

Chapter 2: Itô calculus

(1)

In the absence of external potential, the simplest dynamics of an overdamped colloid is given by

$$\dot{x}(t) = \sqrt{\sigma} \eta(t) \quad (1)$$

when $\eta(t)$ is a Gaussian white noise satisfying $\langle \eta(t) \rangle = 0$
 $\langle \eta(t) \eta(t') \rangle = \delta(t-t')$

Two problems

① $\frac{x(t+\tau) - x(t)}{\tau} \sim \sqrt{\frac{\sigma}{\tau}} \xrightarrow{\tau \rightarrow 0} \infty \Rightarrow x(t)$ not differentiable

② Chain rule + causality predicts $\langle x^2(t) \rangle = C \frac{dt}{dt}$
which is wrong

Itô - calculus

$\dot{x} = F(x) + \eta(t) \Leftrightarrow dx = F(x(t))dt + d\eta$
 $x(t+\delta t) - x(t)$ $x(t)$ for causality

① $x(t)$ is just a notation, only $\int^t ds \dot{x}(s)$ makes sense

② Save causality & modify the chain rule:

$$\frac{d}{dt} [f(x(t))] = f'(x(t)) \dot{x}(t) + \frac{\sigma}{2} f''(x(t)) \quad (7)$$

Stratonovich: $\dot{x} = F(x) + \eta(t) \Leftrightarrow dx = F\left(x + \frac{dx}{2}\right)dt + d\eta$
 $\frac{1}{2}[x(t+\delta t) + x(t)] \Rightarrow$ breaks causality

(7) $\Leftrightarrow df(x(t)) = f'(x(t)) dx + \frac{\sigma}{2} f''(x(t)) dt$

\nearrow not symmetrized \Rightarrow not a Stratonovich prescription

$$f'(x(t)) = f'\left(x(t) + \frac{dx}{2} - \frac{dx}{2}\right) = f'\left(\underbrace{x(t) + \frac{dx}{2}}_{\text{symmetric}}\right) - \frac{dx}{2} f''(x(t)) + O(dx^2) \quad (2)$$

$$f'(x(t)) dx = f'\left(x(t) + \frac{dx}{2}\right) dx - \frac{1}{2} f''(x(t)) dx^2$$

but to order dt , $dx^2 = dz^2 = \sigma^2 dt \Rightarrow$ exactly cancels $\frac{\sigma^2}{2} f''$ in (7)

$$\Rightarrow df(x(t)) = f'\left(x(t) + \frac{dx}{2}\right) dx \Leftrightarrow \frac{df}{dt} = f'(x) \dot{x} \quad (\text{Straton})$$

\Rightarrow simple formula but complicated symmetrization

2.2) Generalization to $f(x(t), t)$

The derivation above generalizes directly to

$$\frac{d}{dt} f(x(t), t) = \frac{\partial f}{\partial t} + \frac{\partial f}{\partial x} \dot{x}(t) + \frac{\sigma^2}{2} \frac{\partial^2 f}{\partial x^2}$$

2.3) N-dimensional Itô formula

$\dot{x}_i = F_i(x_1, \dots, x_N) + z_i$ where the $\{z_i\}$ are correlated Gaussian s.t.

$$\langle z_i(t) \rangle = 0 \quad \langle z_i(t) z_h(t') \rangle = \sigma_{ih} \delta(t - t')$$

Then
$$\frac{d}{dt} f(x_1(t), \dots, x_N(t)) = \sum_i \frac{\partial f}{\partial x_i} \dot{x}_i + \frac{1}{2} \sum_{i,h} \frac{\partial^2 f}{\partial x_i \partial x_h} \sigma_{ih} \quad (8)$$

Comment: Very useful in the presence of deterministic & stochastic variables.

E.g. $\dot{x} = v$; $m \dot{v} = -\gamma v - V'(x) + \sqrt{2\sigma k_B T} z(t)$

$$\Leftrightarrow \dot{x} = v + \xi_x ; \quad \dot{v} = -\frac{\gamma}{m} v - \frac{1}{m} V'(x) + \xi_v$$

when $\langle \xi_x(t) \rangle = 0$; $\langle \xi_x(t) \xi_x(t') \rangle = 0$

$\langle \xi_y(t) \rangle = 0$; $\langle \xi_y(t) \xi_y(t') \rangle = \frac{2\gamma kT}{m^2} \delta(t-t')$

$\langle \xi_x(t) \xi_y(t') \rangle = 0$

$$\frac{d}{dt} f(x(t), v(t)) = \frac{\partial f}{\partial x} \dot{x} + \frac{\partial f}{\partial v} \dot{v} + \frac{\gamma kT}{m^2} \frac{\partial^2 f}{\partial v^2}$$

\Rightarrow only the stochastic variable leads to a second order derivative.

2.4] Back to the paradox

$f(x(t)) = x^2(t)$ & $\dot{x}(t) = \sqrt{2D} \gamma(t)$

$f'(x) = 2x$; $f''(x) = 2$

$$\frac{d}{dt} f(x(t)) = \frac{\partial f}{\partial x} \dot{x} + \frac{1}{2} \cdot \frac{\partial^2 f}{\partial x^2} \cdot 2D = 2x \dot{x} + D = D + \sqrt{2D} x \gamma(t)$$

$$x^2(t) = 2Dt + \sqrt{2D} \int_0^t ds \gamma(s)$$

\Rightarrow ① we recover $\langle x^2(t) \rangle = 2Dt$

② we can characterize the fluctuations of $x^2(t)$ around its mean $2Dt$.

Also works for higher moments:

$$\begin{aligned} \frac{d}{dt} \langle x^4(t) \rangle &= 4 \langle x^3 \dot{x} \rangle + \frac{1}{2} \cdot 2D \cdot 12 \langle x^2 \rangle \\ &= 4 \langle x^3 \rangle \underbrace{\langle \sqrt{2D} \gamma(t) \rangle}_{=0} + 12D \underbrace{\langle x^2 \rangle}_{2Dt} \end{aligned}$$

$\Rightarrow \langle x^4(t) \rangle = 12D^2 t^2 = 3 \times (2Dt)^2 = 3 \langle x^2(t) \rangle^2$ as expected for a GRV.

3] Probability of noise realization

If we say that $\{\gamma(t)\}$ forms a set of GRV, it would be nice to be able to write their probability weight $P[\{\gamma(t)\}] = ?$

Start with N random variables x_i such that $\vec{x} = (x_1, \dots, x_N)$ (4)

$$P(\vec{x}) = \frac{1}{Z} \exp \left[-\frac{1}{2} \vec{x} \cdot (\Gamma \vec{x}) \right] \quad (9)$$

with Γ a matrix symmetric positive definite.

From the pset you know that $\langle x_i x_j \rangle = K_{ij}$, with $K = \Gamma^{-1}$.

From $\langle x_i x_j \rangle = K_{ij}$, we can build $\Gamma = K^{-1}$ & $P(\vec{x})$. Can we do the same from $\langle x(t) x(t') \rangle$?

Now let's call $t_i = i \Delta t$ and $x_i = x(t_i)$ and take the limit $\Delta t \rightarrow 0$ keeping $N \Delta t = t$ fixed. We then rewrite:

$$\vec{x} \cdot (\Gamma \vec{x}) = \sum_{i,j} x_i \Gamma_{ij} x_j = \sum_{i,j} \Delta t \, x(t_i) \frac{\Gamma_{ij}}{\Delta t^2} x(t_j)$$

$$\vec{x} \cdot (\Gamma \vec{x}) \sim \int dt dt' x(t) x(t') \Gamma_c(t, t') \quad \text{where} \quad \boxed{\Gamma_c(t_i, t_j) = \frac{1}{\Delta t^2} \Gamma_{ij}} \quad (10)$$

① Can we build $K_c(t_i, t_j)$?

$$K = \Gamma^{-1} \Rightarrow \sum_h K_{ih} \Gamma_{hj} = \delta_{ij} \quad (11)$$

Take a function $f(t)$ & denote $f_i = f(t_i)$. Then (11) implies

$$\sum_{j,h} K_{ih} \Gamma_{hj} f_j = \sum_j \delta_{ij} f_j = f_i$$

$$\Leftrightarrow \sum_{j,h} \Delta t^2 K_{ih} \frac{\Gamma_{hj}}{\Delta t^2} f_j = f_i$$

$$\Leftrightarrow \int dt' dt'' K_c(t, t') \Gamma_c(t', t'') f(t'') = f(t) \quad \text{with} \quad \boxed{K_c(t_i, t_j) = K_{ij}}$$

$$\Leftrightarrow \int dt'' f(t'') \left[\int dt' K_c(t, t') \Gamma_c(t', t'') \right] = f(t)$$

Since this holds for any function f , one has that

$$\Rightarrow \boxed{\int dt' k_e(t, t') P_e(t', t'') = \delta(t - t'')} \quad (5)$$

This is the generalisation of $k \cdot P = Id$ for convolution kernel.

① Going back to the GWN: $\langle \eta(t) \eta(t') \rangle = 2\hbar T \delta(t - t') = k_e(t, t')$

\Rightarrow What is P_e ?

$$* \int dt f(t) \delta(t - t_j) = f(t_j) = f_j = \sum_i f_i \delta_{ij} = \sum_i dt f_i \frac{\delta_{ij}}{dt} \Rightarrow \delta(t_i - t_j) \simeq \frac{\delta_{ij}}{dt}$$

$$* \langle \eta(t_i) \eta(t_j) \rangle = 2\hbar T \frac{\delta_{ij}}{dt} \Rightarrow K_{ij} = 2\hbar T \frac{\delta_{ij}}{dt}$$

Eq (11) then leads to $\Gamma_{jh} = \frac{1}{2\hbar T} dt \delta_{jh}$

Then, Eq (10) $\Rightarrow P_e(t_i, t_j) = \frac{1}{2\hbar T} \frac{\delta_{jh}}{dt} \simeq \frac{\delta(t_i - t_j)}{2\hbar T}$

Indeed, we check that

$$\int dt k(t, t') P(t', t'') = \frac{2\hbar T}{2\hbar T} \int dt' \delta(t - t') \delta(t' - t'') = \delta(t - t'')$$

From there, we can build the noise probability distribution:

$$\Rightarrow P[\{\eta(t)\}] = \frac{1}{Z} \exp \left[-\frac{1}{4\hbar T} \int dt dt' \eta(t) \eta(t') \delta(t - t') \right]$$

$$\boxed{P[\{\eta(t)\}] = \frac{1}{Z} \exp \left[-\frac{1}{4\hbar T} \int dt \eta(t)^2 \right]} \quad \text{:-)}$$

Colored noise If $\langle \eta(t) \eta(t') \rangle = K(t - t')$

then $P[\{\eta(t)\}] = \frac{1}{Z} \exp \left[-\int dt dt' \eta(t) P(t - t') \eta(t') \right]$

when P is such that $\int dt' k(t - t') P(t' - t'') = \delta(t - t'')$

4) Probability of trajectories $\{x(t)\}$

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If we know $P[\{\eta(t)\}]$ and we know $x(t, \{\eta(s)\})$, can we get $P[\{x(t)\}]$? Yes, but this is painful...

Changing variable n old variables x_1, \dots, x_n to a new set of coordinates $y_i(x_1, \dots, x_n)$

Conservation of probability means that $P(x_1, \dots, x_n) dx_1 \dots dx_n = P(y_1, \dots, y_n) dy_1 \dots dy_n$

$$\Rightarrow P(y_1, \dots, y_n) = P(x_1, \dots, x_n) \cdot \underbrace{\left| \frac{dx_1 \dots dx_n}{dy_1 \dots dy_n} \right|}_{\text{Jacobian of the change of variable}}$$

Here $P[\{x(t)\}] = P[\{\eta(t)\}] \cdot \det J$, where $J = \left| \frac{\partial \eta(t)}{\partial x(t)} \right|$

Q: How do we give a meaning to J ?

Let's time-discretize the Langevin equation $\dot{x} = f(x) + \eta(t)$

x_0 fixed, $x_i = x(t_i)$, $t_i = i \Delta t$. x_1, \dots, x_n are N RVs. Then, we define

$\tilde{z}_i \equiv \int_{t_{i-1}}^{t_i} \eta(s) ds$ so that \tilde{z}_i leads from x_{i-1} to x_i :

$$x_{i+1} = x_i + \int_{t_i}^{t_{i+1}} f(x(s)) ds + \tilde{z}_{i+1} \Rightarrow \tilde{z}_1, \dots, \tilde{z}_n \text{ are } N \text{ GRVs.}$$

$$\Rightarrow \frac{\partial \tilde{z}_{i+1}}{\partial x_j} = \frac{\partial}{\partial x_j} \left[\underbrace{x_{i+1} - x_i}_{\text{easy}} - \underbrace{\int_{t_i}^{t_{i+1}} f(x(s)) ds}_{=?} \right]$$
$$= ? = f(x_i) \Delta t ?$$
$$= f(x_{i+1}) \Delta t ?$$
$$= f(x_i^\alpha) \Delta t \text{ with } x_i^\alpha = \alpha x_{i+1} + (1-\alpha)x_i ?$$

All appear equivalent to order Δt . Let's keep α arbitrary for now.

\Rightarrow the matrix $\frac{\partial \tilde{z}_{i+1}}{\partial x_j}$ is an upper triangular matrix

$$\Rightarrow \det = \prod_i \frac{\partial \tilde{z}_i}{\partial x_i} = \prod_i \left(1 - \alpha \frac{d}{dt} f'(x_i^\alpha) \right) \underset{dt \rightarrow 0}{\approx} \prod_i e^{-\alpha dt f'(x_i^\alpha)} \quad (7)$$

$$\approx e^{-\alpha \sum_i dt f'(x_{i+1}^\alpha)} \approx e^{-\alpha \int_0^t ds f'(x(s))}$$

$$P[\{x(t)\}] = \frac{1}{Z} e^{-\int dt \left[\frac{\dot{x}^2(t)}{4\hbar T} + \alpha f'(x(s)) \right]}$$

But we know that $\dot{x} = f(x) + \eta(t) \Rightarrow \eta(t) = \dot{x} - f(x)$

$$\Rightarrow P[\{x(t)\}] = \frac{1}{Z} e^{-\int dt \frac{(\dot{x} - f(x))^2}{4\hbar T} + \alpha f'(x(s))}$$

Comment: Causality makes us again choose $\alpha=0$. Then

$$P[\{x(t)\}] = \frac{1}{Z} e^{-\int dt \frac{(\dot{x} - f(x))^2}{4\hbar T}}$$

Then, we need to use Itô calculus to compute time-derivatives in the integral.

If we use $\alpha = \frac{1}{2}$, we use what is called Stratonovich time discretization. We can use standard calculus in the exponent, but the computation of averages is harder since \tilde{z}_{i+1} and x_{i+1} are now correlated $\Rightarrow \langle \eta(t) \eta(t) \rangle \neq 0$.

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