

A comparison theorem for integrated stochastic Volterra models with application to the modelling of Lagrangian intermittency in turbulence

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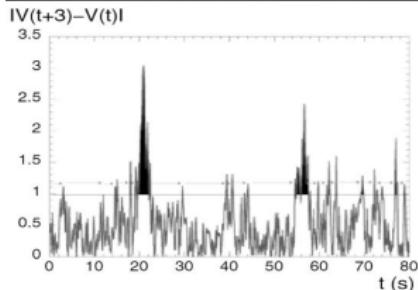
¹ This is an ongoing work, jointly with Mireille Bossy and Kerlyns Martínez.

Introduction

Wind gusts are small-scale wind fluctuations that are by nature **intermittent**.

Given a time scale τ (here 3 seconds) and a threshold δ (here 1 m/s), characterising intermittent fluctuation

$\|\Delta U(\tau)\| = \|U(t+\tau) - U(t)\| > \delta$ having **non Gaussian** properties



- ▶ Some predictive frameworks are ready to use, but assuming **Gaussian statistics**.
- ▶ Goal : develop a **stochastic model** that take into account **Kolomogorov's refined theory**. This involves stochastic processes with **memory**.
- ▶ Kolmogorov's theory predicts **multiscaling** such as anomalous power-laws emerging at the level of the velocity increments : $\mathbb{E}[|\Delta U(\tau)|^p] \simeq \tau^{\zeta(p)}$, with ζ **non-linear** function.

Plan of the talk

1. Modelling with Volterra processes in turbulence

- ▶ Physical context: multifractality in turbulence
- ▶ Effect of Volterra kernels in the statistics

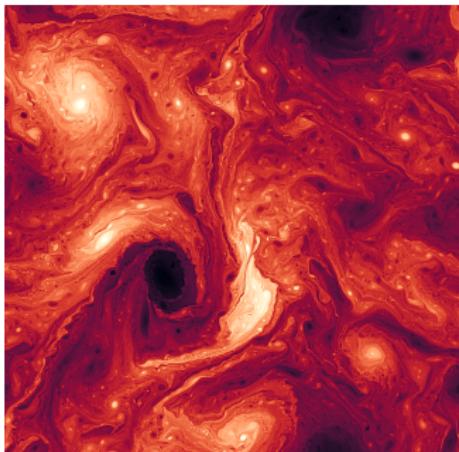
2. A weak comparison theorem for integrated Volterra processes

- ▶ The martingale approach
- ▶ Path derivatives, functionnal Itô formula and PPDEs
- ▶ Main result

3. Applications

- ▶ Applications in view of the modelling
- ▶ Application to the weak convergence of Markovian approximations

1. Modelling with Volterra processes in turbulence



A direct numerical simulation of 2D turbulence, provided by Nicolas Valade (Calisto Team INRIA)

- ▶ **Navier-Stokes** equation:

$$\partial_t \vec{u} + \vec{u} \cdot \nabla \vec{u} = -\nabla p + \frac{1}{\text{Re}} \Delta \vec{u}$$

- ▶ **Energy dissipation:**

$$\varepsilon(t, x) = \frac{\nu}{2} \langle \text{trace} \nabla^T u \nabla u \rangle(t, x)$$

- ▶ In **Lagrangian** setting,

$$X_t = X_0 + \int_0^t u(s, X_s) ds$$

$$\varepsilon_t = \frac{\nu}{2} \langle \text{trace} \nabla^T u \nabla u \rangle(t, X_t)$$

(1) - Physical context: multifractality in turbulence

Kolmogorov's refined theory for fluctuations of the **energy dissipation** ε (can be seen as the volatility behind the velocity U): [Kolmogorov, 1962] [Frisch and Parisi, 1985] [Frisch, 1995]:

- ▶ **stationarity** and **scaling** : $\mathbb{E}[\varepsilon_t] = v\tau_\eta^{-2}$ (Kolmogorov 1941);
- ▶ **log-normality** of ε : with $\mathbb{V}\text{ar}[\log \varepsilon_t] \simeq \log\left(\frac{\tau_L}{\tau_\eta}\right)$; $\tau_L = \frac{1}{\langle \|u\|^2 \rangle(t)} \int_0^{+\infty} \langle u(t+\theta)u(t) \rangle d\theta$
- ▶ **multiscaling** of the one-point statistics: $\mathbb{E}[\varepsilon_t^p] \simeq \left(\frac{\tau_L}{\tau_\eta}\right)^{\zeta(p)}$, where $\zeta(p)$ is a non-linear convex function;
- ▶ **power-law scaling** for the **coarse-grained** dissipation and the velocity: in the inertial range, $\tau_\eta \ll \tau \ll T_L$,

$$\mathbb{E}\left[\left|\frac{1}{\tau} \int_t^{t+\tau} \varepsilon_s\right|^p\right] \simeq \tau^{\zeta(p)},$$

$$\mathbb{E}[|U(t+\tau) - U(t)|^p] \simeq \tau^{\zeta(p)}.$$

(1) - Modelling with Volterra processes

We construct a **stochastic model** for ε in the form $\varepsilon_t = \bar{\varepsilon} \exp(\gamma V_t - \frac{\gamma^2}{2} \text{Var } V_t)$, where V is a Gaussian process to be determined, $\bar{\varepsilon} \in \mathbb{R}_+$, and $\gamma > 0$.

We find different proposals for the choice of V in the literature, in the form of stochastic **Volterra** processes:

- ▶ In [Forde et al., 2022], the authors consider the **fractional Brownian motion** of Riemann-Liouville $V_t = \int_0^t (t-s)^{-\frac{1}{2}+H} dW_s$. They demonstrate that for $\gamma \in (0, \sqrt{2})$, the measure $\xi_H(dt) = \exp(\gamma V_t - \frac{\gamma^2}{2} \text{Var } V_t) dt$ is **locally multifractal** outside of zero in the limit $H \rightarrow 0$, i.e., for all $t \in (0, 1)$,

$$\lim_{\tau \rightarrow 0} \frac{\log(\lim_{H \rightarrow 0} \mathbb{E}[\xi_H([t, t+\tau])^p])}{\log(\tau)} = \zeta(p) + p,$$

with $\zeta(p) = -\frac{1}{2}\gamma^2(p^2 - p)$.

- ▶ [Letournel, 2022] proposes in his thesis to consider the **stationary** process $V_t = \int_{-\infty}^t \left[(t-r+\tau_\eta)^{H-\frac{1}{2}} - (t-r+\tau_L)^{H-\frac{1}{2}} \right] dW_r$, which is **well-defined for $H=0$** , and in this case satisfies $\mathbb{E}[V_s V_t] \simeq \log_+ \frac{1}{t-s}$ for $\tau_\eta \ll s < t \ll \tau_L$, as well as $\text{Var}(V_t) \sim \log(\tau_L/\tau_\eta)$ in the limit $\tau_L/\tau_\eta \rightarrow +\infty$. However, **no rigorous proof** of multifractality is provided.

(1) - How to compare the effects of Volterra kernels ?

We aim to find a **stationary, locally multifractal** process that is **less expensive** to simulate than fBm as $H \rightarrow 0$.

- To achieve this, we will demonstrate a **comparison** result for integrated EVS models. Let $T > t_0 > 0$. For b measurable, $K, \bar{K} \in L^2([0, T], \mathbb{R})$, and $\phi : \mathbb{R} \rightarrow \mathbb{R}$ sufficiently regular, we define

$$X_T = \int_{t_0}^T b(s, V_s) ds; V_s = \int_0^s K(s-r) dW_r$$
$$\bar{X}_T = \int_{t_0}^T b(s, \bar{V}_s) ds; \bar{V}_s = \int_0^s \bar{K}(s-r) dW_r,$$

and we are interested in the "weak" error $\mathcal{E}_T = |\mathbb{E}[\phi(X_T)] - \mathbb{E}[\phi(\bar{X}_T)]|$.

- Note that for $b(s, x) = \exp(\gamma x - \frac{\gamma^2}{2} \text{Var } V_s)$, $\phi(x) = x^p$, $t_0 = t$, $T = t + \tau$, $K(s-r) = (s-r)^{H-\frac{1}{2}}$, we have

$$\mathbb{E}[\phi(X_T)] = \mathbb{E}[\xi_H([t, t+\tau])^p] = \mathbb{E}\left[\left(\int_t^{t+\tau} \exp\left(\gamma V_s - \frac{\gamma^2}{2} \text{Var } V_s\right) ds\right)^p\right].$$

- Thus, controlling \mathcal{E}_T allows us to measure how much an approximation of V by \bar{V} impacts the local multifractality of the induced Gaussian measure ξ .

2. A comparison theorem for integrated Volterra processes

$$\mathbb{E}[\phi(X_T)] - \mathbb{E}[\phi(\bar{X}_T)] = ?$$

- ▶ Usually, weak error expansions (e.g, for Euler scheme) are done with the **Itô formula** and the **Kolomogorov PDE** satisfied by $u(t,x) = \mathbb{E}[\phi(X_T^{t,x})]$.
- ▶ In this case, not possible because V_t is **not a semimartingale** in general and **not a Markov process**
- ▶ We will use a recent technique to obtain martingales and recover Markovianity, at the price of the **extension** of the domain of the x variable to a **functionnal space**

(2) - The martingale approach

- We consider the filtration $\mathcal{F}_s = \sigma(W_r ; r \in [0, s])$ for $s \in \mathbb{T}$. The orthogonal decomposition from [Viens and Zhang, 2019] then writes:

$$\forall s \geq t \in \mathbb{T}, \quad V_s = \underbrace{\int_0^t K(s-r) dW_r}_{\Theta_s^t \in \mathcal{F}_t} + \underbrace{\int_t^s K(s-r) dW_r}_{I_s^t \perp\!\!\!\perp \mathcal{F}_t}.$$

- We derive that for any test function $\phi : \mathbb{R} \rightarrow \mathbb{R}$,

$$\begin{aligned} \mathbb{E}[\phi(X_T) | \mathcal{F}_t] &= \mathbb{E}\left[\phi\left(X_t + \int_t^T b(V_s) ds\right) | \mathcal{F}_t\right] \\ &= \mathbb{E}\left[\phi\left(X_t + \int_t^T b(\Theta_s^t + I_s^t) ds\right) | \mathcal{F}_t\right] \\ &= u(t, X_t, \Theta_{[t,T]}^t), \end{aligned}$$

where $u(t, x, \omega) = \mathbb{E}_{t,x,\omega}[\phi(X_T)] = \mathbb{E}[\phi(X_T) | X_t = x, \Theta_{[t,T]}^t = \omega]$ for all $(t, x, \omega) \in \mathbb{T} \times \mathbb{R} \times C([t, T], \mathbb{R})$.

(2) - The path derivatives of u

Let $\Lambda = \mathbb{T} \times \mathbb{R} \times C^0([t, T], \mathbb{R})$, and $u : \Lambda \rightarrow \mathbb{R}$. For $\omega \in C^0([t, T])$ we set $\|\omega\|_{\mathbb{T}} = \sup_{s \in [t, T]} |\omega_s|$. We define the **path derivative** of u in ω in the direction $\eta \in C([t, T])$ by:

$$\langle \partial_\omega u(t, x, \omega), \eta \rangle = \lim_{\varepsilon \rightarrow 0} \frac{u(t, x, \omega + \varepsilon \eta) - u(t, x, \omega)}{\varepsilon},$$

which is a **Gâteaux** derivative, and we define in the same way the second path derivative $\langle \partial_\omega^2 u(t, x, \omega), (\eta, \zeta) \rangle$.

Definition -

We say that u belongs to $C_+^{2,2}(\Lambda)$ if u is C^2 with respect to x and two times **Fréchet differentiable** with respect to ω , and if there exists $k_u, q_u > 0$ such that

$$|\langle \partial_\omega u(t, x, \omega), \eta \rangle| \lesssim (1 + |x|^{k_u} + e^{q_u \|\omega\|_{\mathbb{T}}}) \|\eta\|_{\mathbb{T}}$$

$$|\langle \partial_\omega^2 u(t, x, \omega), (\eta, \zeta) \rangle| \lesssim (1 + |x|^{k_u} + e^{q_u \|\omega\|_{\mathbb{T}}}) \|\eta\|_{\mathbb{T}} \|\zeta\|_{\mathbb{T}}.$$

(2) - The 2 main tools : functionnal Itô formula and PPDE

Let $u \in C_+^{2,2}(\Lambda)$ and $K^s(r) = K(r-s)$ for $r \geq s$. We have the **functional Itô formula** from [Viens and Zhang, 2019]:

$$\begin{aligned} u(t, X_t, \Theta^t) - u(0, x, 0) &= \int_0^t \left(\partial_t u(s, X_s, \Theta^s) + b(V_s) \partial_x u(s, X_s, \Theta^s) \right. \\ &\quad \left. + \frac{1}{2} \left\langle \partial_\omega^2 u(s, X_s, \Theta^s), (K^s, K^s) \right\rangle \right) ds + \int_0^t \langle \partial_\omega u(s, X_s, \Theta^s), K^s \rangle dW_s. \end{aligned}$$

And we have the following **path-dependent PDE** for u :

Theorem (Thm 2.25 dans [Bonesini et al., 2023])

Under regularity hypothesis for b and ϕ (e.g, C^2 and polynomial growth for ϕ , C^2 and exponential growth for b):

$$\begin{aligned} \partial_t u(t, x, \omega) + b(\omega_t) \partial_x u(t, x, \omega) + \frac{1}{2} \left\langle \partial_\omega^2 u(t, x, \omega), (K^t, K^t) \right\rangle &= 0 \\ \text{with terminal condition } u(T, x, \omega) &= \phi(x), \end{aligned}$$

(2) - Regularity of u : moment bounds

- We introduce the **flow process**:

$$X_T^{t,x,\omega} = x + \int_t^T b(V_s^{t,\omega}) ds$$

$$V_s^{t,\omega} = \omega_s + \int_t^s K(s-r)dW_r, \quad (t,x,\omega) \in \Lambda \text{ and } s \geq t.$$

- By some Gaussian computations, we get the **moment bounds**:

Lemma

Assume that $|b(x)| \leq 1 + e^{k_b x}$ for some $k_b > 0$. Then for all $p \geq 1$,

$$\sup_{s \in [t,T]} \mathbb{E}[\exp(pV_s^{t,\omega})] \lesssim e^{p\|\omega\|_{\mathbb{T}}} \quad \mathbb{E}[|X_T^{t,x,\omega}|^p] \lesssim |x|^p + e^{2pk_b\|\omega\|_{\mathbb{T}}}$$

(2) - Regularity of u : representation of the derivatives

We will use the following formal notations:

$$\langle \partial_\omega X_T^{t,x,\omega}, \eta \rangle = \int_t^T b'(s, V_s^{t,\omega}) \eta_s ds.$$

$$\langle \partial_\omega^2 X_T^{t,x,\omega}, (\eta, \zeta) \rangle = \int_t^T b''(s, V_s^{t,\omega}) \eta_s \zeta_s ds.$$

Proposition

Under the same regularity conditions on ϕ and b as before, the function $u : (t, x, \omega) \mapsto \mathbb{E}[\phi(X_T^{t,x,\omega})]$ belongs to $C_+^{2,2}(\Lambda)$ and for any $\eta, \zeta \in C([t, T])$ we have:

$$\partial_x u(t, x, \omega) = \mathbb{E}[\phi'(X_T^{t,x,\omega})],$$

$$\partial_x^2 u(t, x, \omega) = \mathbb{E}[\phi''(X_T^{t,x,\omega})],$$

$$\langle \partial_\omega u(t, x, \omega), \eta \rangle = \mathbb{E}[\phi'(X_T^{t,x,\omega}) \langle \partial_\omega X_T^{t,x,\omega}, \eta \rangle],$$

$$\langle \partial_\omega \partial_x u(t, x, \omega), (\eta, \zeta) \rangle = \mathbb{E}[\phi''(X_T^{t,x,\omega}) \langle \partial_\omega X_T^{t,x,\omega}, \eta \rangle \zeta_T],$$

$$\begin{aligned} \langle \partial_\omega^2 u(t, x, \omega), (\eta, \zeta) \rangle &= \mathbb{E}[\phi''(X_T^{t,x,\omega}) \langle \partial_\omega X_T^{t,x,\omega}, \eta \rangle \langle \partial_\omega X_T^{t,x,\omega}, \zeta \rangle] \\ &\quad + \mathbb{E}_{t,x,\omega}[\phi'(X_T^{t,x,\omega}) \langle \partial_\omega^2 X_T^{t,x,\omega}, (\eta, \zeta) \rangle]. \end{aligned}$$

(2) - The weak error expansion

Let $\bar{\Theta}_s^t = \int_0^t \bar{K}(s-r)dW_r$. We apply the **functionnal Itô formula** to u and $(t, \bar{X}_t, \bar{\Theta}^t)$, we use the **PPDE** satisfied by u , the bilinearity and symmetry of the map $\langle \partial_{\omega}^2 u(t, x, \omega), (\cdot, \cdot) \rangle$:

$$\begin{aligned}\mathbb{E}[\phi(\bar{X}_T)] - \mathbb{E}[\phi(X_T)] &= \mathbb{E}[u(T, \bar{X}_T, \bar{\Theta}^T)] - \mathbb{E}[u(0, x, 0)] \\ &= \mathbb{E} \int_0^T \partial_t u(t, \bar{X}_t, \bar{\Theta}^t) dt \\ &\quad + \mathbb{E} \int_0^T \left\{ b(\bar{V}^t) \partial_x u(t, \bar{X}_t, \bar{\Theta}^t) + \frac{1}{2} \left\langle \partial_{\omega}^2 u(t, \bar{X}_t, \bar{\Theta}^t), (\bar{K}^t, \bar{K}^t) \right\rangle \right\} dt \\ &= \frac{1}{2} \mathbb{E} \int_0^T \left\langle \partial_{\omega}^2 u(t, \bar{X}_t, \bar{\Theta}^t), (\bar{K}^t - K^t, \bar{K}^t + K^t) \right\rangle dt.\end{aligned}$$

Then due to the **probabilistic representation** of u we write the error as:

$$\begin{aligned}&\frac{1}{2} \int_0^T \mathbb{E} \left[\phi''(X_T^{t, \bar{X}_t, \bar{\Theta}^t}) \left(\int_t^T b'(V_s^{t, \bar{X}^t})(K - \bar{K})(s-t) ds \right) \left(\int_t^T b'(V_s^{t, \bar{X}^t})(K + \bar{K})(s-t) ds \right) \right] dt \\ &\quad + \frac{1}{2} \int_0^T \mathbb{E} \left[\phi'(X_T^{t, \bar{X}_t, \bar{\Theta}^t}) \left(\int_t^T b''(V_s^{t, \bar{X}^t})(K^2 - \bar{K}^2)(s-t) ds \right) \right] dt.\end{aligned}$$

(2) - Main result

By **pushing the expectations** inside the Lebesgues integrals in the last formula, by the **triangle inequality**, the **growth control** of the coefficients and the **moment bounds** on the stochastic terms, we obtain the following result:

Théorème - Weak comparison theorem

$$|\mathbb{E}[\phi(\bar{X}_T)] - \mathbb{E}[\phi(X_T)]| \lesssim \int_0^T \int_0^t |(K - \bar{K})(s)| ds dt + \int_0^T \int_0^t |(K^2 - \bar{K}^2)(s)| ds dt. \quad (1)$$

- **Remark:** With additional regularity on the coefficients, a **second use** of the functional Itô formula allows to expand the second term in the RHS of (1) into:

$$\int_0^T \left| \int_0^t K^2(s) ds - \int_0^t \bar{K}^2(s) ds \right| dt + \int_0^T \int_0^t \left| (K^2(s) - \bar{K}^2(s)) \int_0^s (K^2(u) - \bar{K}^2(u)) du \right| ds dt.$$

It is still an **open question** whereas we can get rid of the pink term when K is singular.

3. Applications



(3) - Some applications: modelling point of view

The comparison theorem may help to determine which sequences of kernels are the most **suitable approximations** of the fractionnal one in our **modelling problem**. In particular:

- ▶ Let $K(r) = r^{H-\frac{1}{2}}$ and $\bar{K}(r) = (r + \tau)^{H-\frac{1}{2}}$. Then $|\mathbb{E}[\phi(\bar{X}_T)] - \mathbb{E}[\phi(X_T)]| \underset{H \rightarrow 0}{\lesssim} \frac{T}{2H} + o(\frac{\tau}{2H})$.
- ▶ Let $K(r) = r^{H-\frac{1}{2}}$ and $\bar{K}(r) = r^{H-\frac{1}{2}} \mathbf{1}_{\{r \geq \tau\}} + \frac{\tau^{H-\frac{1}{2}}}{\sqrt{2H}} \mathbf{1}_{\{r < \tau\}}$. Then $|\mathbb{E}[\phi(\bar{X}_T)] - \mathbb{E}[\phi(X_T)]| \underset{H \rightarrow 0}{\lesssim} \tau \frac{T}{2H} + o(\frac{\tau}{2H})$ **but only if we get rid of the pink term.**

This suggests that there *might* be **better approximations** of the fractionnal than $\bar{K}(r) = (r + \tau)^{H-\frac{1}{2}}$ when H is small, but this is still an open question for now.

(3) - A numerical application

- ▶ **Goal:** for V a Volterra process with non-trivial kernel, approximate the **path** of V to compute the statistics of the integrated model by Monte-Carlo method:

$$\mathbb{E} \left[\phi \left(\int_0^T b(V_s) ds \right) \right] \simeq \frac{1}{N} \sum_{i=1}^N \phi \left(\sum_{j=1}^{n-1} (t_{j+1} - t_j) b(V_{t_j}^{(i)}) \right).$$

- ▶ This can be achieved by **Markovian approximation** of V when the kernel K is **completely monotone**, i.e if there exists a positive, non decreasing function $\lambda : \mathbb{R}_+ \mapsto \mathbb{R}_+$ such that:

$$K(r) = \int_0^{+\infty} e^{-(t-s)x} \lambda(x) dx.$$

- ▶ **Example:** the kernels $K(r) = r^{H-\frac{1}{2}}$ and $K(r) = (r + \tau)^{H-\frac{1}{2}}$ are completely monotones, with associated λ respectively equals to $\lambda(x) = x^{-H-\frac{1}{2}}$ and $\lambda(x) = e^{-\tau x} x^{-H-\frac{1}{2}}$.

(3) - The Markovian approximation from [Carmona et al., 2000]

Applying the **stochastic Fubini theorem** and discretising the **Laplace transform** of K ,

$$\begin{aligned}\int_0^t K(t-s)dW_s &= \int_0^t \left(\int_0^{+\infty} e^{-(t-s)x} \lambda(x) dx \right) dW_s \\ &= \int_0^{+\infty} \lambda(x) dx \left(\int_0^t e^{-(t-s)x} dW_s \right) \\ &\simeq \sum_{i=1}^m w_i Y_t^{x_i},\end{aligned}$$

where

- ▶ $(w_i, x_i)_{\{1 \leq i \leq m\}}$ is an appropriate **Gauss quadrature** of order m for $\int_0^{+\infty} f(x) \lambda(x) dx$,
- ▶ $(Y_t^{x_i})_{t \in [0, T]}$ is a (**Markov**) **Ornstein-Uhlenbeck** process starting from zero :

$$\begin{aligned}dY_t^{x_i} &= -x_i Y_t^{x_i} dt + dW_t \\ Y_0^{x_i} &= 0.\end{aligned}$$

(3) - Convergence of the Markovian approximation

- ▶ Observe that we can write

$$\sum_{i=1}^m w_i Y_t^{x_i} = \int_0^t K_m(t-s) dW_s \text{ with } K_m(r) = \sum_{i=1}^m w_i e^{-rx_i},$$

- ▶ If $(w_i, x_i)_{\{1 \leq i \leq m\}}$ comes from a **Gaussian quadrature method**, it follows from Corollary D.2 in [Bayer and Breneis, 2023] that for every m and r , we have

$$K_m(r) \leq K(r),$$

hence $|K^2(r) - K_m^2(r)| = K^2(r) - K_m^2(r)$.

- ▶ Applying the **comparison theorem** we derive that

$$|\mathbb{E}[\phi(X_T)] - \mathbb{E}[\phi(X_T^{(m)})]| \leq \int_0^T \int_0^t (K^2(s) - K_m^2(s)) ds dt$$

where $X_T^{(m)} = \int_0^T b(\int_0^s K_m(s-r) dW_r) ds$.

- ▶ For example, if $K(r) = r^{H-\frac{1}{2}} = \int_0^{+\infty} x^{-\frac{1}{2}-H} e^{-rx} dx$, the weak error from the Markovian approximation is mainly controlled by the **leftover term**

$$\int_{t_0}^T \int_t^T \left(\int_{x_m}^{+\infty} x^{-\frac{1}{2}-H} e^{-(s-t)x} dx \right)^2 ds dt \lesssim \frac{x_m^{-2H}}{2H}.$$

- ▶ Using the **functionnal Itô formula** from [Viens and Zhang, 2019] and the **PPDEs** from [Bonesini et al., 2023], we obtain a **comparison theorem** between (Lebesgue) integrated Volterra processes in terms of **deterministic integral differences of their kernels**.
- ▶ The error obtained might be improved if we can push the absolute value outside one of the integrals, which would be **crucial for the applications** we have in mind. This is work in progress.
- ▶ One may also think to **extend** the result to **stochastic integrals** of Volterra processes, with respect to a possibly correlated other Brownian motion.

Thanks for your attention!

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