# Langevin equation

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Exercise 5.1.7. Consider the Itô process satisfying

$$dX_t = -\beta X_t \, dt + \alpha \, dB_t \,, \qquad X_0 = x_0 \tag{1}$$

for  $\alpha \in \mathbb{R}$  and  $\beta > 0$ . This equation is called the Langevin equation. Note that this equation can be written equivalently

$$X_t = x_0 + \alpha B_t - \beta \int_0^t X_s \, \mathrm{d}s \, .$$

Show that the solution of this equation reads

$$X_t = x_0 e^{-\beta t} + \alpha \int_0^t e^{-\beta(t-u)} \,\mathrm{d}B_u \,.$$

Consider a deterministic differential equation as follows:

$$x'(t) + \beta x(t) = f(t),$$

for some constant  $\beta$  and function f. We solve it by multiplying both sides by  $e^{\beta t}$  and get

$$e^{\beta t} x'(t) + \beta e^{\beta t} x(t) = f(t) e^{\beta t}$$
  

$$\Leftrightarrow \quad \frac{\mathrm{d}}{\mathrm{d}t} \left[ e^{\beta t} x \right](t) = f(t) e^{\beta t}$$
  

$$\Leftrightarrow \quad e^{\beta t} x(t) = \int f(t) e^{\beta t} \, \mathrm{d}t + C$$
  

$$\Leftrightarrow \quad x(t) = e^{-\beta t} \left[ \int f(t) e^{\beta t} \, \mathrm{d}t + C \right].$$

Taking inspiration from this, we try an ansatz  $X_t = e^{-\beta t} Z_t$  for some Itô process  $(Z_t)_{t \in [0,T]}$  such that  $Z_0 = x_0$ . Since we have

$$d \left[ e^{-\beta t} \right] = 0 dB_t - \beta e^{-\beta t} dt,$$
  
$$dZ_t = V_t dB_t + D_t dt,$$

**Lemma 5.1.9** $^1$  dictates that

$$\begin{split} \mathrm{d}X_t &= \mathrm{d}\left[e^{-\beta t}Z_t\right] = Z_t \mathrm{d}\left[e^{-\beta t}\right] + e^{-\beta t} \,\mathrm{d}Z_t + 0 \cdot V_t \,\mathrm{d}t \\ &= -\beta e^{-\beta t}Z_t \,\mathrm{d}t + e^{-\beta t} \,\mathrm{d}Z_t \\ &= -\beta X_t \,\mathrm{d}t + e^{-\beta t} \,\mathrm{d}Z_t \,. \end{split}$$

Comparing this with (1), we obtain  $Z_t$ :

$$e^{-\beta t} \, \mathrm{d}Z_t = \alpha \, \mathrm{d}B_t \quad \Leftrightarrow \quad \mathrm{d}Z_t = \alpha e^{\beta t} \, \mathrm{d}B_t \quad \Leftrightarrow \quad Z_t = Z_0 + \alpha \int_0^t e^{\beta u} \, \mathrm{d}B_u \,.$$

As a result, we obtain a solution of (1) by using the initial condition  $Z_0 = x_0$ :

$$X_t = e^{-\beta t} Z_t = x_0 e^{-\beta t} + \alpha \int_0^t e^{-\beta(t-u)} dB_u.$$

The process  $(X_t)_{t \in [0,T]}$  satisfying (1) is also called the Ornstein-Uhlenbeck process.

Now, we want to find the expectation value  $\mathbb{E}(X_t)$  and the autocovariance  $\text{Cov}(X_t, X_s)$  of this process. Observe that

$$\int_0^T e^{2\beta u} \, \mathrm{d}u = \left. \frac{e^{2\beta u}}{2\beta} \right|_{u=0}^{u=T} = \frac{e^{2\beta T} - 1}{2\beta} < \infty.$$

Since the process  $(e^{\beta u})_{u \in [0,T]}$  belongs to  $M^2([0,T])$ , we obtain the expectation value of  $X_t$  by using **Proposition 4.2.10**,

$$\mathbb{E}(X_t) = \mathbb{E}\left(x_0 e^{-\beta t}\right) + \alpha e^{-\beta t} \mathbb{E}\left(\int_0^t e^{\beta u} \,\mathrm{d}B_u\right) = x_0 e^{-\beta t} + 0 = x_0 e^{-\beta t}.$$

Now, before finding the autocovariance  $\text{Cov}(X_t, X_s)$ , we prove that increments of a martingale  $(M_t)_{t \in [0,T]}$  are uncorrelated [2, Exercise 5.4]. Consider any times  $t_1, t_2, t_3, t_4$  such that  $t_1 \leq t_2 \leq t_3 \leq t_4$ . Then, we have by using the martingale property,

$$\mathbb{E}(M_{t_4} - M_{t_3} \mid \mathcal{F}_{t_2}) = \mathbb{E}(M_{t_4} \mid \mathcal{F}_{t_2}) - \mathbb{E}(M_{t_3} \mid \mathcal{F}_{t_2}) = M_{t_2} - M_{t_2} = \mathbf{0}$$

Since  $\mathcal{F}_{t_1} \subset \mathcal{F}_{t_2}$  and  $M_{t_1}$  is  $\mathcal{F}_{t_1}$ -measurable,  $M_{t_1}$  is also  $\mathcal{F}_{t_2}$ -measurable. As a result  $M_{t_2} - M_{t_1}$  is  $\mathcal{F}_{t_2}$ -measurable and we have

$$\mathbb{E}\left[(M_{t_2} - M_{t_1})(M_{t_4} - M_{t_3})\right] = \mathbb{E}\left\{\mathbb{E}\left[(M_{t_2} - M_{t_1})(M_{t_4} - M_{t_3}) \mid \mathcal{F}_{t_2}\right]\right\} \\ = \mathbb{E}\left[(M_{t_2} - M_{t_1})\mathbb{E}\left(M_{t_4} - M_{t_3} \mid \mathcal{F}_{t_2}\right)\right] \qquad (\text{Proposition 3.1.3, 4.}) \\ = \mathbb{E}\left[(M_{t_2} - M_{t_1}) \cdot \mathbf{0}\right] = 0.$$

Note that  $(M_t)_{t \in [0,T]}$  defined by  $M_t = \int_0^t Y_u \, \mathrm{d}B_u$  is a martingale for any adapted stochastic process  $(Y_t)_{t \in [0,T]}$  belonging to  $M^2([0,T])$  (**Theorem 4.3.1**). Then, using **Proposition 4.2.10** and the

<sup>&</sup>lt;sup>1</sup>All the statement in bold are from the lecture notes [1].

above property of martingales, we have for any  $s \leq t$ ,

$$\mathbb{E}\left[\left(\int_0^t Y_u \,\mathrm{d}B_u\right)\left(\int_0^s Y_u \,\mathrm{d}B_u\right)\right] = \mathbb{E}\left[\left(\int_0^s Y_u \,\mathrm{d}B_u\right)^2\right] + \mathbb{E}\left[\left(\int_s^t Y_u \,\mathrm{d}B_u\right)\left(\int_0^s Y_u \,\mathrm{d}B_u\right)\right]$$
$$= \int_0^s \mathbb{E}(Y_u^2) \,\mathrm{d}u + \mathbb{E}\left[(M_t - M_s)(M_s - M_0)\right]$$
$$= \int_0^s \mathbb{E}(Y_u^2) \,\mathrm{d}u \,.$$

Now, coming back to the Ornstein-Uhlenbeck process  $(X_t)_{t \in [0,T]}$ , we have for any  $s \leq t$ ,

$$\begin{aligned} \operatorname{Cov}(X_t, X_s) &= \mathbb{E}\left[ (X_t - \mathbb{E}(X_t))(X_s - \mathbb{E}(X_s)) \right] \\ &= \mathbb{E}\left[ \left( \alpha \int_0^t e^{-\beta(t-u)} \, \mathrm{d}B_u \right) \left( \alpha \int_0^s e^{-\beta(s-u)} \, \mathrm{d}B_u \right) \right] \\ &= \alpha^2 e^{-\beta(t+s)} \mathbb{E}\left[ \left( \int_0^t e^{\beta u} \, \mathrm{d}B_u \right) \left( \int_0^s e^{\beta u} \, \mathrm{d}B_u \right) \right] \\ &= \alpha^2 e^{-\beta(t+s)} \int_0^s e^{2\beta u} \, \mathrm{d}u \\ &= \alpha^2 e^{-\beta(t+s)} \frac{e^{2\beta s} - 1}{2\beta} \\ &= \frac{\alpha^2}{2\beta} e^{-\beta(t-s)} \left( 1 - e^{-2\beta s} \right). \end{aligned}$$

Furthermore,  $\left(\int_{0}^{t} e^{\beta u} dB_{u}\right)_{t\in[0,T]}$  is a Gaussian process by **Theorem 4.3.4**. We know that if X is a Gaussian random variable, then aX + b is also a Gaussian random variable for any a, b with  $a \neq 0$ . So  $(X_{t})_{t\in[0,T]}$  is also a Gaussian process since  $X_{t} = x_{0}e^{-\beta t} + \alpha e^{-\beta t}\int_{0}^{t} e^{\beta u} dB_{u}$  for any  $t \in [0,T]$ .

If  $\alpha = \beta = 1$  and  $x_0 = 0$ , then we get  $\mathbb{E}(X_t) = 0$  and  $\operatorname{Cov}(X_t, X_s) = \frac{1}{2}e^{-(t-s)}(1-e^{-2s})$  for  $s \leq t$ , which is the Gaussian process given in **Example 2.2.6**.

## Digression: Langevin equation in physics

Originally, the Langevin equation was proposed as the equation of motion for a small particle in Brownian motion (see [3, Chapter 7]). Consider a particle of mass m undergoing Brownian motion in a fluid. The particle is assumed to be larger and heavier than the constituents of the fluid. In addition, the particle is subjected to a damping force proportional to the particle's velocity with the coefficient  $\gamma$ , and a random force  $\xi(t)$  due to the thermal agitation of molecules composing the fluid. The equation of motion according to Newton's 2<sup>nd</sup> law is

$$m\frac{\mathrm{d}v(t)}{\mathrm{d}t} = -\gamma v(t) + \xi(t),\tag{2}$$

which we write in one dimension for simplicity. The random force  $\xi(t)$  is also called *white noise*, which is assumed to be a Gaussian process with stationary (invariant under time shifts) and Markov

properties.  $\xi(t)$  also has the following averaged properties

$$\langle \xi(t) \rangle = 0, \qquad \langle \xi(t)\xi(t') \rangle = g\delta(t-t'), \tag{3}$$

where  $\delta$  is the delta Dirac function and g is the measure of the noise's strength. In the notation of this course, the equations (2) and (3) can be rewritten as

$$m \,\mathrm{d}V_t = -\gamma V_t \,\mathrm{d}t + \Xi_t \,\mathrm{d}t\,,\tag{4}$$

$$\mathbb{E}(\Xi_t) = 0, \qquad \mathbb{E}(\Xi_t \Xi_{t'}) = g\delta(t - t'), \tag{5}$$

where we replace v and  $\xi$  with their capital counterparts. Comparing (4) with (1), we get  $\beta = \gamma/m$  for the first term and formally for the second term,

$$\Xi_t \ `` = " \ m\alpha \frac{\mathrm{d}B_t}{\mathrm{d}t}.$$

Since we know that the Brownian motion  $(B_t)$  is nowhere differentiable, this expression of  $\Xi_t$  is not well-defined. However, the version (4) of the Langevin equation is widely used in physics. Therefore, a heuristic explanation (see [4]) can be made to justify the usage of  $\Xi_t$  (or  $\xi(t)$ ) and its properties (5). From the definition of the Brownian motion, we have for any  $t, \delta t > 0$ ,

$$(B_{t+\delta t} - B_t) \sim N(0, \delta t) \quad \Rightarrow \quad \Xi_t^{\delta t} := m\alpha \frac{B_{t+\delta t} - B_t}{\delta t} \sim N\left(0, \frac{m^2 \alpha^2}{\delta t}\right).$$

It is clear that  $\mathbb{E}\left(\Xi_t^{\delta t}\right) = 0$  for any  $t, \delta t > 0$ . Since the Brownian motion  $B_t$  is also a martingale, we can use the property that the increments are uncorrelated to compute the autocovariance  $\mathbb{E}(\Xi_t^{\delta t} \Xi_{t'}^{\delta t})$ . Fix the value of t. For any t' such that  $t' + \delta t < t$  or  $t + \delta t < t'$ , we have

$$\mathbb{E}\left[(B_{t+\delta t} - B_t)(B_{t'+\delta t} - B_{t'})\right] = 0 \quad \Rightarrow \quad \mathbb{E}(\Xi_t^{\delta t} \Xi_{t'}^{\delta t}) = 0$$

Now, consider t' such that  $t' \leq t \leq t' + \delta t$ . Then, we have  $t' \leq t \leq t' + \delta t \leq t + \delta t$  and

$$\mathbb{E}\left[(B_{t+\delta t} - B_t)(B_{t'+\delta t} - B_{t'})\right] = \mathbb{E}\left[(B_{t+\delta t} - B_{t'+\delta t} + B_{t'+\delta t} - B_t)(B_{t'+\delta t} - B_t + B_t - B_{t'})\right] \\ = \mathbb{E}\left[(B_{t+\delta t} - B_{t'+\delta t})(B_{t'+\delta t} - B_t)\right] + \mathbb{E}\left[(B_{t'+\delta t} - B_t)^2\right] \\ + \mathbb{E}\left[(B_{t+\delta t} - B_{t'+\delta t})(B_t - B_{t'})\right] + \mathbb{E}\left[(B_{t'+\delta t} - B_t)(B_t - B_{t'})\right] \\ = 0 + (t' + \delta t - t) + 0 + 0 \\ = \delta t - (t - t'),$$

where we use the fact that  $(B_{t'+\delta t} - B_t) \sim N(0, t' + \delta t - t)$ . For the case  $t \leq t' \leq t + \delta t$ , since we also have  $t \leq t' \leq t + \delta t \leq t' + \delta t$ , we can use the above result and interchange t and t':

$$\mathbb{E}\left[(B_{t+\delta t} - B_t)(B_{t'+\delta t} - B_{t'})\right] = \delta t + (t - t').$$

As a result, we get the autocovariance depending only on (t - t'),

$$\mathbb{E}(\Xi_t^{\delta t} \Xi_{t'}^{\delta t}) = \begin{cases} m^2 \alpha^2 \frac{\delta t - |t - t'|}{\delta t^2}, & |t - t'| \le \delta t, \\ 0, & |t - t'| > \delta t. \end{cases}$$

In addition, we have

$$\begin{split} \int_{t-\delta t}^{t+\delta t} (\delta t - |t-t'|) \, \mathrm{d}t' &= \int_{t-\delta t}^{t} (\delta t - t + t') \, \mathrm{d}t' + \int_{t}^{t+\delta t} (\delta t + t - t') \, \mathrm{d}t' \\ &= \left(\delta t^2 - t\delta t + \frac{2t\delta t - \delta t^2}{2}\right) + \left(\delta t^2 + t\delta t - \frac{2t\delta t + \delta t^2}{2}\right) \\ &= \delta t^2. \end{split}$$

Therefore, we get

$$\int_{-\infty}^{\infty} \mathbb{E}(\Xi_t^{\delta t} \Xi_{t'}^{\delta t}) \, \mathrm{d}t' = m^2 \alpha^2 \frac{\delta t^2}{\delta t^2} = m^2 \alpha^2.$$

As  $\delta t$  approaches 0, the region, where  $\mathbb{E}(\Xi_t^{\delta t}\Xi_{t'}^{\delta t})$  has nonzero values, shrinks while  $\mathbb{E}(\Xi_t^{\delta t}\Xi_{t'}^{\delta t}) = m^2 \alpha^2 / \delta t \to \infty$  for t = t'. Meanwhile, the integral of  $\mathbb{E}(\Xi_t^{\delta t}\Xi_{t'}^{\delta t})$  with respect to t or t' on  $\mathbb{R}$  remains a constant. Hence,  $\mathbb{E}(\Xi_t^{\delta t}\Xi_{t'}^{\delta t})$  formally converges to  $m^2 \alpha^2 \delta(t - t')$  as  $\delta t$  goes to 0. Comparing with (5), we get the equality  $\alpha^2 = g/m^2$ . Consequently, we can define formally

$$\Xi_t := \lim_{\delta t \to 0} \Xi_t^{\delta t} = \sqrt{g} \lim_{\delta t \to 0} \frac{B_{t+\delta t} - B_t}{\delta t} \quad \text{``} = \text{''} \quad \sqrt{g} \frac{\mathrm{d}B_t}{\mathrm{d}t}$$

and get all the properties required. In hindsight, we can rewrite (4) in a more rigorous form:

$$m \,\mathrm{d}V_t = -\gamma V_t \,\mathrm{d}t + \sqrt{g} \,\mathrm{d}B_t \,. \tag{6}$$

Even though (4) is mostly used in physics, it is a mnemonic for (6), which is more mathematically precise.

### References

- [1] Serge Richard, Lecture Notes: Introduction to Stochastic Calculus (Fall 2023)
- [2] J.-L. Arguin, A first course in stochastic calculus
- [3] L. E. Reichl, A modern course in statistical physics
- [4] Gillespie, Daniel T. "The Mathematics of Brownian Motion and Johnson Noise." American Journal of Physics 64, no. 3 (March 1, 1996): 225–40. https://doi.org/10.1119/1.18210.