

Anomalous Diffusion and the Generalized Langevin Equation

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The Generalized Langevin Equation (GLE)

Formal definition:

$$m\ddot{x}(t) = -\gamma\dot{x}(t) - \Phi'(x(t)) - \int_{-\infty}^t K(t-s)\dot{x}(s)ds + F(t) + \sqrt{2\gamma}\dot{W}(t)$$

The GLE models the motion of microparticles moving in viscoelastic fluids.

- 1 Introduction: Anomalous diffusion and the linear GLE
- 2 GLE in a non-linear potential well with a special class of power-law memory kernels

Goal: Investigating unique ergodicity in non-linear potential wells.

I. Anomalous diffusion and the linear GLE
(joint work with S. McKinley)

Linear GLE

Classical Langevin Equation (LE): Describes the diffusion of a particle with mass m in a viscous medium.

$$m\dot{v}(t) = -\gamma v(t) + \sqrt{2\gamma}\dot{W}(t),$$

$v(t)$: velocity of the particle at time t

γ : drag constant

$W(t)$: standard Brownian Motion

Note: take $k_B T = 1$ throughout the talk.

$$x(t) := \int_0^t v(s) ds, \text{ position at time } t$$

\Rightarrow Mean-Squared Displacement (MSD) $\mathbb{E} [x^2(t)] \sim t, \quad t \rightarrow \infty,$
(Asymptotically diffusion)

Here, $f(t) \sim g(t), t \rightarrow \infty$ means $\lim_{t \rightarrow \infty} f(t)/g(t) = c \in (0, \infty)$.

Anomalous Diffusion is observed in nature, particularly in viscoelastic fluids, e.g. mucus and cytoplasm.

$$\mathbb{E} [x(t)^2] \sim t^\alpha, \quad t \rightarrow \infty, \quad \alpha \neq 1.$$

- $\alpha \in (0, 1)$: Sub-diffusion
- $\alpha > 1$: Super-diffusion

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- etc.

Assumption (Kubo 1966, Mason & Weitz 1995)

Fluctuation-Dissipation relationship

The memory kernel of the drag term is the same as the covariance of the noise term.

	Langevin	Generalized Langevin
Force due to drag	$-\gamma v(t)$	$-\int_{-\infty}^t K(t-s)v(s)ds$
Thermal fluctuation	$\sqrt{2\gamma}\dot{W}(t)$	$F(t)$ with $\mathbb{E}[F(t)F(s)] = K(t-s)$

Generalized Langevin Equation (GLE)

$$\begin{cases} m\dot{v}(t) = -\int_{-\infty}^t K(t-s)v(s)ds + F(t), \\ \mathbb{E}[F(t)F(s)] = K(t-s). \end{cases}$$

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GLE is able to produce subdiffusive diffusion.

Question: What type of memory $K(t) \Rightarrow$ subdiffusive diffusion?

Physicists' Guess: (Morgado, 2002) $x(t) = \int_0^t v(s)ds$,

$$\alpha \in (0, 1), \quad K(t) \sim t^{-\alpha}, \quad t \rightarrow \infty,$$

$$\Rightarrow \mathbb{E}[x(t)^2] \sim t^\alpha, \quad t \rightarrow \infty.$$

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$$\Rightarrow \mathbb{E}[x(t)^2] \sim t^\alpha, \quad t \rightarrow \infty.$$

Theorem (Kou, 2008)

$$\alpha \in (0, 1), \quad K(t) = |t|^{-\alpha} \Rightarrow \mathbb{E}[x(t)^2] \sim t^\alpha, \quad t \rightarrow \infty.$$

Stationary statistics of MSD

$$\begin{cases} m\dot{v}(t) = - \int_{-\infty}^t K(t-s)v(s)ds + F(t), \\ \mathbb{E}[F(t)F(s)] = K(t-s). \end{cases}$$

Well-posedness:

- Theory of stationary random distributions, (Ito 1954) + Fourier Analysis
- (Weak) Solutions are understood as an operator
 $V : \text{Dom}(V) \subset \mathcal{S}' \rightarrow L^2(\Omega)$
- $v(t) := \langle V, \delta_t \rangle$ and $x(t) := \langle V, 1_{[0,t]} \rangle$ when they are well-defined.

Theorem 1 (McKinley, N., 2017, arXiv:1711.00560 (in review))

Under extra assumptions on the memory kernel $K(t)$,

	$K \in L^1(\mathbb{R})$	$K \notin L^1(\mathbb{R})$ $\exists \alpha \in (0, 1), K(t) \sim t^{-\alpha}, t \rightarrow \infty$
<i>Asymptotics of MSD</i>	$\mathbb{E}[x(t)^2] \sim t,$ $t \rightarrow \infty$	$\mathbb{E}[x(t)^2] \sim t^\alpha,$ $t \rightarrow \infty$

II. GLE in a potential well with a class of power-law memory kernels (joint work with N. Glatt-Holtz, D. Herzorg and S. McKinley)

GLE in potential well

Formal definition of GLE in a potential well with viscous drag: $m, \gamma > 0$,

$$\begin{cases} m\ddot{x}(t) = -\gamma\dot{x}(t) - \Phi'(x(t)) - \int_{-\infty}^t K(t-s)\dot{x}(s)ds + F(t) + \sqrt{2\gamma}\dot{W}(t), \\ \mathbb{E}[F(t)F(s)] = K(t-s). \end{cases}$$

where

- $\Phi(x)$: potential well.
- $W(t)$: standard Brownian motion.
- $F(t)$: stationary Gaussian process with $\mathbb{E}[F(t)F(s)] = K(|t-s|)$.
- $K(t) \sim t^{-\alpha}$, $t \rightarrow \infty$, $\alpha > 0$.

$$\begin{cases} m\ddot{x}(t) = -\gamma\dot{x}(t) - \Phi'(x(t)) - \int_{-\infty}^t K(t-s)\dot{x}(s)ds + F(t) + \sqrt{2\gamma}\dot{W}(t), \\ \mathbb{E}[F(t)F(s)] = K(t-s). \end{cases}$$

- Theory of linear stationary Gaussian processes does not apply.

Question: Does there exist a measure π on \mathbb{R}^2 s.t. $\forall f$ bounded

$$\text{“} \lim_{t \rightarrow \infty} \frac{1}{T} \int_0^T f(x(t), v(t)) dt = \int_{\mathbb{R}^2} f(u, v) \pi(du, dv). \text{”}$$

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\Rightarrow We will use a Markov representation of the GLE

Mori, 1965; Zwanzig, 1970 & 2001; Kupferman 2004; Goychuk, 2009; Pavliotis, 2014.

Well-posedness, stationary structure, unique ergodicity??

A toy model with a double-well potential

$dx(t) = -\Phi'(x(t))dt + dW(t)$, The density of the unique invariant probability measure:

$$\Phi(x) = \frac{1}{4}x^4 - \frac{1}{2}x^2 + \frac{1}{4},$$

$$p(x) \propto e^{-\Phi(x)}$$

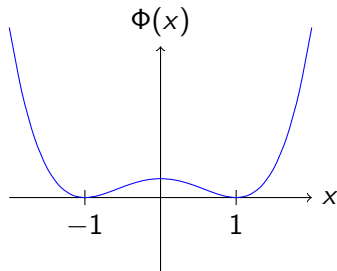
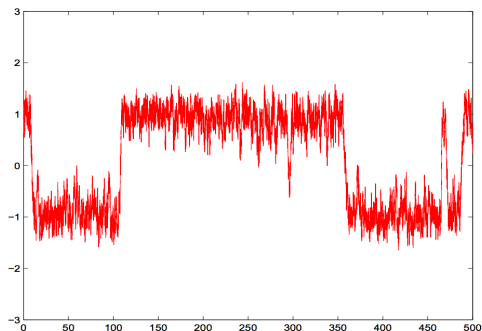


Figure: Trajectory of $x(t)$

Markov representation for exponentials

Theorem (Doob's Theorem)

$F(t)$ stationary Gaussian & $\mathbb{E}[F(t)F(s)] = K(|t-s|) = ce^{-\lambda|t-s|}$
 $\Rightarrow F(t)$ is an Ornstein-Uhlenbeck process, i.e.

$$F(t) = \sqrt{c} \left(e^{-\lambda t} F_0 + \sqrt{2\lambda} \int_0^t e^{-\lambda(t-s)} dW_1(s) \right),$$

where $F_0 \sim \mathcal{N}(0, 1)$.

$$m\ddot{x}(t) = -\gamma\dot{x}(t) - \Phi'(x(t)) + \sqrt{2\gamma}\dot{W}_0(t) \\ - \int_{-\infty}^t K(t-s)\dot{x}(s)ds + F(t)$$

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$$m\ddot{x}(t) = -\gamma\dot{x}(t) - \Phi'(x(t)) + \sqrt{2\gamma}\dot{W}_0(t) \\ - c \int_{-\infty}^t e^{-\lambda(t-s)} \dot{x}(s) ds - \sqrt{c}e^{-\lambda t} F_0 - \sqrt{2c\lambda} \int_0^t e^{-\lambda(t-s)} dW_1(s)$$

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$$m\ddot{x}(t) = -\gamma\dot{x}(t) - \Phi'(x(t)) + \sqrt{2\gamma}\dot{W}_0(t) \\ - \underbrace{\sqrt{c} \left[\sqrt{c} \int_{-\infty}^t e^{-\lambda(t-s)} \dot{x}(s) ds + e^{-\lambda t} F_0 + \sqrt{2\lambda} \int_0^t e^{-\lambda(t-s)} dW_1(s) \right]}_z$$

$$\Rightarrow \begin{cases} m\ddot{x}(t) = -\gamma\dot{x}(t) - \Phi'(x(t)) + \sqrt{2\gamma}\dot{W}_0(t) - \sqrt{c}z(t) \\ \dot{z}(t) = -\lambda z(t) + \sqrt{c}\dot{x}(t) + \sqrt{2\lambda}\dot{W}_1(t) \end{cases}$$

Markov representation for finite sum of exponentials

$$K(t) = \sum_{k=1}^N c_k e^{-\lambda_k |t|}, \quad c_k, \lambda_k > 0, \quad k = 1, \dots, N$$

$$\begin{cases} dx(t) = v(t)dt \\ m dv(t) = \left(-\gamma v(t) - \Phi'(x(t)) - \sum_{k=1}^N \sqrt{c_k} z_k(t) \right) dt + \sqrt{2\gamma} dW_0(t), \\ dz_k(t) = -\lambda_k z_k(t)dt + \sqrt{c_k} v(t)dt + \sqrt{2\lambda_k} dW_k(t), \quad k = 1, \dots, N. \end{cases}$$

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- etc.

Markov approximation for power-tail memory kernel

Proposition (Abate, 1999)

Given $\alpha, \beta > 0$, define $K(t)$

$$K(t) = \sum_{k \geq 1} c_k e^{-\lambda_k |t|}, \text{ where } c_k = \frac{1}{k^{1+\alpha\beta}}, \lambda_k = \frac{1}{k^\beta}, k \geq 1.$$

Then, $K(t) \sim t^{-\alpha}$, $t \rightarrow \infty$.

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Then, $K(t) \sim t^{-\alpha}$, $t \rightarrow \infty$.

We arrive at

$$\begin{cases} dx(t) = v(t)dt \\ m dv(t) = \left(-\gamma v(t) - \Phi'(x(t)) - \sum_{k=1}^{\infty} \sqrt{c_k} z_k(t) \right) dt + \sqrt{2\gamma} dW_0(t), \\ dz_k(t) = -\lambda_k z_k(t) dt + \sqrt{c_k} v(t) dt + \sqrt{2\lambda_k} dW_k(t), \quad k = 1, 2, \dots \end{cases}$$

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Recall Theorem 1 for linear GLE,

$$\begin{cases} m\dot{v}(t) = -\int_{-\infty}^t K(t-s)v(s)ds + F(t) \\ \mathbb{E}[F(t)F(s)] = K(t-s) \end{cases}$$

$K \in L^1, (\alpha > 1)$	$\mathbb{E}[x(t)^2] \sim t, \quad t \rightarrow \infty, \text{ (diffusion)}$
$\alpha \in (0, 1), K(t) \sim t^{-\alpha}$	$\mathbb{E}[x(t)^2] \sim t^\alpha, \quad t \rightarrow \infty, \text{ (subdiffusion)}$
$\alpha = 1, K(t) \sim t^{-1}$	N/A

$$\left\{ \begin{array}{l} dx(t) = v(t)dt, \quad c_k = \frac{1}{k^{1+\alpha\beta}}, \quad \lambda_k = \frac{1}{k^\beta}, \\ mdv(t) = \left(-\gamma v(t) - \Phi'(x(t)) - \sum_{k=1}^{\infty} \sqrt{c_k} z_k(t) \right) dt + \sqrt{2\gamma} dW_0(t), \\ dz(t) = -\lambda_k z_k(t)dt + \sqrt{c_k} v(t)dt + \sqrt{2\lambda_k} dW_k(t), \quad k = 1, 2, \dots \end{array} \right.$$

	Diffusion, $\alpha > 1$	Critical case $\alpha = 1$	Subdiffusion, $0 < \alpha < 1$
Well-posedness			
Existence of invariant measure			
Uniqueness of invariant measure			

Well-posedness

Potential $\Phi \in C^\infty(\mathbb{R})$ satisfies

$$c(\Phi(x) + 1) \geq x^2.$$

Examples:

- 1 Polynomial of even order, e.g., $\Phi(x) = x^{2n}$, $n \in \mathbb{N}^+$.
- 2 $\Phi(x) = e^{x^2}$

Definition

For $s \in \mathbb{R}$, define

$$\mathcal{H}_{-s} = \left\{ X = (x, v, z_1, \dots, z_k, \dots) : x^2 + v^2 + \sum_{k \geq 1} k^{-2s} z_k^2 < \infty \right\},$$

equipped with the norm $\|X\|_{\mathcal{H}_{-s}}^2 = x^2 + v^2 + \sum_{k \geq 1} k^{-2s} z_k^2$.

Note: $\ell^2 = \mathcal{H}_0$.

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Proposition (Glatt-Holtz, Herzog, McKinley, N., 2018, in prep)

Under appropriate assumptions, for all initial conditions $X_0 \in \mathcal{H}_{-s}$, there exists a unique strong solution $X(\cdot, X_0) : \Omega \times [0, \infty) \rightarrow \mathcal{H}_{-s}$.

$$\begin{cases} dx(t) = v(t)dt, & c_k = \frac{1}{k^{1+\alpha\beta}}, & \lambda_k = \frac{1}{k^\beta}, \\ mdv(t) = \left(-\gamma v(t) - \Phi'(x(t)) - \sum_{k=1}^{\infty} \sqrt{c_k} z_k(t) \right) dt + \sqrt{2\gamma} dW_0(t), \\ dz_k(t) = -\lambda_k z_k(t) dt + \sqrt{c_k} v(t) dt + \sqrt{2\lambda_k} dW_k(t), \quad k = 1, 2, \dots \end{cases}$$

	Diffusion, $\alpha > 1$	Critical case $\alpha = 1$	Subdiffusion, $0 < \alpha < 1$
Well-posedness	✓		
Existence of invariant measure			
Uniqueness of invariant measure			

Invariant measure for finite-dimensional system

$$\begin{cases} dx(t) = v(t)dt \\ mdv(t) = \left(-\gamma v(t) - \Phi'(x(t)) - \sum_{k=1}^N \sqrt{c_k} z_k(t) \right) dt + \sqrt{2\gamma} dW_0(t), \\ dz_k(t) = -\lambda_k z_k(t) dt + \sqrt{c_k} v(t) dt + \sqrt{2\lambda_k} dW_k(t), \quad k = 1, \dots, N. \end{cases}$$

Theorem (Pavliotis, 2014)

Let p_N be the density probability measure on \mathbb{R}^{N+2} given by

$$p(x, v, z_1, \dots, z_N) \propto \exp \left\{ -\Phi(x) - \frac{mv^2}{2} - \sum_{k=1}^N \frac{z_k^2}{2} \right\}.$$

Then p_N is the density of the unique invariant probability measure for the finite-dimensional system.

Note: p_N does **not** depend on c_k, λ_k !

Existence of invariant measure for infinite-dimensional system

Definition

Denote by μ the probability measure on \mathbb{R}^∞ given by

$$\mu = \left(c e^{-\Phi(x)} dx \right) \times \mathcal{N}(0, 1/m) \times \prod_{k \geq 1} \mathcal{N}(0, 1).$$

Note: $\mu(\mathcal{H}_{-s}) = \begin{cases} 1, & s > 1/2 \\ 0, & s \leq 1/2 \end{cases}$, where

$$\mathcal{H}_{-s} = \left\{ X = (x, v, z_1, \dots, z_k, \dots) : x^2 + v^2 + \sum_{k \geq 1} k^{-2s} z_k^2 < \infty \right\}$$

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Theorem (Glatt-Holtz, Herzog, McKinley, N., 2018, in prep)

Under appropriate assumptions and $s > 1/2$, μ is an invariant measure.

Finite-dimensional space: (Pavliotis 2014) it suffices to check that

$$\mathcal{L}^* p = 0,$$

where p is the density of the candidate measure and \mathcal{L}^* is the dual of \mathcal{L} , the infinitesimal generator.

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Infinite-dimensional space: $\forall \psi \in C_b^2(\mathcal{H}_{-s})$, we show that

$$\langle \psi, \mathcal{L}^* \mu \rangle := \int_{\mathcal{H}_{-s}} \mathcal{L} \psi(X) \mu(dX) = 0.$$

Then, by an approximating argument,

$$\int_{\mathcal{H}_{-s}} \mathcal{P}_t \psi(X) \mu(dX) = \int_{\mathcal{H}_{-s}} \psi(X) \mu(dX),$$

where $\mathcal{P}_t \psi(X) = \mathbb{E}_X[\psi(X(t))]$ is the Markov process associated with \mathcal{L} .

$$\begin{cases} dx(t) = v(t)dt, & c_k = \frac{1}{k^{1+\alpha\beta}}, & \lambda_k = \frac{1}{k^\beta}, \\ mdv(t) = \left(-\gamma v(t) - \Phi'(x(t)) - \sum_{k=1}^{\infty} \sqrt{c_k} z_k(t) \right) dt + \sqrt{2\gamma} dW_0(t), \\ dz_k(t) = -\lambda_k z_k(t) dt + \sqrt{c_k} v(t) dt + \sqrt{2\lambda_k} dW_k(t), \quad k = 1, 2, \dots \end{cases}$$

	Diffusion, $\alpha > 1$	Critical case $\alpha = 1$	Subdiffusion, $0 < \alpha < 1$
Well-posedness	✓		
Existence of invariant measure	$\mu = \left(ce^{-\Phi(x)} dx \right) \times \mathcal{N}(0, 1/m) \times \prod_{k \geq 1} \mathcal{N}(0, 1)$ is invariant		
Uniqueness of invariant measure			

Uniqueness of invariant measure in diffusion

$$\begin{cases} dx(t) = v(t)dt, & c_k = \frac{1}{k^{1+\alpha\beta}}, & \lambda_k = \frac{1}{k^\beta}, \\ m dv(t) = \left(-\gamma v(t) - \Phi'(x(t)) - \sum_{k=1}^{\infty} \sqrt{c_k} z_k(t) \right) dt + \sqrt{2\gamma} dW_0(t), \\ dz_k(t) = -\lambda_k z_k(t) dt + \sqrt{c_k} v(t) dt + \sqrt{2\lambda_k} dW_k(t), \quad k = 1, 2, \dots \end{cases}$$

Theorem (Glatt-Holtz, Herzog, McKinley, N., 2018, in prep)

Under appropriate assumptions and assume that $\alpha > 1$, μ is the unique invariant probability measure.

Strategy: Asymptotic coupling

Goal: (Hairer, 2002) uniqueness is implied if we can show that $\forall X_0, \tilde{X}_0 \in \mathcal{H}_{-s}$,

$$\mathbb{P}\left\{\lim_{t \rightarrow \infty} \|X(X_0, t) - \tilde{X}(\tilde{X}_0, t)\|_{-s} = 0\right\} = 1$$

This holds if Φ is a 4th-degree polynomial.

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More recent results show that

$$\mathbb{P}\left\{\lim_{t \rightarrow \infty} \|X(X_0, t) - \tilde{X}(\tilde{X}_0, t)\|_{-s} = 0\right\} > 0 \text{ works!}$$

- Hairer, Mattingly, Scheutzow, 2011; Glatt-Holtz, Richards, Mattingly, 2015; Kulik, Scheutzow, 2016.

Constructing stochastic control.

$$dX(t) = LX(t)dt + \Psi(X(t))dt + B dW(t)$$

$$d\tilde{X}(t) = L\tilde{X}(t)dt + \Psi(\tilde{X}(t))dt + B \underbrace{(dW(t) + U(X(t), \tilde{X}(t))1_{(t \leq \tau)}dt)}_{d\tilde{W}(t)}$$

Setting $\bar{X}(t) = X(t) - \tilde{X}(t)$. Pick $U(X(t), \tilde{X}(t))$ and τ s.t.

- $U(X(t), \tilde{X}(t))$ forces $\bar{X}(t) \rightarrow 0, t \rightarrow \infty$.
- τ shuts down $U(X(t), \tilde{X}(t))$ if $\bar{X}(t) \not\rightarrow 0$

Constructing stochastic control.

$$dX(t) = LX(t)dt + \Psi(X(t))dt + B dW(t)$$

$$d\tilde{X}(t) = L\tilde{X}(t)dt + \Psi(\tilde{X}(t))dt + B \underbrace{(dW(t) + U(X(t), \tilde{X}(t))1_{(t \leq \tau)}dt)}_{d\tilde{W}(t)}$$

Setting $\bar{X}(t) = X(t) - \tilde{X}(t)$. Pick $U(X(t), \tilde{X}(t))$ and τ s.t.

- $U(X(t), \tilde{X}(t))$ forces $\bar{X}(t) \rightarrow 0, t \rightarrow \infty$.
- τ shuts down $U(X(t), \tilde{X}(t))$ if $\bar{X}(t) \not\rightarrow 0$

• Girsanov shift $\tilde{W}(t) := W(t) + \int_0^t U(X(r), \tilde{X}(r))1_{(r \leq \tau)}dr$ satisfies

$$\tilde{W}(\cdot) \ll W(\cdot) \text{ on } [0, \infty).$$

• $\mathbb{P} \{ \|\bar{X}(t)\|_{\mathcal{H}_{-s}} \rightarrow 0, t \rightarrow \infty | \tau = \infty \} = 1.$

“ τ is never activated $\Leftrightarrow \bar{X}(t) \rightarrow 0, t \rightarrow \infty$ ”

• $\mathbb{P} \{ \tau = \infty \} > 0.$ “There is a chance that τ is never activated”

Choice of U : $U(X(t), \tilde{X}(t)) = (0, u(X(t), \tilde{X}(t)), 0, \dots)$

$$\left\{ \begin{array}{l} d\bar{x}(t) = \bar{v}(t)dt, \\ md\bar{v}(t) = \left(-\gamma\bar{v}(t) - [\Phi'(x(t)) - \Phi'(\tilde{x}(t))] - \sum_{k=1}^{\infty} \sqrt{c_k} \bar{z}_k(t) \right) dt \\ \quad + u(X(t), \tilde{X}(t))dt, \\ d\bar{z}_k(t) = -\lambda_k \bar{z}_k(t)dt + \sqrt{c_k} \bar{v}(t)dt, \quad k = 1, 2, \dots \end{array} \right.$$

Choice of U : $U(X(t), \tilde{X}(t)) = (0, u(X(t), \tilde{X}(t)), 0, \dots)$

$$\begin{cases} d\bar{x}(t) = \bar{v}(t)dt, \\ md\bar{v}(t) = \left(-\gamma\bar{v}(t) - [\Phi'(x(t)) - \Phi'(\tilde{x}(t))] - \sum_{k=1}^{\infty} \sqrt{c_k} \bar{z}_k(t) \right) dt \\ \quad + u(X(t), \tilde{X}(t))dt, \\ d\bar{z}_k(t) = -\lambda_k \bar{z}_k(t)dt + \sqrt{c_k} \bar{v}(t)dt, \quad k = 1, 2, \dots \end{cases}$$

• $u(X(t), \tilde{X}(t)) = -c\bar{x}(t) + [\Phi'(x(t)) - \Phi'(\tilde{x}(t))] + \sum_{k=1}^{\infty} \sqrt{c_k} \bar{z}_k(t)$

“ u cancels the non-linear term and the memory”

$$\Rightarrow \begin{cases} d\bar{x}(t) = \bar{v}(t)dt, \\ d\bar{v}(t) = (-\gamma\bar{v}(t) - c\bar{x}(t))dt, \end{cases} \quad \text{deterministic, **dissipative**}$$

Choice of U : $U(X(t), \tilde{X}(t)) = (0, u(X(t), \tilde{X}(t)), 0, \dots)$

$$\begin{cases} d\bar{x}(t) = \bar{v}(t)dt, \\ md\bar{v}(t) = \left(-\gamma\bar{v}(t) - [\Phi'(x(t)) - \Phi'(\tilde{x}(t))] - \sum_{k=1}^{\infty} \sqrt{c_k}\bar{z}_k(t) \right) dt \\ \quad + u(X(t), \tilde{X}(t))dt, \\ d\bar{z}_k(t) = -\lambda_k\bar{z}_k(t)dt + \sqrt{c_k}\bar{v}(t)dt, \quad k = 1, 2, \dots \end{cases}$$

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- The structure of Φ + Lyapunov function + choice of τ

$\Rightarrow \bar{x}(t), \bar{v}(t)$ force $\bar{z}_k(t) \rightarrow 0, t \rightarrow \infty$

\Rightarrow (a) + (b).

Choice of U : $U(X(t), \tilde{X}(t)) = (0, u(X(t), \tilde{X}(t)), 0, \dots)$

$$\begin{cases} d\bar{x}(t) = \bar{v}(t)dt, \\ md\bar{v}(t) = \left(-\gamma\bar{v}(t) - [\Phi'(x(t)) - \Phi'(\tilde{x}(t))] - \sum_{k=1}^{\infty} \sqrt{c_k} \bar{z}_k(t) \right) dt \\ \quad + u(X(t), \tilde{X}(t))dt, \\ d\bar{z}_k(t) = -\lambda_k \bar{z}_k(t)dt + \sqrt{c_k} \bar{v}(t)dt, \quad k = 1, 2, \dots \end{cases}$$

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- The structure of Φ + Lyapunov function + choice of τ

$$\Rightarrow \bar{x}(t), \bar{v}(t) \text{ force } \bar{z}_k(t) \rightarrow 0, t \rightarrow \infty$$

\Rightarrow (a) + (b).

- (c) requires $\int_0^{\infty} K(t)dt < \infty \Leftrightarrow \alpha > 1$, (recall $K(t) \sim t^{-\alpha}$, $t \rightarrow \infty$).

$$\begin{cases} dx(t) = v(t)dt, & c_k = \frac{1}{k^{1+\alpha\beta}}, & \lambda_k = \frac{1}{k^\beta}, \\ mdv(t) = \left(-\gamma v(t) - \Phi'(x(t)) - \sum_{k=1}^{\infty} \sqrt{c_k} z_k(t) \right) dt + \sqrt{2\gamma} dW_0(t), \\ dz_k(t) = -\lambda_k z_k(t) dt + \sqrt{c_k} v(t) dt + \sqrt{2\lambda_k} dW_k(t), \quad k = 1, 2, \dots \end{cases}$$

	Diffusion, $\alpha > 1$	Critical case $\alpha = 1$	Subdiffusion, $0 < \alpha < 1$
Well-posedness	✓		
Existence of invariant measure	$\mu = \left(ce^{-\Phi(x)} dx \right) \times \mathcal{N}(0, 1/m) \times \prod_{k \geq 1} \mathcal{N}(0, 1)$ is invariant		
Uniqueness of invariant measure	✓	Open question	

Summary

- Use a Markovian system to represent GLE when memory kernel $K(t) \sim t^{-\alpha}$, $t \rightarrow \infty$ admits a form of infinite sum of exponentials.
- There exists an invariant structure for the Markovian system.
- Unique ergodicity is obtained in diffusive regime ($\alpha > 1$).
The marginal distribution in (x, v) of the invariant probability measure is given by

$$\pi(x, v) \propto \exp \left\{ -\Phi(x) - \frac{mv^2}{2} \right\},$$

which is independent of c_k, λ_k .

- Unique ergodicity when $\alpha \in (0, 1]$ remains **open question**.

Thank You!