

Online probability seminar, Seoul (Online)

Renormalisation and metastable dynamics of the two-dimensional Allen–Cahn equation

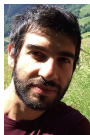
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Joint works with Giacomo Di Gesù (Rome) and Hendrik Weber (Münster)



Project
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TOCH

(Stochastic) Allen–Cahn equation on \mathbb{T}^2

$$d\phi(t, x) = [\nu(\varepsilon t)\Delta\phi(t, x) + \phi(t, x) - \phi(t, x)^3] dt + \sigma dW(t, x)$$

(Online: <https://youtu.be/yX0EAxZHNCQ>)

Eyring–Kramers law for 1D SPDEs: heuristics

$$\partial_t u(t, x) = \Delta u(t, x) + f(u(t, x)) + \sqrt{2\varepsilon} \xi(t, x) \quad (f(u) = u - u^3)$$

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Initial condition: u_{in} near $u_- \equiv -1$ with eigenvalues $\nu_k = \left(\frac{\beta k \pi}{L}\right)^2 + 2$

Target: $u_+ \equiv 1$, $\tau_+ = \inf\{t > 0: \|u_t - u_+\|_{L^\infty} < \rho\}$

Transition state: ($\beta = 1$ for Neumann b.c., $\beta = 2$ for periodic b.c.)

$$u_{\text{ts}}(x) = \begin{cases} u_0(x) \equiv 0 & \text{if } L \leq \beta\pi \quad \text{with ev } \lambda_k = \left(\frac{\beta k \pi}{L}\right)^2 - 1 \\ u_1(x) \text{ } \beta\text{-kink stationary sol.} & \text{if } L > \beta\pi \quad \text{with ev } \lambda'_k \end{cases}$$

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[Faris & Jona-Lasinio 82]: large-deviation principle

\Rightarrow Arrhenius law: $\mathbb{E}^{u_{\text{in}}}[\tau_+] \simeq e^{(V[u_{\text{ts}}] - V[u_-])/\varepsilon}$

[Maier & Stein 01]: formal computation; for Neumann b.c.

$$\Rightarrow \mathbb{E}^{u_{\text{in}}}[\tau_+] \simeq 2\pi \sqrt{\frac{1}{|\lambda_0| \nu_0} \prod_{k=1}^{\infty} \frac{\lambda_k}{\nu_k}} e^{(V[u_{\text{ts}}] - V[u_-])/\varepsilon}$$

The two-dimensional case

- ▷ Large-deviation principle: [Hairer & Weber, 2015]
- ▷ Naive computation of prefactor fails:

$$\begin{aligned} \log \prod_{k \in (\mathbb{N}^2)^*} \frac{1 - \left(\frac{L}{|k|\pi}\right)^2}{1 + 2\left(\frac{L}{|k|\pi}\right)^2} &\simeq \sum_{k \in (\mathbb{N}^2)^*} \log \left(1 - \frac{3L^2}{|k|^2\pi^2}\right) \\ &\simeq - \sum_{k \in (\mathbb{N}^2)^*} \frac{3L^2}{|k|^2\pi^2} \simeq -\frac{3L^2}{\pi^2} \int_1^\infty \frac{r \, dr}{r^2} = -\infty \end{aligned}$$

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- ▷ In fact, the equation needs to be **renormalised**

Theorem: [Da Prato & Debussche 2003]

Let ξ^δ be a mollification on scale δ of white noise. Then

$$\partial_t u = \Delta u + [1 + 3\varepsilon C(\delta)]u - u^3 + \sqrt{2\varepsilon}\xi^\delta$$

with $C(\delta) \simeq \log(\delta^{-1})$ admits local solution converging as $\delta \rightarrow 0$

(Global version: [Mourrat & Weber 2015])

[Mourrat & Weber 2014]: **Renormalised** eq = scaling limit of Ising–Kac model

Renormalisation

Problem: Stoch. convolution $w_t(x) = \int_0^t e^{\Delta(t-s)} \xi(s, x) ds$ is **distribution**

▷ δ -mollification should be equivalent to Galerkin approx. $|k| \leq N = \delta^{-1}$:

$$w_N(x, t) = \sum_{|k| \leq N} a_k(t) \frac{1}{L} e^{i\Omega k \cdot x} \quad a_k = \int_0^t e^{-\mu_k(t-s)} dW_s^{(k)}$$
$$\mu_k = (\Omega|k|)^2 \quad \Omega = \beta\pi/L$$

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▷ $\lim_{t \rightarrow \infty} \int_0^t e^{(\Delta-1)(t-s)} \xi_N(s, x) ds = \phi_N$ is a **Gaussian free field**, s.t.

$$L^2 C_N := L^2 \mathbb{E} \phi_N^2 = \mathbb{E} \|\phi_N\|_{L^2}^2 = \sum_{|k| \leq N} \frac{1}{2(\mu_k+1)} = \frac{\text{Tr}(P_N[-\Delta+1]^{-1})}{2} \simeq \log(N)$$

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▷ **Wick powers**

$$:\phi_N^2: = \phi_N^2 - C_N$$

$$:\phi_N^3: = \phi_N^3 - 3C_N \phi_N$$

$$:\phi_N^4: = \phi_N^4 - 6C_N \phi_N^2 + 3C_N^2$$

have zero mean and uniformly bounded variance (when integrated)

Nelson's estimate

Lemma: For X random variable in n^{th} inhomogeneous Wiener chaos

$$\mathbb{E}[X^{2p}]^{\frac{1}{2p}} \leq C_n (2p - 1)^{\frac{n}{2}} \mathbb{E}[X^2]^{\frac{1}{2}}$$

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$$\sup_N \mathbb{E}\left[\left(\int_{\mathbb{T}^2} : \phi_N^n(x) : dx\right)^{2p}\right] < \infty$$

$$\forall M > N : \mathbb{E}\left[\left(\int_{\mathbb{T}^2} : \phi_M^n(x) : dx - \int_{\mathbb{T}^2} : \phi_N^n(x) : dx\right)^{2p}\right]^{\frac{1}{p}} \leq C'_n(2p-1) \frac{(\log N)^{n-2}}{N}$$

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Corollary:

$$\mathbb{E}\left[\exp\left\{-\frac{\varepsilon}{4} \int_{\mathbb{T}^2} : \phi_N^4(x) : dx\right\}\right] \leq 1 + \mathcal{O}(\varepsilon)$$

- ▷ Integrand is bounded below by term of order $-C_N^2$
- ▷ Use Markov's ineq to bound tails of integral and integrate by parts

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- ▷ Integrand is bounded below by term of order $-C_N^2$
- ▷ Use Markov's ineq to bound tails of integral and integrate by parts

Useful as $\text{cap}(A, B) \leq \sqrt{\frac{|\lambda_0| \varepsilon}{2\pi}} \prod_{0 < |k| \leq N} \sqrt{\frac{2\pi \varepsilon}{\lambda_k}} \mathbb{E}\left[\exp\left\{-\frac{\varepsilon}{4} \int_{\mathbb{T}^2} : u_N^4(x) : dx\right\}\right]$

Computation of the prefactor

- ▷ Consider for simplicity $L < \beta\pi \Rightarrow$ transition state in 0
- ▷ Galerkin-truncated renormalised potential

$$V_N = \frac{1}{2} \int_{\mathbb{T}^2} [\|\nabla u_N(x)\|^2 - u_N(x)^2] dx + \frac{1}{4} \int_{\mathbb{T}^2} :u_N(x)^4: dx$$

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- ▷ Using Nelson estimate: $\text{cap}(A, B) \simeq \sqrt{\frac{|\lambda_0|\varepsilon}{2\pi}} \prod_{0 < |k| \leq N} \sqrt{\frac{2\pi\varepsilon}{\lambda_k}}$
- ▷ Symmetry argument:

$$\int_{B^c} h_{A,B}(z) e^{-V_N(z)/\varepsilon} dz = \frac{1}{2} \int e^{-V_N(z)/\varepsilon} dz = \frac{1}{2} \mathcal{Z}_N(\varepsilon)$$

- ▷ $\mathcal{Z}_N(\varepsilon) \simeq 2 \prod_{|k| \leq N} \sqrt{\frac{2\pi\varepsilon}{\nu_k}} e^{-V_N(L,0)/\varepsilon}$ where $-V_N(L,0) = \frac{1}{4}L^2 + \frac{3}{2}L^2 C_N \varepsilon$
- ▷ Prefactor proportional to (since $\nu_k = \lambda_k + 3$)

$$\prod_{0 < |k| \leq N} \frac{\lambda_k}{\lambda_k + 3} e^{3/\lambda_k} \quad \text{converges since} \quad \log \left[\frac{\lambda_k}{\lambda_k + 3} e^{3/\lambda_k} \right] = \mathcal{O}\left(\frac{1}{|k|^4}\right)$$

Main result in dimension 2

Theorem: [B, Di Gesù, Weber, 2017]

For $L < 2\pi$, appropriate $A \ni u_-$, $B \ni u_+$, $\exists \mu_N$ probability measures on ∂A :

$$\limsup_{N \rightarrow \infty} \mathbb{E}^{\mu_N}[\tau_B] \leq \frac{2\pi}{|\lambda_0|} \sqrt{\prod_{k \in \mathbb{Z}^2} \frac{|\lambda_k|}{\nu_k} e^{\frac{\nu_k - \lambda_k}{|\lambda_k|}} e^{(V[u_{ts}] - V[u_-])/\varepsilon} [1 + c_+ \sqrt{\varepsilon}]}$$

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▷ Inverse of prefactor involves Carleman–Fredholm determinant:

$$\det_2(\mathbb{1} + T) = \det(\mathbb{1} + T) e^{-\text{Tr} T}$$

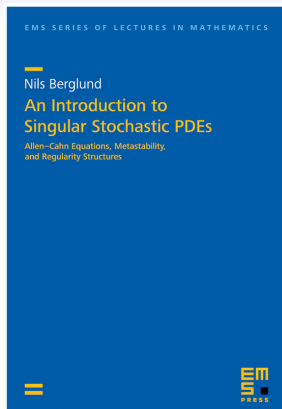
with $T = 3(-\Delta_{\perp} - 1)^{-1}$

\det_2 defined whenever T is only Hilbert–Schmidt (true for $d \leq 3$)

▷ [Tsatsoulis & Weber 2018]: Same result for $\mathbb{E}^{u_0}[\tau_B]$

References

- ▷ N. B., Giacomo Di Gesù & Hendrik Weber, *An Eyring–Kramers law for the stochastic Allen–Cahn equation in dimension two*, *Electronic J. Probability* **22**, 1–27 (2017)
- ▷ N. B. & Rita Nader, *Stochastic resonance in stochastic PDEs*, *Stochastics & PDEs: Analysis and Computation*, (2022)
- ▷ ———, *Concentration estimates for slowly time-dependent singular SPDEs on the two-dimensional torus*, [arXiv/2209.15357](https://arxiv.org/abs/2209.15357) (2022)
- ▷ N. B., *An Introduction to Singular Stochastic PDEs*, EMS Press (2022)



Thanks for your attention!

Slides available at <https://www.idpoisson.fr/berglund/Seoul23b.pdf>