



Geometric and large scale problems in SPDEs

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The mathematics of subjective probability

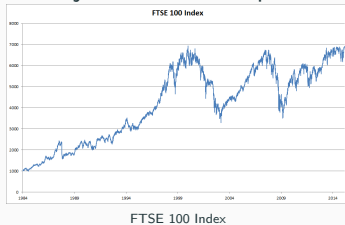
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Roughness in random systems

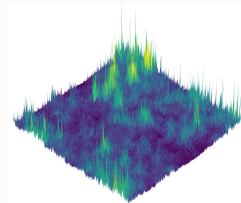
Many random systems are **rough**.

Examples:

Trajectories of stock prices



Liouville Quantum Gravity

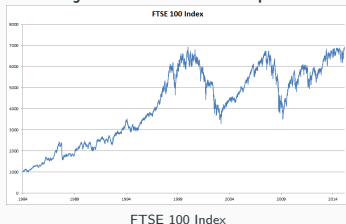


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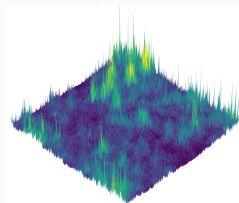
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Difficulty: calculus requires regularity of functions.

Goal: explain how to handle roughness.

- **Black–Scholes** (1967), **Merton** (1973) – infinitesimal change in price proportional to current price:

$$S_{t+\delta t} = S_t + \sigma S_t (B_{t+\delta t} - B_t) .$$

Brownian noise: $B_{t+\delta t} - B_t$ is

- ▶ independent of past &
 - ▶ distributed like normal random variable with variance δt .
- In differential form:

$$\frac{dS_t}{dt} = \sigma S_t \frac{dB_t}{dt} .$$

- How to interpret this equation?
- If B is differentiable, then

$$S_t = S_0 e^{\sigma B_t} .$$

- What if B_t is Brownian noise?
- Take discrete approximation: for $N > 0$, solve **difference equation**

$$S_{(k+1)/N} = S_{k/N} + \sigma S_{k/N} (B_{(k+1)/N} - B_{k/N}) .$$

where $B_0, B_{1/N}, B_{2/N}, \dots$ is symmetric random walk on $\frac{1}{\sqrt{N}}\mathbb{Z}$.

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- Then the limit is given by

$$S_t = S_0 e^{\sigma B_t - \sigma^2 t/2} .$$

- What? Why $\sigma^2 t/2$?

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- What? Why $\sigma^2 t/2$?
- Can be **guessed**: average of $e^{\sigma B_t}$ is $e^{\sigma^2 t/2}$.
- Brownian motion is **rough**: sensitive to approximation scheme.



Credit: Jacobs, Konrad

K. Itô: rewrite in integral form

$$S_t = S_0 + \int_0^t \sigma S_r dB_r$$

and define the integral $\int \sigma S_r dB_r$ as limit *in probability* of Riemann sums

$$\lim_{n \rightarrow \infty} \sum_{[r,s] \in \pi_n} S_r (B_s - B_r) .$$

Solve for S in space of *stochastic processes*.

Intrinsically probabilistic: difficult to control the solution map $B \mapsto S$.

Try to solve SDE $S: [0, T] \rightarrow \mathbb{R}^n$

$$\frac{d}{dt}S_t = f(S)\frac{dB_t}{dt}$$

- $\frac{dB_t}{dt}$ is white noise,
- f smooth.

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- Integration adds one derivative $\Rightarrow S \in \mathcal{C}^{\frac{1}{2}-\kappa} \Rightarrow f(S) \in \mathcal{C}^{\frac{1}{2}-\kappa}$.

Theorem (Multiplication of distributions)

Suppose $\alpha \leq \beta$. Multiplication

$$(f, g) \mapsto fg ,$$

defined on

$$\mathcal{C}^\infty \times \mathcal{C}^\infty \rightarrow \mathcal{C}^\infty ,$$

extends to continuous map

$$\mathcal{C}^\alpha \times \mathcal{C}^\beta \rightarrow \mathcal{C}^\alpha$$

if and only if $\alpha + \beta > 0$.

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- $-\frac{1}{2} - \kappa + \frac{1}{2} - \kappa < 0 \Rightarrow f(S)\frac{dB_t}{dt}$ **analytically ill-defined**.

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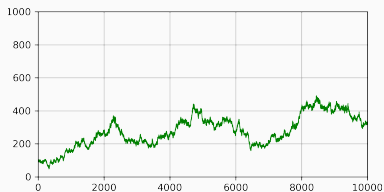
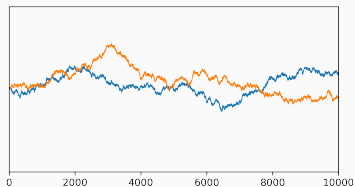
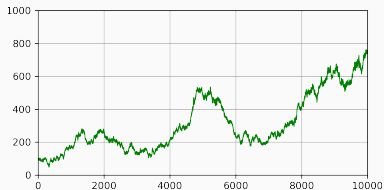
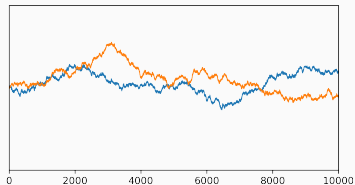
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Theorem: there exists f such that any Banach space on which the solution map $B \mapsto S$ is continuous cannot contain smooth functions and 2D Brownian motion.
[Lyons '91]

Instability of solution map

Equations with two noises: $dS_t = f_1(S_t)dB_t^{(1)} + f_2(S_t)dB_t^{(2)}$.



Consider B smooth $\Rightarrow dS_t = f(S_t) dB_t$ well-posed.

Expand f in Taylor series

$$f(S_t) = f(S_0) + f'(S_0)(S_t - S_0) + \dots$$

and substitute back into equation:

$$\begin{aligned} S_t &= S_0 + \int_0^t f(S_s) dB_s \\ &= S_0 + f(S_0) \int_0^t dB_s + f'(S_0) \int_0^t \left(\int_0^s dB_r \right) dB_s + \dots \end{aligned}$$

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If $\int_0^t \left(\int_0^s dB_r \right) dB_s$ big (order $\geq t$), cannot ignore **second term**.

Idea: View solution $dS_t = f(S_t) dB_t$ as function of $(B_t, \int_0^t \int_0^s dB_r dB_s)$.

Theorem (Lyons '98)

Fix $\alpha \in (\frac{1}{3}, \frac{1}{2})$. There exists a metric space of pairs $(B_t, \int_0^t \int_0^s dB_r dB_s)$ with

$$\sup_{u \neq t} \frac{|B_t - B_u|}{|t - u|^\alpha} + \sup_{u \neq t} \frac{|\int_u^t \int_u^s dB_r dB_s|}{|t - u|^{2\alpha}} < \infty$$

such that solution map $(B_t, \int_0^t \int_0^s dB_r dB_s) \mapsto S$ is continuous.

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For many stochastic B and approximations $B^{(N)}$

$$\lim_{N \rightarrow \infty} \left(B_t^{(N)}, \int_0^t \int_0^s dB_r^{(N)} dB_s^{(N)} \right) = \left(B_t, \int_0^t \int_0^s dB_r dB_s \right). \quad (\star)$$

$(\int_0^t \int_0^s dB_r dB_s$ **defined** as $\lim_{N \rightarrow \infty} \int_0^t \int_0^s dB_r^{(N)} dB_s^{(N)} - \text{It\^o vs. Stratonovich})$

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The point:

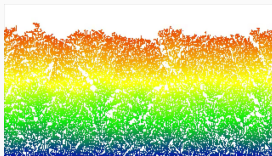
- Probability enters only in showing (\star) .
- Alternative approach to SDEs, applies beyond (semi)martingales.

Stochastic (Partial) Differential Equations

Model **randomness**:

$$\partial_t h = \Delta h + F(h, \nabla h, \xi)$$

- stochastic quantisation equations (Yang–Mills, Φ_d^4 , Sine–Gordon)
- spread of populations (Parabolic Anderson Model)
- crystal growth (Khardar–Parisi–Zhang: $\partial_t h = \Delta h + (\partial_x h)^2 + \xi$)



Credit: Nils Berglund

Difficulties: solutions h are **rough** functions or distributions

\rightsquigarrow non-linearity $F(h, \nabla h, \xi)$ ill-defined (e.g. $(\partial_x h)^2$ in KPZ).

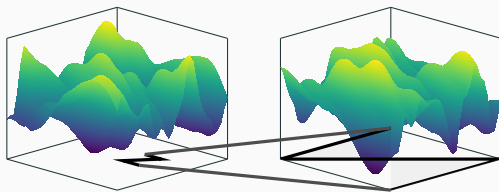
Ultraviolet scaling

Consider cubic equation:

$$(\partial_t - \Delta)u = -u^3 + \xi.$$

Zoom to small scales

$$\tilde{u}(t, x) = \varepsilon^\beta u(\varepsilon^2 t, \varepsilon x).$$



$$(\partial_t - \Delta)\tilde{u} = -\varepsilon^{2-2\beta}\tilde{u}^3 + \tilde{\xi}$$

where

$$\tilde{\xi}(t, x) = \varepsilon^{2+\beta}\xi(\varepsilon^2 t, \varepsilon x).$$

For $\xi \in \mathcal{C}^{-2-\beta}$, $\|\tilde{\xi}\|_{\mathcal{C}^{-2-\beta}} \sim \|\xi\|_{\mathcal{C}^{-2-\beta}}$. **Non-linearity disappears** if $\beta < 1$.

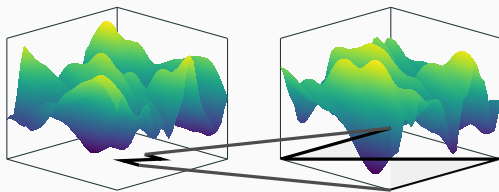
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\Rightarrow on **small scales** u locally looks like solution of $(\partial_t - \Delta)\tilde{u} = \tilde{\xi}$.

E.g. For space-time white noise on $\mathbb{R} \times \mathbb{R}^d$, $\xi \in \mathcal{C}^{>-3} \Leftrightarrow d < 4$.

- regularity structures [Hairer, *Invent. Math.* '14]
- paracontrolled distributions [Gubinelli–Imkeller–Perkowski, *FoM Pi* '15].

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Theorem (Bruned, Chandra, C., Hairer, Zambotti '14-'17)

Sub-critical SPDEs on $\mathbb{R}_+ \times \mathbb{T}^d$ with stationary noise ξ

$$\partial_t A = \Delta A + F(A, \nabla A, \dots) \xi$$

*admit **local** solutions via “renormalised” smooth approximations*

$$\partial_t A^\varepsilon = \mathcal{L}A^\varepsilon + F(A^\varepsilon, \nabla A^\varepsilon, \dots) \xi^\varepsilon + \sum_{i=1}^n C_{i,\varepsilon} F_i(A^\varepsilon, \nabla A^\varepsilon, \dots) .$$

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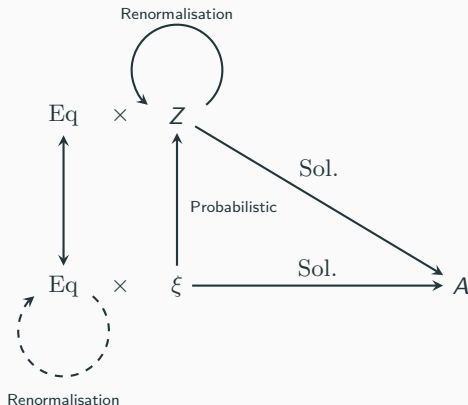
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Probabilistic step: build object $Z = (\xi^\varepsilon, (G * \xi^\varepsilon)^{:2:} = \text{diagram}, \dots)$,
 $G = (\partial_t - \mathcal{L})^{-1}$. **Renormalisation:** $(G * \xi^\varepsilon)^2 \mapsto (G * \xi^\varepsilon)^{:2:} = (G * \xi^\varepsilon)^2 - C^\varepsilon$.

Analytic step: continuous solution map $Z \mapsto A$.

Algebraic step: find counterterms F_i .

Also [Otto, Weber, Sauer, Smith, Linares, Tempelmayr, Tsatsoulis '16-'21]
and renormalisation group: [Kupiainen '16', Duch '21].



Automatic **local** solution theory.

Global solution theory less developed - only specific equations

[Mourrat–Weber '17, Moinat–Weber '20, Gubinelli–Hofmanova '21, Bringmann–Cao '24,...].

Infrared scaling - global solutions

Consider $(\partial_t - \Delta)u = -u^3 + \xi$ and **critical scaling** $\tilde{u}(t, x) = \varepsilon u(\varepsilon^2 t, \varepsilon x)$.

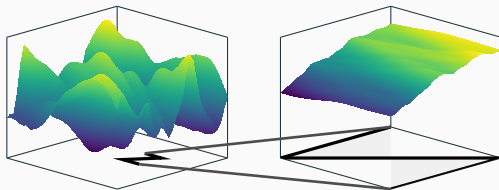
Then

$$(\partial_t - \Delta)\tilde{u} = -\tilde{u}^3 + \tilde{\xi}$$

where $\tilde{\xi}(t, x) = \varepsilon^3 \xi(\varepsilon^2 t, \varepsilon x)$. Then

$$\|\tilde{\xi}\|_{C^\alpha} \lesssim \varepsilon^{3+\alpha} \|\xi\|_{C^\alpha}$$

Noise disappears for $\alpha > -3$.



Large scale bound: choose $\varepsilon > 0$ such that $\|\tilde{\xi}\|_{C^\alpha} \ll 1$ but still order 1.

Then by local stability and coercivity at $\xi = 0$,

$$\|\tilde{u}\|_\infty = \varepsilon \|u\|_{\infty; B_0(\varepsilon)} \lesssim 1 \quad \Rightarrow \quad \|u\|_{\infty; B_0(\varepsilon)} \lesssim \varepsilon^{-1} \lesssim \|\xi\|_{C^\alpha}^{1/(3+\alpha)}.$$

Consider a subcritical SPDE

$$(\partial_t - \Delta)u = P(u, \nabla u) + f(u, \nabla u)\xi . \quad (\star)$$

We say (\star) is **coercive** at $\xi \in \mathcal{C}^\alpha$ if, for any solution in the ball $B_0(1)$,

$$|u(z)| \lesssim \|\xi\|_{\mathcal{C}^\alpha}^\varrho + \|z\|^{-\beta}$$

where $\|z\|$ is distance of z to boundary of $B_0(1)$.

Theorem (C.–Gubinelli '25+)

*Suppose (\star) is **coercive** at $\xi = 0$ and f does not grow too quickly at ∞ . Then (\star) is **coercive** for all ξ for a suitable ϱ .*

Space-time localisation. Extends and simplifies [Moinat–Weber '20, Chandra–Moinat–Weber '22, Bonnefoi–CMW '22, Jin–Perkowski '25]

- Take point z that maximises

$$C := \frac{|u(z)|}{\|\xi\|_{C^\alpha}^g + \|z\|^{-\beta}}$$

- Zoom with **infrared scaling** around z , so $\tilde{u}(t, x) = \varepsilon^\beta u(z + (\varepsilon^2 t, \varepsilon x))$ solves

$$(\partial - \Delta)\tilde{u} = P(\tilde{u}, \nabla\tilde{u}) + \tilde{f}(\tilde{u}, \nabla\tilde{u})\tilde{\xi},$$

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- Choose ε such that $|\tilde{u}(0)| = 1$. Subcriticality \Rightarrow **if $C \gg 1$** , then $\|\tilde{f}\tilde{\xi}\| \ll 1$.

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- Choose ε such that $|\tilde{u}(0)| = 1$. Subcriticality \Rightarrow **if $C \gg 1$** , then $\|\tilde{f}\tilde{\xi}\| \ll 1$.
- Maximisation of z : $\|\tilde{u}\|_{\infty; B_0(1)} \leq 1 + \delta$.
- If $C \gg 1$** , coercivity and stability of equation at $\tilde{\xi} = 0 \Rightarrow |\tilde{u}(0)| < 1 - \delta$, which contradicts scaling choice.

Rough analysis: deterministic approach to stochastic equations.

- Keep track of underlying process **and** additional data.
- Calculus for rough objects.
- Scaling: guide for local and global solution theories.

Thank you for your attention!