

Renormalisation of singular stochastic PDEs

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Overview

- 1 Introduction
- 2 Renormalisation of SPDEs

Stochastic PDEs

We consider stochastic PDEs/Cauchy problems of the form

$$(\partial_t - \mathcal{L})u = \sum_{i=0}^n F_i(u, \nabla u, \dots) \xi_i,$$

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- \mathcal{L} is an elliptic differential operator;
- ξ_i are “sufficiently nice” noises;
- $F_i(u, \nabla u, \dots)$ is a smooth function of the jet of u .

Examples

- Dynamical Φ_3^4 model:

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

where $u : \mathbb{R}_+ \times \mathbb{T}^3 \rightarrow \mathbb{R}$ and ξ is space-time white noise.

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- Generalised parabolic Anderson model (gPAM):

$$(\partial_t - \Delta)u = \sum_{i,j=1}^2 f_{i,j}(u) \partial_i u \partial_j u + g(u) \xi,$$

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- We allow $d = 0$! SDEs/rough paths:

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Stability in the limit

What we want: a deterministic theory which takes as input ξ^ε and outputs the solution to

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We want to do this in spaces where the noises a.s. take values.

Singular equations

Main difficulty: these equations can be singular.

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Such equations appear in mathematical physics.

- Scaling limits of statistical models (KPZ, PAM, Φ_3^4).
- Quantization of euclidean quantum field theories (Φ_3^4 , Φ_2^p , Yang-Mills, sine-Gordon).

Stability in the limit

In fact, stability is impossible even for SDEs.

Theorem (Lyons '91)

There does not exist a Banach space $E \subset C([0, 1], \mathbb{R}^2)$ such that

- *E contains all smooth paths,*
- *E contains a.e. sample path of Brownian motion,*
- *the quadratic map*

$$C^\infty([0, 1], \mathbb{R}^2) \ni (W_1, W_2) \mapsto \int_0^1 \int_0^t dW_1(s) dW_2(t) dt$$

extends continuously to all of E .

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$$(\partial_t - \Delta)\tilde{u} = \varepsilon \sum_{i,j=1}^2 f_{i,j}(\varepsilon\tilde{u}) \partial_i \tilde{u} \partial_j \tilde{u} + g(\varepsilon\tilde{u})\tilde{\xi}.$$

The non-linearities disappear in the formal limit $\varepsilon \rightarrow 0$.

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In QFT, this corresponds to super-renormalisable theories.

Generalised Taylor expansion

Consider just PAM

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Idea: View u as a function of $(\xi, \xi(G * \xi))$.

Identical to the idea in rough paths to consider iterated integrals.

Extra terms

Hence we instead consider as input $(\xi, \xi(G * \xi))$ to solve PAM.
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For a distribution ξ on $\mathbb{R}_+ \times \mathbb{T}^d$:

- These terms together must satisfy certain algebraic constraints.
- They can be given *extrinsically*.
- For smooth ξ^ε , there is a canonical choice for these terms.

Continuity of the solution map

- Given such a collection of terms $\mathbf{\Pi} = (\xi, \xi(G * \xi), \dots)$ (a model), one can build a solution map

$$\mathcal{S}_A : \mathbf{\Pi} \mapsto U$$

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- U encodes a function which locally looks like terms of $\mathbf{\Pi}$ and solves

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- One then applies a “reconstruction” map

$$\mathcal{R} : U \mapsto u \in \mathcal{S}'(\mathbb{R}_+ \times \mathbb{T}^d).$$

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- Moreover, they commute with the “canonical lift” Ψ

$$\Psi : C^\infty(\mathbb{R}_+ \times \mathbb{T}^d) \ni \xi^\varepsilon \mapsto \mathbf{\Pi} = (\xi^\varepsilon, \xi^\varepsilon(G * \xi^\varepsilon), \dots).$$

and the classical solution map \mathcal{S}_C

$$\begin{array}{ccc} \mathbf{\Pi} & \xrightarrow{\mathcal{S}_A} & U \\ \uparrow \Psi & & \downarrow \mathcal{R} \\ \xi^\varepsilon & \xrightarrow{\mathcal{S}_C} & u \end{array}$$

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What is *not* continuous is Ψ (and thus \mathcal{S}_C).

One-dimensional case

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- As $\varepsilon \rightarrow 0$, we have convergence a.s.

$$\Psi(\xi^\varepsilon) = \mathbf{\Pi} = (\xi^\varepsilon, \xi^\varepsilon(G * \xi^\varepsilon)) \rightarrow \left(\xi, \int_0^\cdot \xi(t) dt \circ \xi(\cdot) \right)$$

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(G is Green's function of ∂_t).

- Therefore $u^\varepsilon \rightarrow u$ a.s. where u solves an SDE.

Multi-dimensional case

In higher dimensions, this typically fails!

Example

For ξ^ε mollification of white noise on \mathbb{T}^2 and generic $\psi \in C^\infty(\mathbb{T}^2)$,

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As a consequence, we have divergence (as distributions) of solutions to PAM

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

Renormalisation

Remark

Replacing $\xi^\varepsilon(G * \xi^\varepsilon)$ by $\xi^\varepsilon(G * \xi^\varepsilon) - C_\varepsilon$,

$$C_\varepsilon := \mathbb{E}[\xi^\varepsilon(G * \xi^\varepsilon)(0)],$$

it holds that for all $\psi \in C^\infty(\mathbb{T}^2)$

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in probability (where the RHS is now a definition).

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In fact, we have convergence in a space of models

$$\hat{\Pi}^\varepsilon = (\xi^\varepsilon, \xi^\varepsilon(G * \xi^\varepsilon) - C_\varepsilon) \rightarrow \Pi = (\xi, \xi(G * \xi)).$$

Renormalised equations

Recall that a model can be used as input to drive a PDE.

Question

What does it mean to drive the PDE

$$“(\partial_t - \Delta)u = u\xi”$$

with the couple $(\xi^\varepsilon, \xi^\varepsilon(G * \xi^\varepsilon) - C_\varepsilon)$?

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Claim: this amounts to solving the classical PDE

$$(\partial_t - \Delta)u^\varepsilon = u^\varepsilon(\xi^\varepsilon - C_\varepsilon).$$

A renormalised equation

Recall the ansatz

$$u^\varepsilon = u_0 + u_1 G * \xi^\varepsilon + R.$$

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$$\begin{aligned} u &= u_0 G * \xi^\varepsilon + u_1 G * (\xi^\varepsilon (G * \xi^\varepsilon) - C) + \tilde{R} \\ &= u_0 G * (\xi^\varepsilon - C) + u_1 G * (\xi^\varepsilon (G * \xi^\varepsilon)) + \tilde{R} \quad (\text{using } u_0 = u_1) \\ &= G * (u^\varepsilon (\xi^\varepsilon - C)) \quad (\text{using } u \approx u_0) \end{aligned}$$

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The usual Itô–Stratonovich correction appears for identical reasons.

A general approach

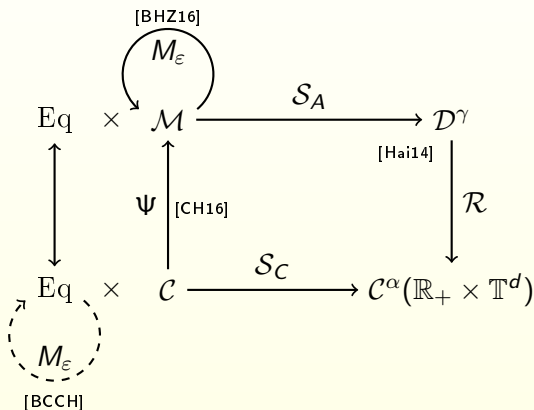
We aim to give a general description of this phenomenon.

Three earlier works are very important

- Bruned–Hairer–Zambotti 2016 (algebraic)
- Chandra–Hairer 2016 (analytic/stochastic)
- Hairer 2014 (core theory)

A general approach

The general theory can be summarised as follows.



Non-linearities and trees

Consider the equation

$$(\partial_t - \mathcal{L})u = \sum_{i=0}^n F_i(u, \nabla u, \dots) \xi_i.$$

For every rooted decorated tree we recursively use $(F_i)_{i=0}^n$ to construct a function of the jet of u .

Non-linearities and trees

Every rooted decorated tree can be uniquely written as either

$$\Xi_j X^P, \quad (\text{no edges})$$

or

$$\Xi_j X^P \mathcal{I}_{p_1}[\tau_1] \dots \mathcal{I}_{p_k}[\tau_k], \quad (k \text{ edges at the root})$$

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where

- Ξ_j is a noise term, $j \in \{0, \dots, n\}$
- X^p is a polynomial term $p \in \mathbb{N}^{d+1}$
- \mathcal{I}_{p_i} is a convolution with $\partial_{p_i} G$, $p_i \in \mathbb{N}^{d+1}$
- τ_i is another rooted tree.

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- For $j \in \{0, \dots, d\}$

$$\partial^j F = \sum_{p \in \mathbb{N}^{d+1}} Y_{p+j} D_p F$$

where Y_{p+j} is multiplication by the coordinate $(p+j) \in \mathbb{N}^{d+1}$.

Non-linearities and trees

- For the base case $\tau = \Xi_j X^p$ (no edges)

$$F^\tau := \partial^p F_j$$

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- Then inductively for every other tree

$$\tau = \Xi_j X^p \mathcal{I}_{p_1}[\tau_1] \dots \mathcal{I}_{p_k}[\tau_k],$$

$$F^\tau := (\text{comb. factor}) \left(\prod_{i=1}^k F^{\tau_i} \right) \partial^p \left(\prod_{i=1}^k D_{p_i} \right) F_j.$$

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Final ingredient: every tree τ comes with a degree $|\tau|$ defined inductively in terms of

- Regularising effect of the Green's function G .
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Equation is subcritical \leftrightarrow finitely many trees below any degree.

Black-box convergence theorem

Theorem (Renormalised SPDEs)

Consider a subcritical SPDE on $\mathbb{R}_+ \times \mathbb{T}^d$

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Suppose that $(\xi_i)_{i=0}^n$ are “sufficiently nice” stationary noises and $(\xi_i^\varepsilon)_{i=0}^n$ are mollifications.

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$$(\partial_t - \mathcal{L})u = \sum_{i=0}^n F_i(u, \nabla u, \dots) \xi_i.$$

Suppose that $(\xi_i)_{i=0}^n$ are “sufficiently nice” stationary noises and $(\xi_i^\varepsilon)_{i=0}^n$ are mollifications.

Then there exists a family of constants

$$\{C_{\tau, \varepsilon} \in \mathbb{R} \mid |\tau| < 0, \varepsilon > 0\}$$

such that

Black-box convergence theorem

Theorem (Renormalised SPDEs)

the solutions to the classical PDE

$$(\partial_t - \mathcal{L})u^\varepsilon = \sum_{i=0}^n F_i(u^\varepsilon, \nabla u^\varepsilon, \dots) \xi_i^\varepsilon + \sum_{|\tau| < 0} C_{\tau, \varepsilon} F^\tau(u^\varepsilon, \nabla u^\varepsilon, \dots),$$
$$u^\varepsilon(0, \cdot) = u_0 \in C^\alpha(\mathbb{T}^d),$$

converges in probability to a locally defined distribution on $\mathbb{R}_+ \times \mathbb{T}^d$ (blow-up is possible) and the limit is a continuous function of u_0 .

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Remarks

- The constants $C_{\tau, \varepsilon}$ are *not* unique; a possible choice is given by the BPHZ renormalisation of [BHZ16].
- The limit is used to define a solution of the original SPDE.

Example

Example (gPAM)

Recall gPAM on $\mathbb{R}_+ \times \mathbb{T}^2$:

$$(\partial_t - \Delta)u = \sum_{i,j=1}^2 f_{i,j}(u) \partial_i u \partial_j u + g(u) \xi.$$

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- Degrees determined by $|\Xi_0| = 0$, $|\Xi| = -1 - \kappa$, $|\mathcal{I}| = 2$.
- There are two trees of negative degree (which need renormalisation)

$$\begin{aligned} \tau &= \Xi \mathcal{I}[\Xi], & |\tau| &= -2\kappa, \\ \sigma_{i,j} &= \Xi_0 \mathcal{I}_i[\Xi] \mathcal{I}_j[\Xi], & |\sigma_{i,j}| &= -2\kappa. \end{aligned}$$

Example

Example (gPAM)

The counterterms:

$$F^\tau = g(u)g'(u),$$
$$F^{\sigma_{i,j}} = g(u)^2 f_{i,j}(u).$$

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$$F^T = g(u)g'(u),$$
$$F^{\sigma_{i,j}} = g(u)^2 f_{i,j}(u).$$

The renormalised SPDE takes the form

$$(\partial_t - \Delta)u^\varepsilon = \sum_{i,j=1}^2 f_{i,j}(u^\varepsilon) \partial_i u^\varepsilon \partial_j u^\varepsilon + g(u^\varepsilon) \xi^\varepsilon$$
$$+ C_\varepsilon g(u^\varepsilon) g'(u^\varepsilon) + \sum_{i,j=1}^2 C_\varepsilon^{i,j} g(u^\varepsilon)^2 f_{i,j}(u^\varepsilon).$$

Thank you!

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