Math 279 Lecture 4 Notes

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1 Final Overview of Stochastic PDEs

1.1 The KPZ equation

Last time, we argued that by Itô calculus, we can make sense of the SPDE

$$Z_t = Z_{xx} + Z\xi$$

when d = 1. We want to use this solution to come up with a candidate of a solution to the KPZ equation

$$h_t = h_{xx} + |h_x|^2 + \xi.$$

We may use the Hopf-Cole transform to get a solution for this equation utilizing the previous SPDE. To achieve this, we smoothize ξ in the first SPDE by replacing ξ with $\xi^{\varepsilon} *_{x} \chi^{\varepsilon}$, which is white in time and smooth in space. Here, $\chi^{\varepsilon}(x) = \frac{1}{\varepsilon} \chi(\frac{x}{\varepsilon})$ with χ a smooth function of compact support and total integral 1. Then

$$Z_t^{\varepsilon} = Z_{xx}^{\varepsilon} + Z^{\varepsilon} \xi^{\varepsilon}.$$

As we saw last time, for fixed x, $\xi(x,t)$ is a multiple of standard white noise with

$$\mathbb{E}[\xi^{\varepsilon}(x,t)\xi^{\varepsilon}(x,s)] = \delta_0(t-s),$$

$$\int (\chi^{\varepsilon})^{2}(y) dy = \delta_{0}(t-s)\varepsilon^{-1} \underbrace{\int \chi^{2}(y) dy}_{\subseteq} =: \delta_{0}(t-s)C^{\varepsilon}.$$

In other words, if B represents a standard Brownian motion, we can represent

$$\xi^{\varepsilon}(x,t) \stackrel{d}{=} \sqrt{C^{\varepsilon}} \dot{B}(t).$$

Writing $z(t) = Z^{\varepsilon}(x,t)$, we can write the smoothized equation as

$$dz = \underbrace{b(t)}_{Z^{\varepsilon}_{xx}(x,t)} dt + Z^{\varepsilon}(x,t) \sqrt{C^{\varepsilon}} dB.$$

We now apply Hopf-Cole:

$$d(\underbrace{\log z}_{h^{\varepsilon}}) = \frac{dz}{z} - \frac{(Z^{\varepsilon})^{2}C^{\varepsilon}}{z^{2}}dt$$

(using $(dB)^2 = dt$). Simplifying, we get

$$dh^\varepsilon = \left(\frac{Z^\varepsilon_{xx}}{Z^\varepsilon} - \frac{C^\varepsilon}{2}\right)\,dt + \sqrt{C^\varepsilon}\,dB.$$

Here,

$$h^{\varepsilon} = \log Z^{\varepsilon}, \qquad h_{x}^{\varepsilon} \frac{Z_{x}^{\varepsilon}}{Z^{\varepsilon}}, \qquad h_{xx}^{\varepsilon} = \frac{Z_{xx}^{\varepsilon}}{Z^{\varepsilon}} - (h_{x}^{\varepsilon})^{2}.$$

Hence,

$$h_t^\varepsilon = h_{xx}^\varepsilon + \left[(h_x^\varepsilon)^2 - \frac{C^\varepsilon}{2} \right] + \xi^\varepsilon.$$

Thus, we can renormalize the KPZ equation by subtracting a constant multiple of $1/\varepsilon$ from the right hand side:

$$h_t = h_{xx} + (h_x^2 - \infty) + \xi$$

1.2 Stochastic quantization

In Euclidean Quantum Field Theory, we need to make sense of probability measures that are formally expressed as

$$\frac{1}{Z}e^{-\mathcal{H}(\phi)}\,D\phi,$$

where ϕ is a field, i.e. $\phi: \mathbb{R}^d \to \mathbb{R}$, and $D\phi$ is a Lebesgue-like measure on the space of ϕ s. This may be compared with the following finite dimensional model: $H: \mathbb{R}^N \to \mathbb{R}$ and the minimizer of H correspond to the equilibrium states. If we take into account the thermal fluctuations, we would have equilibrium measures of the form

$$\frac{1}{Z}e^{-H(x)}\underbrace{dx}_{\text{Leb in }\mathbb{R}^N}.$$

Observe that a gradient ODE would allow us to give a dynamical approximation to our equilibrium states. For example, $\dot{x} = -\nabla H(x)$ would allow us to approximate the minimizer of H. As for $\frac{1}{Z}e^{-H(x)}\,dx$, we need to solve

$$\dot{x} = -\nabla H(x) + \dot{B}(t).$$

Then the law of x(t) as $t \to \infty$ is exactly $\frac{1}{Z}e^{-H(x)} dx$.

In 1981, Parisi and Wu suggested that a dynamical approximation as in this previous equation would approximate the formal probability measures with a mathematically more

tractable model. Indeed, if we have a candidate for an inner product on our function space, then

$$\phi_t - \partial \mathscr{H}(\phi) + \xi(x,t),$$

which is called the **stochastic quantization**. Hopefully, $\phi(\cdot,t) \approx \frac{1}{Z}e^{-\mathcal{H}(\phi)}D\phi$ for large t.

Let's consider some examples:

Example 1.1. Consider

$$\mathscr{H}(\phi) = \int_{\mathbb{R}^d} \left(\frac{1}{2} |\nabla \phi|^2 + V(\phi) \right) dx,$$

where $V: \mathbb{R} \to \mathbb{R}$. We may replace \mathbb{R}^d with a bounded domain with a suitable boundary condition. If we use the L^2 inner product, then

$$(\partial \mathcal{H})_{\phi}\psi = \int (-\Delta \psi + V'(\phi)) \psi.$$

Hence, the stochastic quantization equation becomes

$$\phi_t = \Delta_x \phi + V'(\phi) + \xi.$$

This is a perturbation of the SHE. The best we can hope for is a regularity of the form $\phi \in \mathcal{C}^{(1-d/2)-}$, which means that ϕ is a function only when d=1. Hence, $V'(\phi)$ is the main challenge when V' is nonlinear.

1.3 The Gaussian Free Field

Here is a brief history of $\frac{1}{Z}e^{-\mathscr{H}(\phi)}D\phi$ and stochastic quantization. First consider the case V=0 (or $V(\phi)=m^2\phi^2/2$). Then what we have for our formal probability measure is a Gaussian measure though in infinite dimension. Using the L^2 inner product and when V=0, what we have is

$$\frac{1}{Z}e^{-\frac{1}{2}\langle(-\Delta)\phi,\phi\rangle}$$
.

This is the celebrated **Gaussian Free Field (GFF)**. Its covariance is $(-\Delta)^{-1}$, which has a kernel known as Green's function. In a domain D, we write $G^D(x,y)$ for this kernel: Under GFF,

$$\mathbb{E}[\phi(x)\phi(y)] = G^D(x,y).$$

However, we expect $\phi \in \mathcal{C}^{(1-d/2)-}$, hence not a function when d > 1.

For example, when $d=1,\,D=(0,\infty),$ and we have the boundary condition $\phi(0)=0,$ then

$$G^D(x,y) = \min(x,y).$$

This is the correlation of Brownian motion in d=1. Similarly, for $D=(0,\ell)$ with 0 boundary condition, we get

$$G^{D}(x,) = \min(x,y) - \frac{1}{\ell}xy,$$

which corresponds to a Brownian bridge in $(0, \ell)$.

More generally, we have Feynman-Kac

$$\frac{1}{Z}e^{-\int(\frac{1}{2}|\phi'(x)|^2+V(\phi(x)))\,dx}\,D\phi = e^{-\int V(\phi(x))\,dx}\,\underbrace{\mu_0(d\phi)}_{\text{law of BM}}.$$

Next, consider d=2. In this case, the GFF is "conformally invariant." This has to do with the fact that if $h:D\to D'$ is conformal, then $G^D(z,z')=G^{D'}(h(z),h(z'))$. In fact, ϕ in GFF can be used to study Schramm-Loewner Evolution in critical statistical mechanics $(\dot{z}=e^{\gamma\phi(z)})$. Also, there are models for randomly selected Riemannian metrics that can be expressed as $e^{\gamma\phi(x,y)}(dx^2+dy^2)$, where ϕ is selected according to the GFF.

Finally, let us go back to the PDE

$$\phi_t = \Delta \phi - B'(\phi) + \xi$$

and examine the existence of a solution when V' is not linear. As a classical example, consider $V(\phi) = \phi^4/4$, so that $V'(\phi) = \phi^3$. Again, it is not clear how to make sense of ϕ^3 when $d \geq 2$, as ϕ is a distribution. To get a feel for this, first let us figure out when this equation is subcritical. Let ϕ solve this equation, and set $\widehat{\phi}(x,t) = \lambda^{d/2-1}$. Then we can readily show

$$\widehat{\phi}_t = \Delta \widehat{\phi} - \lambda^{4-d} \widehat{\phi}^3 + \widehat{\xi}.$$

So the model is subcritical iff $d \le 3$. The case d = 2 was solved back in the late 80s. The case d = 3 was solved in 2014 by Hairer. We need to renormalize the equation as

$$\phi_t^{\varepsilon} = \Delta \phi^{\varepsilon} - [(\phi^{\varepsilon})^3 - c_{\varepsilon} \phi^{\varepsilon}] + \xi^{\varepsilon}$$

with $c_{\varepsilon} = O(\varepsilon^{-1})$.