NUMERICAL SIMULATION OF SDES WITH DISTRIBUTIONAL DRIFT

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1 Introduction

We would like to simulate numerically sample paths of the solution of the stochastic differential equation

$$\mathrm{d}X_t = b(X_t)\ \mathrm{d}t + \mathrm{d}W_t \tag{1}$$

where $b \in H_q^s(\mathbb{R}),\ s \in \left]-\frac{1}{2}, 0\right[,\ t \in [0,T]$, and W_t is a standard Brownian motion. This equation is studied in [1] in which the authors prove existence and unicity in law of a virtual solution for equation (1).

Example 1.1. *An example of such drift b is given by the derivative of a sample path of a fractional Brownian motion B_x^H with Hurst index $1/2 < H < 1$. These stochastic processes are gaussian processes verifying*

$$\mathbb{E}\left[B_t^H B_s^H\right] = \frac{1}{2}\left(t^{2H} + s^{2H} + |t-s|^{2H}\right).$$

We note $s = H - 1$. Given $B_x^H(\omega) \in H_q^{s+1}(\mathbb{R})$, we can take $b(x) = \frac{\partial}{\partial x} B_x^H(\omega) \in H_q^s(\mathbb{R})$. We will use this in our numerical simulations.

As far as the drift b is not a function but a distribution, it must be approximated if we want to evaluate it at points. In order to do so, we will use a series representation of b and truncate it. That is why we will consider two steps in our algorithm:

1. approximate the drift b by a function b^N meant to converge to b as $N \to \infty$.
2. approximate the solution X_t^N of the approximated SDE

   $$\mathrm{d}X_t^N = b^N\left(X_t^N\right)\ \mathrm{d}t + \mathrm{d}W_t \tag{2}$$

   by $X_t^{N,n}$ defined with the Euler-Maruyama scheme

   $$X_t^{N,n} = X_0 + \int_0^t b^N\left(X_{\eta_n(t)}^{N,n}\right) \mathrm{d}t + W_{\eta_n(t)}$$

   where $\eta_n(t) = t_k$ if $t \in [t_k, t_k + 1]$, for $t_k = \frac{k}{n}$ with $k \in [\![0, \lceil 2^n T \rceil]\!]$.

2 Numerical simulation of fractional Brownian motion

To simulate a sample path of a fractional brownian motion B_x^H on a finite grid $(x_k)_{k\in[\![1,n]\!]}$, we simulate n independent standard gaussian random variables $(X_k)_{k\in[\![1,n]\!]}$ and then correlate them with the definite positive correlation matrix

$$C_{k,s} = \mathbb{E}\left[B_{x_k}^H B_{x_s}^H\right] = \frac{1}{2}\left(x_k^{2H} + x_s^{2H} + |x_k - x_s|^{2H}\right).$$

To do so, we use the Cholesky decomposition method and calculate the triangular matrix M such that $C = MM^\top$. Therefore, defining

$$X = \begin{pmatrix} X_1 \\ \vdots \\ X_n \end{pmatrix} \text{ and } B^H = MX,$$

B^H contains the values of a fractional brownian motion evaluated on the grid $(x_k)_{k\in[\![1,n]\!]}$.

3 Approximation of the drift

3.1 Series representation

We use Haar wavelets to give a series representation of b. By doing so, we will be able to approximate it numerically by truncating the series.

Definition 3.1 (Haar wavelets)**.** *We define the Haar wavelets $h_{j,m}$ on $\mathbb{R}$ with $j \in \mathbb{N} \cup \{-1\}$ and $m \in \mathbb{Z}$ by:*

$$\begin{cases} h_M & : x \longmapsto \left(\mathbb{1}_{[0,\frac{1}{2}[} - \mathbb{1}_{[\frac{1}{2},1[}\right)(x) \\ h_{-1,m} & : x \longmapsto \sqrt{2}|h_M(x-m)| \\ h_{j,m} & : x \longmapsto h_M(2^j x - m) \end{cases}$$

Theorem 3.1 (See [2])**.** *Let $b \in H_q^s(\mathbb{R})$ for $2 \leq q \leq \infty$, and $s \in \left]-\frac{1}{2}, \frac{1}{q}\right[$. Therefore,*

$$b = \sum_{j=-1}^{+\infty} \sum_{m\in\mathbb{Z}} \mu_{j,m} h_{j,m} \tag{3}$$

where $\mu_{j,m} = 2^j \int_{\mathbb{R}} b(x) h_{j,m}(x)\, \mathrm{d}x$ in the sense of dual pairing.

Definition 3.2. *With the same notation $\mu_{j,m}$, let $b \in H_q^s(\mathbb{R})$ for $2 \leq q \leq \infty$, and $s \in \left]-\frac{1}{2}, \frac{1}{q}\right[$. Given $N \in \mathbb{N}^*$ we define b^N by:*

$$b^N = \sum_{m=N}^{N-1} \mu_{-1,m} h_{-1,m} + \sum_{j=0}^{N} \sum_{m=-N2^j}^{N2^j-1} \mu_{j,m} h_{j,m}. \tag{4}$$

Remark 3.1. *We can note that* Supp $b^N \subset [-N, N]$. *Moreover, we have:*

$$\left\| b - b^N \right\|_{H_q^s(\mathbb{R})} \underset{N \to +\infty}{\longrightarrow} 0.$$

3.2 Computation of the coefficients $\mu_{j,m}$ when b is the derivative of a fractional brownian motion

Faber basis

4 Numerical results

5 Convergence

5.1 Convergence of $X_s^{N,n}$ to X_s^N in L^2

Recently, Leobacher and Szölgyenyi proved in [3] the convergence of the Euler-Maruyama scheme for SDE with discontinuous but piecewise Lipschitz drift and with a degenerate diffusion coefficient. This framework applies to the scheme we use with piecewise constant drift b^N and a constant diffusion coefficient.

Theorem 5.1 (Theorem 3.1. in [3])**.** $\forall \varepsilon > 0$, $\exists C_N > 0$, $\exists n_0 \in \mathbb{N}$ *such that* $\forall n \geq n_0$

$$\mathbb{E}\left[\sup_{0\leq t\leq T}\left|X_t^{N,n} - X_t^N\right|^2\right]^{1/2} \leq C_N \delta^{1/4-\varepsilon} \tag{5}$$

with $\delta = \frac{1}{2^n}$ *the step size.*

TO DO: make C_N explicit.

5.2 Convergence of X_s^N to X_s

We want to estimate the weak error $\mathbb{E}[f(X_T) - f(X_T^N)]$ for our approximation algorithm. In order to do so, we must go back to the definition of the virtual solution of the SDE (1) given in [1]. The authors define the virtual solution of SDE (1) by:

$$\begin{cases} X_t = \Psi(t, Y_t) = \varphi^{-1}(t, Y_t) \\ Y_t = y + (\lambda+1)\int_0^t u(s, Y_s)\ \mathrm{d}s + \int_0^t (\nabla u(s, Y_s) + 1)\ \mathrm{d}W_s \end{cases} \tag{6}$$

where u is the mild solution in $H_p^{1+\delta}$ of the following parabolic PDE:

$$\begin{cases} \partial_t u + \frac{1}{2}\Delta u + b\nabla u - (\lambda+1)u = -b & \text{on } [0,T]\times\mathbb{R} \\ u(T) = 0 & \text{on } \mathbb{R} \end{cases} \tag{7}$$

and $\varphi(t, x) = x + u(t, x)$.

We also define another similar PDE by replacing b by b^N. We call u^N its mild solution in $H_p^{1+\delta}$.

$$\begin{cases} \partial_t u^N + \frac{1}{2}\Delta u^N + b^N\nabla u^N - (\lambda+1)u^N = -b^N & \text{on } [0,T]\times\mathbb{R} \\ u^N(T) = 0 & \text{on } \mathbb{R} \end{cases}. \tag{8}$$

We recall a useful lemma concerning the solutions of (7) and (8).

Lemma 5.2 (Lemma 20 in [1])**.** *Let $(\delta, p) \in K(\beta, q)$ and let v_λ be the mild solution to (7) in $H_p^{1+\delta}$. Fix ρ such that the integral operator is a contraction and let $\lambda > \rho$. Then $v_\lambda(t) \in \mathcal{C}^{1,\alpha}$ with $\alpha = \delta - 1/p$ for each fixed t and*

$$\sup_{(t,x)\in[0,T]\times\mathbb{R}} |\nabla v_\lambda(t,x)| \to 0, \ \textit{as}\ \lambda \to \infty \tag{9}$$

where the choice of λ depends only on $\delta, \beta, \|b\|_{H_p^{-\beta}}$, and $\|b\|_{H_q^{-\beta}}$.

By lemma 5.2, we choose λ big enough for ∇u and ∇u^N to be bounded by $\frac{1}{2}$. λ can be chosen independently of N as far as $\left\|b - b^N\right\|_{H_q^s(\mathbb{R})} \underset{N\to\infty}{\longrightarrow} 0$ (See Step 2 of the proof of Proposition 29 in [1]). Therefore u^N and u are $\frac{1}{2}$-lipschitz. We recall that in this case, by lemma 22 in [1], $\Psi(t, \cdot)$ is 2-lipschitz.

Applying fractional Morrey inequality, $\exists c > 0,\ \forall t \in [0, T]$:

$$\begin{cases} \left\|u^N(t) - u(t)\right\|_{L^\infty} \le \left\|u^N(t) - u(t)\right\|_{\mathcal{C}^{1,\alpha}} \le c\left\|u^N(t) - u(t)\right\|_{H^{-\beta}_{\tilde{q},q}} \\ \left\|\nabla u^N(t) - \nabla u(t)\right\|_{L^\infty} \le \left\|u^N(t) - u(t)\right\|_{\mathcal{C}^{1,\alpha}} \le c\left\|u^N(t) - u(t)\right\|_{H^{-\beta}_{\tilde{q},q}}. \end{cases}$$

Now, with

$$\left\|u^N(t)-u(t)\right\|_{H^{-\beta}_{\tilde{q},q}} \leq e^{\rho T}\left\|u^N(t)-u(t)\right\|^{(\rho)}_{H^{-\beta}_{\tilde{q},q}} \leq Ke^{\rho T}\left\|b^N-b\right\|_{H^{-\beta}_q}$$

from lemma 23 in [1], we have

$$\begin{cases}\left\|u^N(t)-u(t)\right\|_{L^\infty} \leq cKe^{\rho T}\left\|b^N-b\right\|_{H^{-\beta}_q} \\ \left\|\nabla u^N(t)-\nabla u(t)\right\|_{L^\infty} \leq cKe^{\rho T}\left\|b^N-b\right\|_{H^{-\beta}_q}.\end{cases}.$$

Let f be μ-Hölder with constant C_f and $\mu \in (0,1]$.

$$\mathbb{E}\left[f\left(X_T\right)-f\left(X_T^N\right)\right]=\mathbb{E}\left[f\left(\Psi\left(T,Y_T\right)\right)-f\left(\Psi\left(T,Y_T^N\right)\right)\right]$$

$$\leq 2^\mu C_f\mathbb{E}\left[\left|Y_T-Y_T^N\right|^\mu\right] \leq 2^\mu C_f\mathbb{E}\left[\left|Y_T-Y_T^N\right|\right]^\mu$$

by Jensen's inequality. Let $t\in[0,T]$.

$$Y_t-Y_t^N=(\lambda+1\ )\int_0^t\left\{u\left(t,\Psi\left(t,Y_t\right)\right)-u^N\left(t,\Psi\left(t,Y_t^N\right)\right)\right\}\ \mathrm{d}t$$
$$+\int_0^t\left\{\nabla u\left(t,\Psi\left(t,Y_t\right)\right)-\nabla u^N\left(t,\Psi\left(t,Y_t^N\right)\right)\right\}\ \mathrm{d}W_t$$

For clarity purpose, we note $\tilde{u}\left(t,Y_t\right)=u\left(t,\Psi\left(t,Y_t\right)\right)$ and use the same notation for the gradient and the approximated mild solution. We apply Meyer-Tanaka's formula to obtain:

$$\left|Y_t-Y_t^N\right|=(\lambda+1)\ \int_0^t\mathrm{sign}(Y_t-Y_t^N)\left\{\tilde{u}\left(t,Y_t\right)-\tilde{u}^N\left(t,Y_t^N\right)\right\}\ \mathrm{d}t$$
$$+\int_0^t\mathrm{sign}(Y_t-Y_t^N)\left\{\nabla\tilde{u}\left(t,Y_t\right)-\nabla\tilde{u}^N\left(t,Y_t^N\right)\right\}\ \mathrm{d}W_t+L_t^0(Y\_Y^N)$$

Taking the expectation:

$$\mathbb{E}\left|Y_t-Y_t^N\right|=(\lambda+1)\ \mathbb{E}\left[\int_0^t\mathrm{sign}(Y_t-Y_t^N)\left\{\tilde{u}\left(t,Y_t\right)-\tilde{u}^N\left(t,Y_t^N\right)\right\}\ \mathrm{d}t\right]$$
$$+\mathbb{E}\left[L_t^0(Y\_Y^N)\right]$$

References

[1] F. Flandoli, E. Issoglio, and F. Russo. Multidimensional stochastic differential equations with distributional drift. *Transactions of the American Mathematical Society*, 369 (3):1655–1688, 3 2017.

[2] E. Issoglio and F. Russo. On a class of Markov BSDEs with generalized driver. submitted. arXiv:1805.02466v1.

[3] G. Leobacher and M. Szölgyenyi. Convergence of the Euler–Maruyama method for multidimensional SDEs with discontinuous drift and degenerate diffusion coefficient. preprint. arXiv:1610.07047v5.