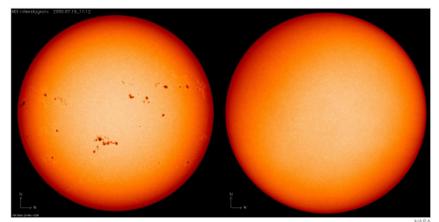
Analysis of Stochastic PDEs CBMS-NSF Course at Michigan State University

Davar Khoshnevisan

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Is the Sun Missing Its Spots?



SUN GAZING These photos show sunspots near solar maximum on July 19, 2000, and near solar minimum on March 18, 2009. Some global warming skeptics speculate that the Sun may be on the verge of an extended slumber.

By KENNETH CHANG Published: July 20, 2009

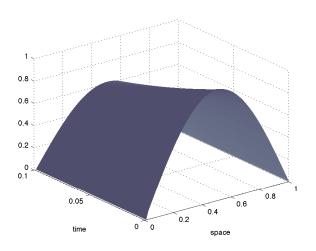


Figure: $\lambda = 0$; $u_t(x) = \sin(\pi x) \exp(-\pi^2 t/2)$

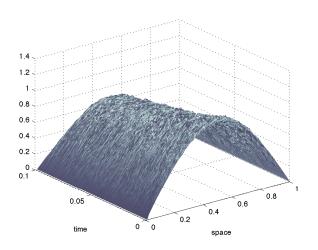


Figure: $\lambda = 0.1$; max. peak ≈ 1.4

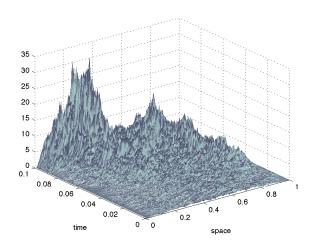


Figure: $\lambda = 2$; max. peak ≈ 35

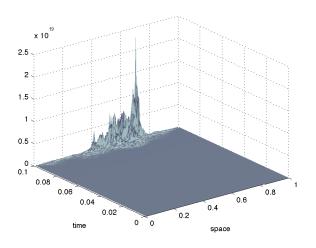


Figure: $\lambda = 5$; max. peak $\approx 2.5 \times 10^{19}$

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- ▶ Complex problems in random media are associated to intermittency: As the systems feels more noise, it can begin to act erratically.
- ▶ Many field theories (SPDEs) yield intermittent solutions.



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<u>White noise</u> on \mathbf{R}^m is a mean-zero set-indexed Gaussian random field [GRF] $\{\xi(A)\}_{A\in\mathscr{L}(\mathbf{R}^m)}$ with

$$\operatorname{Cov}(\xi(A_1), \xi(A_2)) = |A_1 \cap A_2| \qquad (A_i \in \mathcal{L}(\mathbf{R}^m)),$$

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► Easy fact: White noise exists and is an $L^2(\Omega)$ -valued countably-additive measure on $\mathcal{L}(\mathbf{R}^m)$.

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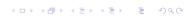
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Gaussian random fields [GRFs] (Lecture 2) Wiener integrals

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 - ▶ If $h, g \in L^2(\mathbf{R}^m)$ and $h \perp g$ then $\int h \, \mathrm{d}\xi$ is independent from $\int g \, d\xi$.

Stochastic Convolutions

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▶ Proposition (A stochastic Young inequality)

If $f \in L^2(\mathbf{R}^m)$, then there is a modification of $f * \xi$ that is measurable [jointly in (x, ω)]. Moreover, for all Borel measures μ on \mathbf{R}^m ,

$$\mathbb{E}\left(\left|\int_{\mathbf{R}^m} (f * \xi)(x) \, \mu(\mathrm{d}x)\right|^2\right) \leqslant [\mu(\mathbf{R}^m)]^2 \cdot \|f\|_{L^2(\mathbf{R}^m)}^2.$$

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- ► The rest follows from the Cauchy–Schwarz inequality.

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- ► B has a continuous modification [Kolmogorov continuity thm].

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► Proposition

For all
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▶ In particular, if $\xi = \xi(t, x)$ is space-time white noise and W is Br. sheet on \mathbb{R}^2 then

$$\frac{\partial^2}{\partial t \partial x} W(t, x) = \xi(t, x).$$

Proof in the case that m=1

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▶ LHS $\rightarrow \int \phi \, d\xi$ by definition.



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► Corollary (Stochastic Fubini)

If $f \in L^2(\mathbf{R}^m)$ and μ is a finite Borel measure on \mathbf{R}^m , then

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► Step 1: If $f \in C_c^{\infty}(\mathbf{R}^m)$, then by ordinary Fubini,

LHS=
$$(-1)^m \int_{\mathbf{R}^m} \mu(\mathrm{d}x) \int_{\mathbf{R}^m} \mathrm{d}y \ B(y) \frac{\partial^m f(x-y)}{\partial y_1 \cdots \partial y_m}$$

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▶ By Step 1, LHS = $\int (f_n * \xi) d\mu$; owing to the stochastic Young inequality, it suffices to prove that $f_n * \xi \to f * \xi$ in $L^2(\Omega)$, but this holds also by the Wiener isometry.

Example: fractional Brownian motion [fBm]

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An <u>fBm with index H</u> is a centered Gaussian process $\{X_t\}_{t\geqslant 0}$ with $X_0 = 0$ and $\mathrm{E}\left(|X_t - X_s|^2\right) = |t - s|^{2H} \ (s, t \geqslant 0)$.

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- fBm(1/2) = BM.
- ▶ fBm(H) has a Hölder-continuous modification [Kolmogorov continuity thm] of index < H.

Example: fractional Brownian motion [fBm] (some details)

▶ Define for all $t \ge 0$ and $H, s \in \mathbf{R}$,

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▶ Then we can construct fBm(H) as

$$X_t := \frac{1}{\sqrt{C_H}} \int f_H(t, s) \, \xi(\mathrm{d}s) \qquad (t > 0).$$

Example: fractional Brownian motion [fBm] (some background facts)

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- ▶ Let $\{X_t\}_{t\geq 0}$ be a fBm(H).
- ► Theorem (Marcus, 1968; Shao, 1996; ...)

 With probability one:

$$\limsup_{\varepsilon\downarrow 0}\frac{X_{t+\varepsilon}-X_t}{\varepsilon^H\sqrt{2\ln\ln(1/\varepsilon)}}=1\quad\forall t\geqslant 0;\quad and$$

$$\lim_{n \to \infty} \sum_{a \geq n \leq j \leq b \geq n} \left| X_{(j+1)/2^n} - X_{j/2^n} \right|^{1/H} = \mathbf{E}\left(|\mathcal{N}|^{1/H} \right) \cdot (b - a);$$

 $\forall 0 \leq a < b < \infty$, where N is a standard normal r.v.

A Linear Heat Equation (Lecture 3)

A non-random heat equation $(\partial_t u = (\nu/2)\partial_x^2 u + \mu)$

▶ Let μ be a finite signed Borel measure on **R**. Want to solve the initial-value problem

$$\frac{\partial}{\partial t}u = \frac{\nu}{2}\frac{\partial^2}{\partial x^2}u + \mu,\tag{HE}$$

 $[u := u_t(x)]$ for $x \in \mathbf{R}$ with t > 0, subject to a nice initial function $u_0 : \mathbf{R} \to \mathbf{R}$.

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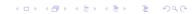
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▶ Definition

We say that $u = u_t(x)$ is a <u>weak solution</u> to (HE) if $u \in L^1_{loc}(\mathbf{R}_+ \times \mathbf{R})$ and

$$-\int_{\mathbf{R}_{+}\times\mathbf{R}} u \frac{\partial}{\partial t} \varphi \, \mathrm{d}t \, \mathrm{d}x = \frac{\nu}{2} \int_{\mathbf{R}_{+}\times\mathbf{R}} u \frac{\partial^{2}}{\partial x^{2}} \varphi \, \mathrm{d}t \, \mathrm{d}x + \int \varphi \, \mathrm{d}\mu,$$

for all $\varphi \in C_c^{\infty}((0,\infty) \times \mathbf{R})$.



A non-random heat equation $(\partial_t u = (\nu/2)\partial_x^2 u + \mu)$

▶ Define the heat kernel

$$p_t(x) := \frac{1}{\sqrt{2\nu\pi t}} \exp\left(-\frac{x^2}{2\nu t}\right) \qquad (t > 0, x \in \mathbf{R}).$$

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The following is the unique weak solution to (HE):

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A random heat equation $(\partial_t u = (\nu/2)\partial_x^2 u + \xi)$

▶ Now we study the "linear stochastic heat equation,"

$$\frac{\partial}{\partial t}u = \frac{\nu}{2}\frac{\partial^2}{\partial x^2}u + \xi, \tag{SHE}$$

subject to u_0 := nice and non random; ξ := space-time white noise. $[\xi = \partial_t \partial_x W]$

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The mild solution is a weak solution to (SHE).

- ▶ Sketch of proof: Use stochastic Fubini.
- ► The solution is a GRF!



Structure theory

▶ Immediate goal: Describe the local behavior of the solution to (SHE). Let

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- ▶ 2-sided BM is any GRF $\{B(x)\}_{x \in \mathbf{R}}$ with $\mathrm{E}(|B(x) B(y)|^2) \propto |x y|$.



Structure theory (some corollaries; $Z_t(x) := \int_{(0,t)\times \mathbf{R}} p_{t-s}(y-x) \, \xi(\mathrm{d} s \, \mathrm{d} y)$.)

Corollary (Swanson, 2007; Pospišil–Tribe, 2007)

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- ► Theorem (Lei–Nualart, 2009; Foondun–K–Mahboubi, 2013)
 - (i) \forall fixed $x \in \mathbf{R}$, $\exists f Bm(1/4) \{X_t\}_{t \geqslant 0}$ such that

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► A version of (ii) was first found in Walsh (1986).



Ideas of proof [Lei–Nualart; $Z_t(x) := \int_{(0,t)\times\mathbf{R}} p_{t-s}(y-x) \, \xi(\mathrm{d} s \, \mathrm{d} y)$]

► Expand

$$Z_{t+\varepsilon}(x) - Z_t(x) = J_1 + J_2,$$

where

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- :. $E(|Z_{t+\varepsilon}(x) Z_t(x)|^2) = E(J_1^2) + E(J_2^2).$
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▶ Let η be an independent white noise on \mathbf{R} , and define $T_t := (2\nu\pi)^{-1/2} \int_{-\infty}^{\infty} z^{-1} (1 - \exp\{-\nu t z^2/2\}) \, \eta(\mathrm{d}z)$. Then T is smooth, and similar computations show that

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► Therefore,

$$E\left(\left|Z_{t+\varepsilon}(x) + T_{t+\varepsilon} - Z_t(x) + T_t\right|^2\right) = \sqrt{\frac{2\varepsilon}{\nu\pi}} \qquad [fBm(1/4)].$$

Ideas of proof [Foondun-K-Mahboubi]

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where $S(x) := \int_{(t,\infty)\times\mathbf{R}} \left[p_s(w-x) - p_s(w)\right] \zeta(\mathrm{d} s \, \mathrm{d} w)$, for an independent space-time white noise ζ .

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Approximation by interacting BMs

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A Linear Heat Equation (Lecture 3)

Approximation by interacting BMs

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 - ▶ There are, more interesting, nonlinear versions as well.
 - ▶ I omit the proof, as it takes us too far afield.
 - ► The preceding says that we can think of the linear stochastic heat equation as the infinite-density limit of a system of interacting BMs with nearest-neighbor gravitational attraction.



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- ► The same sort of remark applies to space-time white noise, as long as we "regularize the Laplacian" [e.g., replace it with $-(-\Delta)^{1+\delta}$ for a suitable $\delta > 0$].



► Now consider the SHE,

$$\frac{\partial}{\partial t}Z = \frac{\nu}{2}\Delta Z + \xi \qquad (t > 0, x \in \mathbf{R}^d, d \geqslant 2),$$
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- ► Similar issues arise in the Itô theory of SDEs.



Stochastic integration

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- $\{\mathscr{F}_t\}_{t\geq 0}$ the "Brownian filtration."

The stochastic integral

▶ $(t,x) \mapsto \Phi_t(x)$ is an elementary random field when $\exists 0 \leq a < b$ and an \mathscr{F}_a -meas. $X \in L^2(\Omega)$ and $\phi \in L^2(\mathbf{R})$ such that

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► The stochastic integral is Wiener's; well-defined iff $h_t(x)\phi(x) \in L^2([a,b] \times \mathbf{R}).$



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▶ $\int h\Phi \,d\xi$ is defined unambiguously, as a result.

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- $||Z||_p := \{ E(|Z|^p) \}^{1/p}$ $L^p(\Omega)$ norm
- ▶ Choose and fix $\beta > 0$ and define for every space-time random field v the norm,

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Definition

Let $\mathcal{L}^{\beta,2} :=$ the completion of all simple random fields in norm $\mathcal{N}_{\beta,2}$.



Stochastic integration

▶ If $\Phi \in \mathcal{L}^{\beta,2}$, then $I := \int h\Phi \,\mathrm{d}\xi$ well-defined, and $\mathrm{E}(I^2) \leq [\mathcal{N}_{\beta,2}(\Phi)]^2 \int_0^\infty \mathrm{e}^{\beta s} \,\mathrm{d}s \int_{-\infty}^\infty \mathrm{d}y \; [h_s(y)]^2$, provided that h is meas. and the preceding integral converges.

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 $M_t := \int_{(0,t)\times\mathbf{R}} h\Phi \,\mathrm{d}\xi$ is a continuous $L^2(\Omega)$ -martingale with quadratic variation $\langle M \rangle_t = \int_0^t \mathrm{d}s \int_{-\infty}^\infty \mathrm{d}y \ [h_s(y)]^2 |\Phi_s(y)|^2$.

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▶ Proof: Check when Φ is simple; appeal to Doob's maximal inequality when $\Phi \in \mathcal{L}^{\beta,2}$.



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If M_t is a continuous $L^2(\Omega)$ -martingale with quadratic variation $\langle M \rangle_t$, then for all real numbers $k \in [2, \infty)$,

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► See the lecture notes [Appendix B] for proofs etc.

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- ▶ See the lecture notes [Appendix B] for proofs etc.
- Equivalently, $E(|M_t|^k) \leq (4k)^{1/2} E(\langle M \rangle_t^{k/2}).$

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BDG inequality

► Proposition

If Φ and h are as before, then $\forall t \geq 0$,

$$\left\| \int_{(0,t)\times\mathbf{R}} h\Phi \,d\xi \right\|_{k}^{2} \leqslant 4k \int_{0}^{t} ds \int_{-\infty}^{\infty} dy \, \left[h_{s}(y) \right]^{2} \|\Phi_{s}(y)\|_{k}^{2}.$$

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▶ Proof. The quadratic variation of $M_t := \int_{(0,t)\times \mathbf{R}} h\Phi \,\mathrm{d}\xi$ is $\langle M \rangle_t = \int_0^t \mathrm{d}s \int_{-\infty}^\infty [h_s(y)]^2 [\Phi_s(y)]^2$, whence by BDG,

$$||M_t||_k^2 \le 2k \left\| \int_0^t ds \int_{-\infty}^{\infty} [h_s(y)]^2 [\Phi_s(y)]^2 \right\|_{k/2}.$$

Apply Minkowski's inequality.

Good integrands

▶ Remaining question. When is a random field Φ in $\mathcal{L}^{\beta,2}$?

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We say that Φ is a *space-time random field* [random field, for short] if: (i) Φ is *adapted*; i.e., $\Phi_t(x)$ is \mathscr{F}_t -meas. for all $t \geq 0$ and $x \in \mathbf{R}$; and

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$$\lim_{n \to \infty} \sup_{\substack{(s,y),(t,x) \in [0,N] \times \mathbf{R} \\ |s-t|,|x-y| < 1/n}} \mathrm{E}\left(\left|\Phi_s(y) - \Phi_t(x)\right|^2\right) = 0.$$

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▶ Proposition

Suppose Φ is a space-time random field that is continuous in $L^2(\Omega)$ and $\mathcal{N}_{\beta,2}(\Phi) < \infty$, then $\Phi \in \bigcap_{\alpha > \beta} \mathcal{L}^{\alpha,2}$.



Good integrands (Idea of proof)

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$$S^{n,N}_t(x) := \Phi_{\lfloor nt \rfloor/n}(\lfloor nx \rfloor/n) \cdot \mathbf{1}_{[0,N] \times \mathbf{R}}(t\,,x),$$

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- $\phi_j(x) := \mathbf{1}_{[j/n,(j+1)/n)}(x).$
- ▶ Prove that $\mathcal{N}_{\alpha,2}\left(S^{n,N} \Phi\right) \to 0$ as $n, N \to \infty$, for all $\alpha > \beta$.



Stochastic Convolutions

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For a random field Φ , define the <u>stochastic convolution</u> of p and Φ as

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$$\blacktriangleright : p \circledast \bullet : \cup_{\beta>0} \mathcal{L}^{\beta,2} \to \cup_{\beta>0} \mathcal{L}^{\beta,2}.$$



The key step of the proof [see the lecture notes for the rest]

▶ If $\beta > 0$ and $k \in [2, \infty)$, then

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- When k=2 this is a familiar norm.
- ▶ Proposition (Foondun–K, 2009; Conus–K, 2010) For all $\beta > 0$, $k \in [2, \infty)$, and $\Phi \in \mathcal{L}^{\beta,2}$,

$$\mathcal{N}_{\beta,k}(p \circledast \Phi) \leqslant \frac{k^{1/2}}{(\nu \beta/2)^{1/4}} \cdot \mathcal{N}_{\beta,k}(\Phi).$$

Proof of the stochastic Young inequality $[\mathcal{N}_{\beta,k}(p\circledast\Phi)\leqslant \frac{k^{1/2}}{(\nu\beta/2)^{1/4}}\cdot\mathcal{N}_{\beta,k}(\Phi)]$

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$$||p \circledast \Phi||_k^2 \leqslant 4k \int_0^t ds \int_{-\infty}^\infty dy [p_{t-s}(y-x)]^2 ||\Phi_s(y)||_k^2$$

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$$= 4k [\mathcal{N}_{\beta,k}(\Phi)]^{2} e^{2\beta t} \int_{0}^{t} \frac{e^{-2\beta r} dr}{(4\nu\pi r)^{1/2}}.$$

▶ Do the remaining arithmetic.

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Existence and uniqueness

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- ▶ Because $|\sigma(x)| \leq |\sigma(0)| + \text{Lip}|x|$ and $|b(x)| \leq |b(0)| + \text{Lip}|x|$,

$$|\sigma(x)| \lor |b(x)| \le \text{Lip}(1+|x|) \quad \forall x \in \mathbf{R}.$$

Existence and uniqueness

► Theorem

There exists a random field $u \in \bigcup_{\beta>0} \mathcal{L}^{\beta,2}$ that solves this initial value problem. Moreover, it is [a.s.] the only solution for which there exists a positive and finite L such that

$$\sup_{x \in \mathbf{R}} E\left(|u_t(x)|^k\right) \leqslant L^k \exp\left\{Lk^3t\right\} \qquad \forall k \in [1, \infty), \ t > 0.$$

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There exists a random field $u \in \bigcup_{\beta>0} \mathcal{L}^{\beta,2}$ that solves this initial value problem. Moreover, it is [a.s.] the only solution for which there exists a positive and finite L such that

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- We will see soon that the exponent bound of k^3 is not artificial.



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▶ $\mathcal{N}_{16k^2,k}(u^{(n)}) < \infty$ and continuity in $L^2(\Omega) \Rightarrow u^{(n)} \in \mathcal{L}^{64,2}$ $\forall n$, and existence works, as in PDEs, by taking Cauchy limits.



Uniqueness; sketch of proof

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► $L_t^x(X) := \int_0^t \delta_x(X_s) \, \mathrm{d}s$ is a continuous random field. local times

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$$\frac{\partial}{\partial t}u = \frac{\nu}{2}\frac{\partial^2}{\partial x^2}u + u\xi,\tag{PAM}$$

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► Theorem (Bertini–Cancrini, 1995)

For all integers $k \geqslant 1$, and all reals $t \geqslant 0$ and $x \in \mathbf{R}$,

$$E\left(|u_t(x)|^k\right) \geqslant \exp\left(\frac{k(k^2-1)t}{24\nu}\right).$$

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▶ Because $(p_t * 1)(x) = 1$ and u is mild, $u = 1 + (p \circledast u)$, whence Feynman $u = 1 + (p \circledast 1) + (p \circledast 1 \circledast 1) + \cdots$.

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▶ By the Feynman–Kac formula,

$$U_t(x) = \mathbb{E}\left[\exp\left(\int_0^t G_{t-s}(B_s + x) ds\right)\right],$$

where $\{G_t\}_{t\geq 0}$ is BM with speed ν .



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Now consider the case where G is a smooth approximation to ξ : A GRF with $EG_t(x) = 0$ and $Cov(G_t(x), G_s(y)) = p_{\varepsilon}(s-t)p_{\eta}(x-y)$, where $\varepsilon, \eta \approx 0$ are positive.



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- $X_t^{(i,j)} := B_t^{(j)} B_t^{(i)}$ is a BM with speed 2ν .
- ► This and Brownian scaling together motivate [Itô vs Stratonovich]:

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Theorem (Bertini–Cancrini, 1995; Hu–Nualart, 2009; Conus, 2011)

For all integers $k \ge 2$ and all reals $t \ge 0$ and $x \in \mathbf{R}$,

$$\mathrm{E}\left(|u_t(x)|^k\right) = \mathrm{E}\exp\left(\frac{1}{\nu}\sum_{1\leqslant i< j\leqslant k} L^0_{\nu t}\left(b^{(j)} - b^{(i)}\right)\right),\,$$

where the $b^{(i)}$'s are i.i.d. BMs with speed one.

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• $\mathrm{E}(|u_t(x)|^k) = \mathrm{E}\exp\{\nu^{-1}\mathcal{L}_t\}, \text{ where }$

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- ► Thus, $\langle M \rangle_t = \sum_{j=1}^k \int_0^t \left[\sum_{i=1}^k \operatorname{sgn} \left(b_s^{(j)} b_s^{(i)} \right) \right]^2 ds$

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Some motivation

Let $\psi := \{\psi_{\ell}(z)\}_{\ell \geqslant 0, z \in \mathbf{Z}}$ be a [discrete] space- [discrete] time non negative random field and $z \mapsto \psi_{\ell}(z)$ is i.i.d. mean one $\forall \ell \geqslant 0$.

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▶ If $2 \le k \le K$, then $\frac{\gamma(k)}{k} \le \frac{\gamma(K)}{K}$, by Jensen's inequality. The issue is with strict inequalities.

$$k^{-1}\log \mathrm{E}([\psi_{\ell}(z)]^k)\leqslant K^{-1}\log \mathrm{E}([\psi_{\ell}(z)]^K) \text{ when } k< K$$

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The function $k \mapsto k^{-1}\gamma(k)$ is well-defined and convex on $(0, \infty)$. Moreover, if $\gamma(k_0) > 0$ for some $k_0 > 1$, then $k \mapsto k^{-1}\gamma(k)$ is strictly increasing on $[k_0, \infty)$.

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- ▶ Because $\gamma(1) = 0$, convexity yields

$$\gamma(k) \leqslant \alpha \gamma(K) + (1 - \alpha)\gamma(1) = \frac{k - 1}{K - 1}\gamma(K).$$

Rearrange, using the facts that: (i) $\gamma(k) > 0$ for all $k \ge k_0$; and (ii) (k-1)/(K-1) < k/K.

Separation of scales

Separation of scales

► Lemma (Paley–Zygmund, 1932)

Fix reals $n > m \ge 2$, and let $X \in L^n(\Omega)$ be non negative with $P\{X > 0\} > 0$. Then $\forall \delta \in (0, 1)$,

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Solve to finish.

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► Lemma

$$\begin{split} \forall m \in [2\,,\infty) \ and \ \delta \in (0\,,1), \\ \liminf_{\ell \to \infty} \frac{1}{\ell} \log \mathrm{P}\left\{\psi_{\ell}(z) \geqslant \delta \|\psi_{\ell}(0)\|_{m}\right\} \geqslant -\inf_{n > m} \left(\frac{m\gamma(n) - n\gamma(m)}{n - m}\right). \end{split}$$

$$\forall m \in [2, \infty) \text{ and } \delta \in (0, 1),$$

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Take logs etc.

Separation of scales

► There is an easy corresponding upper bound too:

$$P\left\{\max_{1\leqslant z\leqslant \exp(\theta N)}\psi_N(z)\geqslant \|\psi_N(0)\|_m\right\}$$

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▶ Borel–Cantelli: $\exists 0 < \theta_1 < \theta_2 < \cdots$ such that a.s. $\forall i$,

$$\begin{split} 0 &< \limsup_{N \to \infty} \frac{1}{N} \max_{1 \leqslant z \leqslant \exp(\theta_i N)} \log \psi_N(z) \\ &< \liminf_{N \to \infty} \frac{1}{N} \max_{1 \leqslant z \leqslant \exp(\theta_{i+1} N)} \log \psi_N(z) < \infty. \end{split}$$

Back to SPDEs

► Consider the drift-free SHE $[b \equiv 0]$ $\partial_t u = (\nu/2)\partial_x^2 u + \sigma(u)\xi$, $u_0 \in L^{\infty}(\mathbf{R})$ non random — all as before.

Back to SPDEs

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The \underline{lower} and $upper\ Lyapunov$ exponents:

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► Fact. If $\gamma_2(x) > 0 \ \forall x$ then $k \mapsto k^{-1}\gamma_k(x)$ is strictly increasing; same for upper L. exponents.

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► Theorem (Foondun–K, 2009; see also Döring–Savov, 2010)

If
$$\inf |u_0| > 0$$
 then $\inf_{x \in \mathbf{R}} \gamma_2(x) \geqslant (4\nu)^{-1} \inf_{z \in \mathbf{R} \setminus \{0\}} \left| \frac{\sigma(z)}{z} \right|^4$.
 $\inf |u_0| > 0$ and $|\sigma(z)/z| \geqslant c \Rightarrow$ "weak intermitency."

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Back to SPDEs

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$$\begin{split} \mathrm{E}(|u_{t}(x)|^{2}) &= |(p_{t} * u_{0})(x)|^{2} + \int_{0}^{t} \mathrm{d}s \int_{-\infty}^{\infty} \mathrm{d}y \ [p_{t-s}(y-x)]^{2} \mathrm{E}(\sigma^{2}(u_{s}(y))) \\ &\geqslant \inf |u_{0}|^{2} + c \int_{0}^{t} I(s) \, \mathrm{d}s \int_{-\infty}^{\infty} [p_{t-s}(y-x)]^{2} \\ &= \inf |u_{0}|^{2} + c' \int_{0}^{t} \frac{I(s)}{\sqrt{t-s}} \, \mathrm{d}s, \end{split}$$

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Back to SPDEs

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▶ Apply the "key renewal theorem" to see that $I(t) \ge c_3 \exp\{c_4 t\}$.



Intermittency Fronts (Lecture 8)

▶ We just showed that if $\inf |u_0| > 0$ then a cone conditions such as "L_{\sigma} := $\inf_z |\sigma(z)/z| > 0$ " automatically ensures weak intermittency $[\gamma_2 > 0]$.

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- ▶ What if $|u_0| = 0$, say u_0 has compact support?
- ▶ From now, consider a non-random initial function $u_0: \mathbf{R} \to \mathbf{R}$ that is measurable and bounded [as before], has compact support, and is strictly positive on an open subinterval of $(0, \infty)$.

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- ▶ Synopsis of behavior. A kind of weak intermittency occurs. Roughly, tall peaks arise as $t \to \infty$, but the farthest peaks move roughly linearly with time away from the origin. interm. fronts



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- ▶ If there exists α_* that is both a lower front and an upper front then α_* is <u>the</u> intermittency front. phase transition

► Theorem (Conus–K, 2012)

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Under the present conditions, the SHE has a nontrivial intermittency lower front. In fact, $\mathscr{S}(\alpha) < 0$ if $\alpha > \frac{1}{2}\mathrm{Lip}_{\sigma}^2$. If, in addition, $L_{\sigma} := \inf_{z \neq 0} |\sigma(z)/z| > 0$, then there exists $\alpha_0 > 0$ such that $\mathscr{S}(\alpha) > 0$ if $\alpha \in (0, \alpha_0)$.

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- ▶ The existence of an intermittency front has been proved recently by Le Chen–Dalang; in fact, they proved that the intermittency front is at $C^2/2$.
- ▶ A closely-related result: Because $\sigma(0) = 0$ and $u_0 \in L^2(\mathbf{R})$, $u_t \in L^2(\mathbf{R})$ a.s. for all t > 0 [Dalang–Mueller, 2003].



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▶ Proposition

For all $c \in \mathbf{R}$, $\beta > c^2 \nu/4$, and $\Phi \in \mathcal{L}^{\beta,2}$,

$$\mathcal{N}_{\beta,c}(p \circledast \Phi) \leqslant \frac{\mathcal{N}_{\beta,c}(\Phi)}{(\nu(4\beta - c^2\nu))^{1/4}}.$$

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► Also,

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$$\leq \mathcal{N}_{0,c}(u_0) \exp\left(-t \left[\beta - \frac{c^2 \nu}{2}\right]\right).$$

• Apply this with $\beta := c^2 \nu/2$ to see that

$$\mathcal{N}_{c^2\nu/2,c}\left(u^{(n+1)}\right) \leqslant \mathcal{N}_{0,c}(u_0) + \frac{\operatorname{Lip}_{\sigma}}{\sqrt{|c|\nu}} \mathcal{N}_{c^2\nu/2,c}\left(u^{(n)}\right).$$

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- ▶ ∴

$$\int_{\alpha t}^{\infty} dx \int_{0}^{t} ds \int_{-\infty}^{\infty} dy \left[p_{t-s}(y-x) \right]^{2} \operatorname{E} \left(|u_{s}(y)|^{2} \right)$$

$$\geqslant \int_{0}^{t} ds \left(\int_{\alpha(t-s)}^{\infty} [p_{t-s}(z)]^{2} dz \right) \left(\int_{\alpha s}^{\infty} \operatorname{E} \left(|u_{s}(y)|^{2} \right) dy \right)$$

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▶ Laplace transform: $(\mathcal{L}\phi)(\beta) := \int_0^\infty \mathrm{e}^{-\beta t} \phi(t) \, \mathrm{d}t$.



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$$(\mathscr{L}T)(0) = \frac{1}{2\nu\pi} \int_0^\infty \frac{\mathrm{d}t}{t} \int_{\alpha t}^\infty \mathrm{d}z \ \mathrm{e}^{-z^2/(\nu t)} \to \infty \text{ as } \alpha \downarrow 0.$$

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▶ Therefore, $\exists \alpha, \beta > 0$ such that $(\mathcal{L}M)(\beta) = \infty$.

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$$M(t) := \int_{|x| > \alpha t} E(|u_t(x)|^2) |dx, T(t) = \int_{\alpha t}^{\infty} [p_t(z)]^2 dz.$$

$$(\mathscr{L}M)(\beta)$$

$$\geqslant \int_0^\infty e^{-\beta t} dt \int_{|x| > \alpha t} dx |(p_t * u_0)(x)|^2 + L_\sigma^2(\mathscr{L}T)(\beta)(\mathscr{L}M)(\beta).$$

▶ Direct computation:

$$(\mathscr{L}T)(0) = \frac{1}{2\nu\pi} \int_0^\infty \frac{\mathrm{d}t}{t} \int_{\alpha t}^\infty \mathrm{d}z \ \mathrm{e}^{-z^2/(\nu t)} \to \infty \text{ as } \alpha \downarrow 0.$$

- ▶ Therefore, $\exists \alpha, \beta > 0$ such that $(\mathcal{L}M)(\beta) = \infty$.
- Argue by contradiction to see that for this choice of α, β , $\mathscr{S}(\alpha) = \limsup_{t \to \infty} t^{-1} \sup_{|x| > \alpha t} \log \mathrm{E}(|u_t(x)|^2) \geqslant \beta > 0$.

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Theorem (KCT)
$$\varrho(w) := \sum_{j=1}^m |w_j|^{\alpha_j} \qquad (w \in \mathbf{R}^m).$$

Suppose \exists finite C > 0 and $k > H := \sum_{j=1}^{m} \alpha_j^{-1}$ so that

$$||X_t - X_s||_k \leqslant C\varrho(t - s) \quad \forall s, t \in T.$$

Then X has a continuous modification \bar{X} that is Hölder continuous. In fact, $\forall q \in (0, 1 - (H/k))$,

$$E\left(\sup_{\substack{s,t\in T:\\s\neq t}}\left|\frac{\bar{X}_t - \bar{X}_s}{[\varrho(t-s)]^q}\right|^k\right) < \infty.$$

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- ► Garsia's integral[s]:

$$\mathcal{I}_k := \int_{\mathbf{R}^m} \mathrm{d}x \int_{\mathbf{R}^m} \mathrm{d}y \left| \frac{f(x) - f(y)}{\mu(\varrho(x - y))} \right|^k \qquad \forall k \geqslant 1.$$

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Theorem (Garsia's theorem)

If $\mathcal{I}_k < \infty$ for some $k \in [1, \infty)$ and $\int_0^{r_0} |\mathbf{B}_{\varrho}(r)|^{-2/k} d\mu(r) < \infty$, then $f = \bar{f}$ a.e., where $\bar{f} : \mathbf{R}^m \to \mathbf{R}$ satisfies

$$\left| \bar{f}(s) - \bar{f}(t) \right| \leqslant 12 \mathcal{I}_k^{1/k} \cdot \int_0^{\varrho(s-t)} |\mathbf{B}_{\varrho}(r)|^{-2/k} \, \mathrm{d}\mu(r),$$

for all $s, t \in \mathbf{R}^m$ that satisfy $\varrho(s-t) \leqslant r_0$.

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▶ \forall meas. $Q \subset \mathbf{R}^m$ with |Q| > 0, define

$$\bar{f}_Q(x) := \frac{1}{|Q|} \int_Q f(x+z) dz \qquad (x \in \mathbf{R}^m).$$

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▶ Lemma (Garsia's lemma)

$$\forall k \geqslant 1 \text{ and bounded and meas. } Q \subset Q' \subset \mathbf{R}^m \text{ with } |Q| > 0,$$

$$\sup_{x \in \mathbf{R}^m} \left| \bar{f}_Q(z) - \bar{f}_{Q'}(z) \right| \leqslant \sup_{a \in Q, b \in Q'} \mu(\varrho(a-b)) \cdot \left(\frac{\mathcal{I}_k}{|Q|^2} \right)^{1/k}.$$

$$\mathcal{I}_k := \int_{\mathbf{R}^m} \mathrm{d}x \int_{\mathbf{R}^m} \mathrm{d}y \left| \frac{f(x) - f(y)}{\mu(\varrho(x - y))} \right|^k$$

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• Choose and fix $\alpha > \sup_{a \in O} \sup_{b \in O'} \mu(\varrho(a-b)) \Rightarrow$

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▶ Let $\alpha \downarrow \sup_{a \in Q} \sup_{b \in Q'} \mu(\varrho(a - b))$ to finish.



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▶ Define $r_n \downarrow 0$ via: $r_0 > 0$ fixed; $\mu(2r_n) = 2^{-n}\mu(2r_0)$; equivalently,

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▶ Lemma $Suppose \exists k \in [1, \infty) \text{ so that:}$

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Suppose $\exists k \in [1, \infty)$ so that:

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Suppose $\exists k \in [1, \infty)$ so that:

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- $\int_0^{r_0} |\mathbf{B}_{\varrho}(r)|^{-2/k} \, \mathrm{d}\mu(r) < \infty.$

Then, $\bar{f} := \lim_{n \to \infty} \bar{f}_n$ exists, and

$$\sup_{z \in \mathbf{R}^m} \left| \bar{f}(z) - \bar{f}_{\ell}(z) \right| \leqslant 4\mathcal{I}_k^{1/k} \cdot \int_0^{r_{\ell+1}} |\mathbf{B}_{\varrho}(r)|^{-2/k} \, \mathrm{d}\mu(r) \quad \forall \ell \in \{1, 2, \ldots\}.$$

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Consequently, $f = \bar{f}$ a.e.

$$\mathcal{I}_k := \int_{\mathbf{R}^m} dx \int_{\mathbf{R}^m} dy \left| \frac{f(x) - f(y)}{\mu(\varrho(x - y))} \right|^k$$

▶ Proof. If $a \in B_{\varrho}(r_n)$ and $b \in B_{\varrho}(r_{n+1})$, then

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► Garsia's lemma ⇒

$$|\bar{f}_{\ell+L}(z) - \bar{f}_{\ell}(z)| \le \sum_{n=\ell}^{\ell+L-1} |\bar{f}_{n+1}(z) - \bar{f}_{n}(z)|$$

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$$\leqslant \mathcal{I}_{k}^{1/k} \cdot \sum_{n=\ell}^{\infty} \frac{\mu(2r_{n})}{|\mathbf{B}_{\varrho}(r_{n+1})|^{2/k}} \ \forall \ell, L \geqslant 0.$$

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► Since $\mu(2r_n) = 2\mu(2r_{n+1})$, we can write $\mu(2r_n) = 4\{\mu(2r_{n+1}) - \mu(2r_{n+2})\}.$



$$\mathcal{I}_{k} := \int_{\mathbf{R}^{m}} dx \int_{\mathbf{R}^{m}} dy \left| \frac{f(x) - f(y)}{\mu(\varrho(x - y))} \right|^{k} \\ \therefore \left| \bar{f}_{\ell + L}(z) - \bar{f}_{\ell}(z) \right| \leqslant 4\mathcal{I}_{k}^{1/k} \cdot \sum_{n = \ell}^{\infty} \frac{\mu(2r_{n+1}) - \mu(2r_{n+2})}{|\mathbf{B}_{\varrho}(r_{n+1})|^{2/k}}$$

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Lemma

Under the preceding integrability conditions, \bar{f} is continuous. In fact, if $s, t \in \mathbf{R}^m$ satisfy $\varrho(s-t) \leq r_0$, then

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▶ This concludes the proof of Garsia's theorem.



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- ▶ $\operatorname{E} u_t(x) = 1 = ||u_t(x)||_1$. Therefore, by Fatou's lemma, $\lim \inf_{|x| \to \infty} u_t(x) < \infty$. So the $\lim \sup$ is not a \lim .

▶ $h_t(x) = \log u_t(x)$ "Cole–Hopf solution to KPZ":

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► The KPZ equation is:

$$\frac{\partial}{\partial t}h = \frac{\nu}{2}\frac{\partial^2}{\partial x^2}h - \left[\frac{\partial}{\partial x}h\right]^2 + \xi - \infty.$$



▶ Let us say that $F(z) \times G(z)$ for all z > 1 when $\exists c \in (1, \infty)$ such that

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- ► So far (Conus–Joseph–K, 2012; Mueller–Nualart, 2008):

$$\log P\{h_t(x) < -z\} \le -c \left| \frac{\log(1/z)}{z} \right|^{3/2} \quad 0 < z \ll 1$$



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Suppose X is non negative and $\exists a, C > 0$ and b > 1 such that $\mathrm{E}(X^k) \leqslant C^k \exp\{ak^b\}$ $\forall k \in [1, \infty)$. Then,

$$\operatorname{E}\exp\left(\alpha(\log_+X)^{b/(b-1)}\right)<\infty \qquad \forall \alpha\in\left(0\,,\frac{1-b^{-1}}{(ab)^{1/(b-1)}}\right).$$

In particular, Chebyshev inequality
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► The probability bound follows from the expectation bound and the Chebyshev inequality.



Proof of the expectation bound

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- $\therefore P\left\{e^{\alpha(\log_+ X)^{b/(b-1)}} > z\right\} \leqslant e^{-\sup_{k\geqslant 1} g(k)} = e^{-c\log(z)} = z^{-c}, \text{ where } c := \frac{1 b^{-1}}{\alpha \cdot (ab)^{1/(b-1)}}.$
- Choose α small so that c > 1.



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$$\geqslant \frac{9}{16} L^{2m} \exp\left(-Qm^{3}t\right) \qquad Q := 8\ell - 2L.$$

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$$P\{X > z\} \geqslant \exp\left(-Q\frac{|\log z|^{3/2}(1 + o(1))}{\sqrt{t\ell^3}}\right) \qquad (z \to \infty).$$

▶ Proof. By the Paley–Zygmund inequality,

$$P\left\{X \geqslant \frac{1}{2} ||X||_{m}\right\} \geqslant \left(1 - 2^{-m}\right)^{2} \frac{\left[E(X^{m})\right]^{2}}{E(X^{2m})}$$
$$\geqslant (1 - 2^{-2})^{2} \frac{L^{2m} \exp(2Lm^{3}t)}{\exp(8\ell m^{3}t)}$$
$$\geqslant \frac{9}{16} L^{2m} \exp\left(-Qm^{3}t\right) \qquad Q := 8\ell - 2L.$$

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 - ▶ If $u_t(x) \gg 1$ then $|x| \gg 1$; therefore, the collection of y "near" x with $u_t(y) \gg 1$ should be "relatively small." Anderson localization

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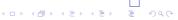
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