

Discussion on "Singular kinetic equations" by Rongchan Zhu

Workshop "Higher structures emerging from renormalisation"
ESI, Vienna, November 18, 2021

Singular SPDEs

• Parabolic SPDEs on \mathbb{T}^d

$$\partial_t \phi = \Delta \phi + F(\phi, \nabla \phi, \xi) \quad \xi: \text{space-time white noise}$$

Important examples:

* Φ_d^G model: $F = -\phi^3 + \xi$ (stochastic quantization)

* KPZ eq: $F = -(\partial_x \phi)^2 + \xi$ (interface growth)

* PAM: $F = \phi \xi(x)$ (diffusion in random medium)
↑ spatial white noise

• Extensions featured in this talk:

- \mathbb{R}^d instead of \mathbb{T}^d
using new type of weighted Besov spaces

Prior work: e.g. Hairer & Labbé, Mourrat & Weber,
Moinat & Weber (using "coming down from infinity")

- less regularising differential operator
using kinetic semigroup

- nonlocal non-linearity F (McKean-Vlasov equ.)

Why one needs to renormalise

Mild solution: $\phi = \underbrace{(\partial_t - \Delta)^{-1}}_{\text{heat kernel}} F(\phi, \nabla \phi, \xi)$

Two important facts:

- 1) $\xi \in \mathcal{C}_x^{-\frac{d+2}{2}-\varepsilon} \quad \forall \varepsilon > 0$
← Besov-Hölder space with parabolic scaling
- 2) $\phi \in \mathcal{C}_x^\alpha \Rightarrow (\partial_t - \Delta)^{-1} \phi \in \mathcal{C}_x^{\alpha+2}$ (Schauder estimate)

Consequence: $(\partial_t - \Delta)^{-1} \xi \in \mathcal{C}_x^{\frac{2-d}{2}-\varepsilon} \quad \forall \varepsilon > 0$

Problem: $\frac{2-d}{2} - \varepsilon < 0 \quad \forall d \geq 2$

- \Rightarrow stoch. convolution $(\partial_t - \Delta)^{-1} \xi$ is a distribution
- \Rightarrow its powers not well-defined

Renormalisation:

Stoch. convolution solves stoch. heat equation

$$\partial_t \phi = \Delta \phi + \xi$$

Fourier basis: $\{e_k\}_{k \in \mathbb{Z}^d}, \quad -\Delta e_k = \lambda_k e_k$
 $\lambda_k \sim \|k\|^2$

$$\phi(k, x) = \sum_k \phi_k(t) e_k(x)$$

$$\Rightarrow \dot{\phi}_k = -\lambda_k \phi_k + \xi_k \leftarrow \text{i.i.d. Wiener processes}$$

$\Rightarrow \phi_k$ is an OU process with asymptotic variance λ_k^{-1}

$\Rightarrow \phi_k$ approaches Gaussian Free Field (GFF)

$$\phi_{\text{GFF}}(x) = \sum_k \frac{Z_k}{\sqrt{\lambda_k}} e_k(x) \quad Z_k \text{ i.i.d. } \sim \mathcal{N}(0, 1)$$

(say we forget $k=0$ mode)

$$\phi_{\text{GFF}}^2 = \sum_k (\phi * \phi)_k e_k$$

$$\mathbb{E}[\phi_{\text{GFF}}^2] \rightarrow (\phi * \phi)_0 = \sum_k \phi_k^2 = \sum_k \frac{Z_k^2}{\lambda_k}$$

$$\rightarrow \mathbb{E}[\phi_{\text{GFF}}^2] \sim \sum_k \frac{1}{\lambda_k} \sim \sum_k \frac{1}{\|k\|^2}$$

$$\begin{cases} < \infty & \text{if } d=1 \\ +\infty & \text{if } d \geq 2 \end{cases}$$

Renormalisation: subtract divergent expectations
 (e.g. after spectral Galerkin approx, then removing UV cut-off)

Remark: almost sure improvement of Sobolev embedding

→ "Probabilistic calculations", very important e.g. for Schrödinger equation

Fractional Sobolev space:

$$\phi = \sum_k \phi_k e_k \Rightarrow \|\phi\|_{H^s}^2 := \sum_k \langle k \rangle^{2s} \phi_k^2$$

"Japanese bracket"
 $\langle k \rangle = \sqrt{1 + \|k\|^2}$

Deterministic: Say $d=1$

$H^{s,2} \hookrightarrow L^p \forall p < \infty$, false for $H^s, s < \frac{1}{2}$

Stochastic: $\phi = \sum_k \frac{z_k}{\sqrt{\lambda_k}} e^{ikx}$ z_k iid $\sim \mathcal{N}(0,1)$

By rotation inv, $\phi(x) \sim \mathcal{N}_{\mathbb{C}}(0, \sum_k \frac{1}{\lambda_k}) = \mathcal{N}_{\mathbb{C}}(0, \mathbb{E}[\|\phi\|_2^2])$

\Rightarrow if $\phi \in L^2$, then $\phi \in L^p \forall p < \infty$ a.s.

One gains $\frac{1}{2}$ of regularity in stochastic case

General theories allowing to solve fixed-point equations for renormalised SPDEs

Regularity Structures
Hairer 2014

Hölder-type (local) conditions
General results
Strongly algebraic



Paracontrolled calculus
Gubinelli-Imkeller-Perkowski 2015

Spectral conditions
Not as general
More analytical

Dictionary:
Baileul-Hoshino 2021

Remark on mean-field particle systems: Deont's equ.

Consider for simplicity case with no interaction

$X_i(t), i=1, \dots, N$ indep. Brownian paths

Empirical distribution: $\hat{\rho}_N(t, x) = \frac{1}{N} \sum_{i=1}^N \delta(x - X_i(t))$

φ test function

Itô's formula: $d\varphi(X_i(t)) = \frac{1}{2} \varphi''(X_i) dt + \varphi'(X_i) dX_i$

$$\begin{aligned} d\langle \hat{\rho}_N, \varphi \rangle &= \frac{1}{2} \langle \hat{\rho}_N, \varphi'' \rangle dt + \frac{1}{N} \sum_i \varphi'(X_i) dX_i \\ &= \frac{1}{2} \langle \partial_{xx} \hat{\rho}_N, \varphi \rangle dt + \frac{1}{N} \sum_i \langle \delta(x - X_i), \varphi' \rangle dX_i \\ &= -\langle \partial_x \delta(x - X_i), \varphi \rangle \end{aligned}$$

\Rightarrow Formally,

$$d\hat{\rho}_N = \frac{1}{2} \partial_{xx} \hat{\rho}_N + d\eta(x, t)$$

$$\text{where } d\eta(x, t) = -\frac{1}{N} \sum_i \partial_x (\delta(x - X_i)) dX_i$$

Covariance:

$$\begin{aligned} \mathbb{E}[d\eta(x, t) d\eta(y, s)] &= \frac{1}{N^2} \sum_{i,j} \partial_x (\delta(x - X_i)) \partial_y (\delta(y - X_j)) \mathbb{E}[dX_i(t) dX_j(s)] \\ &= \frac{1}{N^2} \partial_x \partial_y \sum_i \delta(x - X_i) \delta(y - X_j) \delta(t - s) \\ &= \frac{1}{N} \delta(t - s) \partial_x \partial_y [\hat{\rho}_N(x) \delta(x - y)] \end{aligned}$$

Let $\tilde{\eta}(x, t) = \frac{1}{\sqrt{N}} \partial_x (\sqrt{\hat{\rho}_N} \xi(x, t))$
space-time white noise

Then $\mathbb{E}[d\tilde{\eta}(x, t) d\tilde{\eta}(y, s)] = \mathbb{E}[d\eta(x, t) d\eta(y, s)]$

Hence one has formally

$$\partial_t \hat{\rho}_N - \frac{1}{2} \partial_{xx} \hat{\rho}_N = \frac{1}{\sqrt{N}} \partial_x (\sqrt{\hat{\rho}_N} \xi(t, x))$$

However, $\partial_x (\sqrt{\hat{\rho}_N} \xi)$ does not make sense,
and does not seem to be accessible to
regularity structures / paracontrolled calculus...

C.F. Konarovskiy, Lehmann, von Renesse

arXiv: 1812.11068/1806.05018