristics present in the direct numerical simulation (DNS).

- \blacktriangleright The PDF of θ obtained by the DNS shows the presence of heavy tails at small times.
- ▶ The process θ also seem to have two regimes, being super-diffusive (i.e $\mathbb{E}[|\theta_t|^2] \sim t^{\alpha}$ with $\alpha>1$) at small times, and eventually converging to a diffusive regime (i.e $\mathbb{E}[|\theta_t|^2] \sim t$).

To enhance the diffusive model, we choose to replace the Brownian motion in the SDE by a time inhomogeneous truncated stable process L_t , with Lévy measure

$$
\nu_s(dz)ds = \left\{ \sqrt{s} \mathbf{1}_{s < T_*} + \sqrt{T_*} \mathbf{1}_{s \ge T_*} \right\} |z|^{-1-\alpha} \mathbf{1}_{|z| < z_*}.
$$
 (10)

Hence, one can compute

$$
\mathbb{E}[|L_t|^2] = \begin{cases} 2^{\frac{t^{3/2}}{3/2} \frac{z^2 - \alpha}{2 - \alpha}} & \text{if } t \le T_*\\ \mathbb{E}[|L_{T_*}|^2] + 2(t - T_*) \frac{z^2 - \alpha}{2 - \alpha} & \text{if } t \ge T_*. \end{cases}
$$
(11)

Comparison of the models

- \blacktriangleright First results in the shear case are promising, though more calibration of the parameters is required.
- ▶ In the close future, we plan to extend our results to the multi-dimensional case. As an application, we could build a 3D Lévy noise model for non spherical particles in turbulence. However, the physics of the 3D turbulence is much more complex.
- ▶ Another important part of my PhD will be about modelling deformable fibers in turbulence, involving SPDEs analysis, and modelling intermittence with Stochastic Volterra Equations.

Thank you for your attention !