

**Exercise 3.** We want to study discretizations of the ODE with noise (also called SDE) for  $X_t \in \mathbb{R}$

$$\frac{d}{dt}X_t = -X_t + \sqrt{2}\frac{dB_t}{dt}.$$

A straightforward generalization of the Euler method to the stochastic case is the so-called Euler-Maruyama method. It is the same as the Euler-Method, just that the noise needs to be multiplied by  $\sqrt{dt}$  instead of  $dt$ . The discretization of the above would be

$$x_{n+1} = x_n - \delta t x_n + \sqrt{2\delta t} \xi_n.$$

$x_n$  is an approximation of  $X_{n\delta t}$ . Assume  $x_0$  is set to  $x_0 = 1$ .

Define  $\Xi_i \sim N(0,1)$  for  $i = 0, 1, \dots, n, \dots$

We assume that the  $\xi_i$ 's are realisations of the  $\Xi_i$  RVs.

(i) What is the distribution of  $x_1$  and  $x_2$ ?

$$x_1 = x_0 - \delta t x_0 + \sqrt{2\delta t} \xi_0 \quad \text{with } \xi_0 \text{ being sampled from } \Xi_0 \sim N(0,1) \text{ and } x_0 = 1$$

$$x_1 = 1 - \delta t + \sqrt{2\delta t} \xi_0$$

Therefore, we can see this as a simple linear transformation, i.e. we know the pdf of  $\pi_{x_1}$  belongs to a normal distribution. We simply have to find the mean and variance of  $x_1$ .

$$\bar{x}_1 = \mathbb{E}[\sqrt{2\delta t} \xi_0 + 1 - \delta t] = \sqrt{2\delta t} \underbrace{\mathbb{E}[\xi_0]}_{=0} + 1 - \delta t = 1 - \delta t$$

$$\sigma_1^2 = \text{Var}(\sqrt{2\delta t} \xi_0 + 1 - \delta t) = 2\delta t \text{Var}(\xi_0) = 2\delta t$$

$$\rightarrow \pi_{x_1}(x) = \mathcal{N}(x; \bar{x}_1, \sigma_1^2) \quad \text{with } \bar{x}_1 = 1 - \delta t, \sigma_1^2 = 2\delta t$$

$$x_2 = x_1 - \delta t x_1 + \sqrt{2\delta t} \xi_1$$

This can be seen as the sum of two normal distributions. Therefore, also the pdf of  $\pi_{x_2}$  belongs to a normal distribution.

$$\bar{x}_2 = \mathbb{E}[x_1 - \delta t x_1 + \sqrt{2\delta t} \xi_1] = \mathbb{E}[x_1] - \delta t \mathbb{E}[x_1] + \sqrt{2\delta t} \mathbb{E}[\xi_1]$$

$\downarrow$   
 $x_1$  and  $\xi_1$  are independent

$$\begin{aligned} \sigma_2^2 &= \text{Var}((1-\delta t)x_1 + \sqrt{2\delta t}\xi_1) = (1-\delta t)^2 \text{Var}(x_1) + 2\delta t \text{Var}(\xi_1) \\ &= (1-\delta t)^2 2\delta t + 2\delta t \\ &= 2\delta t ((1-\delta t)^2 + 1) \\ &= 2\delta t (\delta t^2 - 2\delta t + 2) = 2(\delta t)^3 - 4(\delta t)^2 + 4\delta t \end{aligned}$$

$$\rightarrow \pi_{x_2}(x) = \mathcal{N}(x; \bar{x}_2, \sigma_2^2) \quad \text{with } \bar{x}_2 = (1-\delta t)^2, \sigma_2^2 = 2\delta t ((1-\delta t)^2 + 1)$$