

Notes on:

April 10, 2023

Symbol	Definition

1 Brownian Motion

Let $B_t \in (-\infty, \infty)$ be an ordinary Brownian motion. This has the explicit exact solution as a Gaussian of variance t from the initial condition:

$$\begin{aligned} B_t &\stackrel{d}{=} \mathcal{N}(B_0, t) \\ \mathbf{E}[B_t] &= B_0 \\ \mathbf{Var}[B_t] &= t \end{aligned}$$

(and we can also calculate sample paths, or the joint distribution for any collection of times t_1, \dots, t_n etc for B_t)

2 Ornstein-Unlenbeck Process with parameter θ

Define the OU process $O_t \in (-\infty, \infty)$ with a parameter θ by the SDE:

$$dO_t = -\theta dt + dB_t$$

This has the explicit exact solution

$$\begin{aligned} O_t &\stackrel{d}{=} \mathcal{N}\left(O_0 e^{-\theta t}, \frac{1}{2\theta} (1 - e^{-2\theta t})\right) \\ \mathbf{E}[O_t] &= O_0 e^{-\theta t} \\ \mathbf{Var}[O_t] &= \frac{1}{2\theta} (1 - e^{-2\theta t}) \end{aligned}$$

(and we can also calculate sample paths, or the joint distribution for any collection of times t_1, \dots, t_n etc for O_t)

Note that in the limit $t \rightarrow \infty$, the OU process approaches the steady state distribution

$$\lim_{t \rightarrow \infty} O_t \stackrel{d}{=} \mathcal{N}\left(0, \frac{1}{2\theta}\right)$$

So by tuning θ , we can choose how narrow or how wide the steady state distribution is

3 Sigmoid-OU

See a plot of how this thing evolves here <https://www.desmos.com/calculator/aihfuiprtw>

Define the process $S_t \in (0, 1)$ by applying the sigmoid function to O_t . i.e. with $\sigma(x) = \frac{e^x}{1+e^x} \in (0, 1)$

$$S_t = \sigma(O_t)$$

By Ito's lemma, the SDE for S_t is:

$$\begin{aligned} dS_t &= \sigma'(O_t)dO_t + \frac{1}{2}\sigma''(O_t)(dO_t)^2 \\ (\text{where we have used } dB_t^2 &= dt) = \sigma'(O_t)(-\theta O_t dt + dB_t) + \frac{1}{2}\sigma''(O_t)dt \\ &= \left(-\theta O_t \sigma'(O_t) + \frac{1}{2}\sigma''(O_t)\right)dt + \sigma'(O_t)dB_t \end{aligned}$$

This can be simplified by using $\sigma'(x) = \sigma(x)(1 - \sigma(x))$ and $\sigma''(x) = \sigma(x)(1 - \sigma(x))(1 - 2\sigma(x))$ to see that:

$$dS_t = \left(-\theta \sigma^{-1}(S_t)S_t(1 - S_t) + \frac{1}{2}S_t(1 - S_t)(1 - 2S_t)\right)dt + S_t(1 - S_t)dB_t$$

where $\sigma^{-1}(x) = \ln(\frac{x}{1-x})$ is the logit function.

Note also that we have the exact solution for S_t at any time t by pushing forward the exact solution of O_t , namely:

$$S_t \sim \sigma \left[\mathcal{N} \left(O_0 e^{-\theta t}, \frac{1}{2\theta} (1 - e^{-2\theta t}) \right) \right]$$

Note that in the limit $t \rightarrow \infty$, S_t will settle to a distribution which is centered around $\frac{1}{2}$. This can be seen by using the Taylor series expansion for small x , that

$$\begin{aligned} \sigma(x) &\approx \sigma(0) + \sigma'(0)x + \frac{1}{2}\sigma''(0)x^2 + \frac{1}{6}\sigma^{(3)}(0)x^3 + \frac{1}{24}\sigma^{(4)}(0)x^4 + O(x^5) \\ &= \frac{1}{2} + \frac{1}{4}x + 0 + \frac{1}{6 \cdot 8}x^3 + 0 + O(x^5) \end{aligned}$$

And so:

$$\begin{aligned} \lim_{t \rightarrow \infty} S_t &\sim \sigma \left[\mathcal{N} \left(0, \frac{1}{2\theta} \right) \right] \\ &= \sigma \left[\frac{1}{\sqrt{2\theta}} Z \right] \\ &\approx \frac{1}{2} + \frac{1}{4\sqrt{2\theta}} Z + \frac{1}{48(2\theta)^{3/2}} Z^3 + \dots \end{aligned}$$

4 Notes on the Sigmoid-Gaussian distribution

where $G \sim \mathcal{N}(\mu, v)$, $G = \mu + \sqrt{v}Z$, $Z \sim \mathcal{N}(0, 1)$ be a Gaussian of mean μ and variance v . Lets examine the law of $\sigma(Z)$. The CDF is:

$$\begin{aligned} CDF(x) &= \mathbf{P}(\sigma[G] \leq x) = \mathbf{P}\left(Z \leq \frac{\sigma^{-1}(x) - \mu}{\sqrt{v}}\right) \\ &= \frac{1}{2} + \frac{1}{2} \text{erf}\left(\frac{\sigma^{-1}(x) - \mu}{\sqrt{2v}}\right) \end{aligned}$$

And the pdf is obtained by taking the derivative:

$$\begin{aligned} PDF(x) &= CDF(x)' \\ &= \rho\left(Z = \frac{\sigma^{-1}(x) - \mu}{\sqrt{v}}\right) \frac{1}{\sqrt{v}} (\sigma^{-1}(x))' \\ &= \frac{1}{\sqrt{2\pi v} x(1-x)} \exp\left(-\frac{(\sigma^{-1}(x) - \mu)^2}{2v}\right) \end{aligned}$$

where we used $\sigma^{-1}(x) = \ln\left(\frac{x}{1-x}\right) = \ln(x) - \ln(1-x)$ so its derivative is $[\sigma^{-1}(x)]' = \frac{1}{x} + \frac{1}{1-x} = \frac{1}{x(1-x)}$
see <https://www.desmos.com/calculator/aihfujujprtw> for plotting this thing.