

ROUGH PATHS THEORY APPLIED TO COMPUTATION OF SENSITIVITIES

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Preliminaries

- $d \in \mathbb{N}^*$ and $T > 0$.
- B^H a d -dimensional fractional Brownian motion (FBM) with Hurst parameter $H > 1/4$.
- $\mu : \mathbb{R}^d \rightarrow \mathbb{R}^d$ and $\sigma : \mathbb{R}^d \rightarrow GL_d(\mathbb{R})$ of class $C^{[1/H]+1}$, bounded, with bounded derivatives and σ^{-1} bounded.
- X the solution on $[0, T]$, in rough paths sense, of the stochastic differential equation (SDE)

$$dX_t = \mu(X_t) dt + \sigma(X_t) dB_t^H \quad (1)$$

with a deterministic initial condition $x \in \mathbb{R}^d$.

The problem

Existence and computation of

$$\Delta^{x, \hat{x}} := \partial_x \mathbb{E}[F(X_T)] \quad \text{and} \quad \mathcal{V}^{\sigma, \hat{\sigma}} := \partial_\sigma \mathbb{E}[F(X_T)]$$

for $F : \mathbb{R}^d \rightarrow \mathbb{R}$ piecewise continuous, satisfying the following assumption :

Assumption 1. There exists $C > 0$ and $N \in \mathbb{N}^*$ such that : $|F(a)| \leq C(1 + \|a\|)^N$; $\forall a \in \mathbb{R}^d$.

Notations

- \mathcal{H}^1 the Cameron-Martin's space of B^H .
- \mathcal{H} the reproducing kernel Hilbert space of B^H .
- I_H the canonical isometry from \mathcal{H} into \mathcal{H}^1 .
- D the Malliavin derivative operator for B^H and δ the associated divergence.
- $\delta_{1/2}$ the divergence for the Brownian motion associated to B^H in its representation as a Volterra process.
- $J_{x \leftarrow 0}$ the Jacobian matrix of $x \mapsto X$.

Theorem 1

- If F is continuously differentiable and F and DF satisfy Assumption 1, $\Delta^{x, \hat{x}}$ and $\mathcal{V}^{\sigma, \hat{\sigma}}$ exist. Moreover,

$$\Delta^{x, \hat{x}} = \mathbb{E} \left[\langle D(F \circ X_T), I_H^{-1}(h^{x, \hat{x}}) \rangle_{\mathcal{H}} \right] \quad \text{and} \quad \mathcal{V}^{\sigma, \hat{\sigma}} = \mathbb{E} \left[\langle D(F \circ X_T), I_H^{-1}(h^{\sigma, \hat{\sigma}}) \rangle_{\mathcal{H}} \right]$$

where,

$$h^{x, \hat{x}} := \frac{1}{T} \int_0^T \sigma^{-1}(X_s) J_{s \leftarrow 0} \hat{x} ds \quad \text{and} \quad h^{\sigma, \hat{\sigma}} := \frac{1}{T} \int_0^T \sigma^{-1}(X_s) J_{s \leftarrow T} (\partial_\sigma X_T, \hat{\sigma}) ds.$$

- If F is piecewise continuous and satisfies Assumption 1, for $H > 1/2$; $\Delta^{x, \hat{x}}$ and $\mathcal{V}^{\sigma, \hat{\sigma}}$ exist. Moreover,

$$\Delta^{x, \hat{x}} = \mathbb{E} \left[F(X_T) \delta \left[I_H^{-1}(h^{x, \hat{x}}) \right] \right] \quad \text{and} \quad \mathcal{V}^{\sigma, \hat{\sigma}} = \mathbb{E} \left[F(X_T) \delta \left[I_H^{-1}(h^{\sigma, \hat{\sigma}}) \right] \right]$$

with, for $h = h^{x, \hat{x}}$ or $h^{\sigma, \hat{\sigma}}$:

$$\delta \left[I_H^{-1}(h) \right] = \frac{1}{\Gamma(3/2 - H)} \int_0^T \left[t^{H-1/2} \frac{d}{dt} \int_0^t (t-s)^{1/2-H} s^{1/2-H} h_s ds \right] \delta_{1/2} B_t.$$

An application in finance

Consider a financial market consisting of d risky assets and S the associated prices process :

$$\begin{cases} S_t := \kappa(X_t) \\ dX_t = \mu(X_t) dt + \sigma(Y_t) dB_t^1 \\ dY_t = \vartheta(Y_t) dB_t^2 \end{cases}$$

with :

- B^1 and B^2 two independent d -dimensional FBM.
- $\kappa : \mathbb{R}^d \rightarrow \mathbb{R}_+^d$ such that $F \circ \kappa$ satisfies Assumption 1.
- $\vartheta : \mathbb{R}^d \rightarrow GL_d(\mathbb{R})$ satisfying the same assumptions than σ .

Theorem 1 allows to compute

$$\langle \partial_\vartheta \mathbb{E}[F(S_T)] ; \hat{\vartheta} \rangle \quad \text{as} \quad \langle \partial_V \mathbb{E}[(F \circ \kappa \circ \rho_{\mathbb{R}^d})(Z_T)] ; \hat{V} \rangle$$

with $Z := (X, Y)$ satisfying :

$$dZ_t = \begin{bmatrix} \mu \circ \rho_{\mathbb{R}^d} \\ 0 \end{bmatrix} (Z_t) dt + V(Z_t) dW_t$$

for $W := (B^1, B^2)$,

$$V(x, y) := \begin{bmatrix} \sigma(y) & 0 \\ 0 & \vartheta(y) \end{bmatrix} \quad \text{and} \quad \hat{V}(x, y) := \begin{bmatrix} 0 & 0 \\ 0 & \hat{\vartheta}(y) \end{bmatrix} ; \quad \forall (x, y) \in \mathbb{R}_+^d \oplus \mathbb{R}_+^d.$$

Simulations

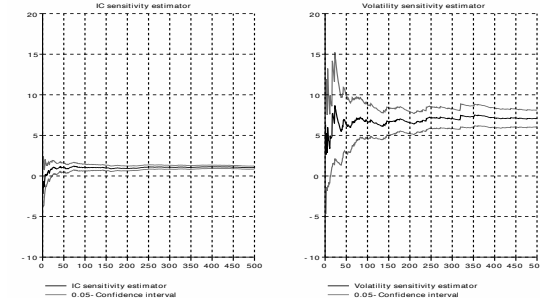
Consider X^n , Y^n and Z^n ($n \in \mathbb{N}^*$) the forward step- n Euler schemes for X , $\partial_x X$ and $\partial_\sigma X \cdot \hat{\sigma}$ in dimension 1.

Each Euler scheme converges uniformly in $L^r(\Omega)$ with rate $n^{r(1-2\alpha)}$; $1/2 < \alpha < H$ et $r \geq 1$.

Then, for n sufficiently high, the law of large numbers allows to approximate Δ^x and $\mathcal{V}^{\sigma, \hat{\sigma}}$ by :

$$\Theta_m^n(x) := \frac{1}{m} \sum_{k=1}^m \hat{F}[X_k^n(T)] Y_k^n(T) \quad \text{and} \quad \Theta_m^n(\sigma, \hat{\sigma}) := \frac{1}{m} \sum_{k=1}^m \hat{F}[X_k^n(T)] Z_k^n(T).$$

The central limit theorem provides confidence intervals.



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