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# **SDS AND GENERATORS**

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Motivation

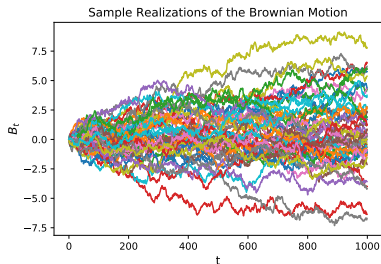
SDE Theory

The Koopman Generator

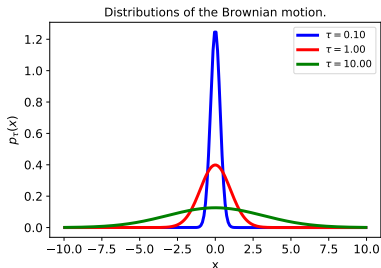
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# Brownian Motion Revisited

Brownian motion with transition kernel  $p_\tau(x, \cdot) \sim \mathcal{N}(x, \sqrt{\tau})$ :



Paths of the Brownian motion started at  $X_0 = 0$ .



Distributions at times  $\tau \in \{0.1, 1.0, 10.0\}$ .

# Brownian Motion

## Definition

A stochastic process  $B_t \in \mathbb{R}$  is a *Brownian motion* started at  $a \in \mathbb{R}$  if

- (i)  $B_0 = a$  almost surely.
- (ii) The paths  $B_t$ ,  $t \geq 0$  are almost surely continuous.
- (iii) The process possesses independent increments: For all  $t \geq s \geq 0$ ,  $B_t - B_s$  is independent of  $B_s$ , and the distribution of  $B_t - B_s$  is a normal distribution with mean zero and spread  $\sqrt{t - s}$ .

A Brownian Motion in  $\mathbb{R}^d$  is just a vector of  $d$  independent one-dim. Brownian motions.

## Motivation for SDEs

Consider a deterministic ODE  $\dot{X}_t = b(x_t)$ :

$$(X_{t+dt} - X_t) = dX_t \approx b(X_t)dt.$$

Let us add some noise by means of an increment of the Brownian motion:

$$\begin{aligned}(X_{t+dt} - X_t) &\approx b(X_t)dt + \sigma(X_t)(B_{t+dt} - B_t) \\ &= b(X_t)dt + \sigma(X_t)dB_t,\end{aligned}$$

where  $\sigma(\cdot)$  is a matrix field. Brownian Motion is used to generate normally distributed noise.



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## Formal Definition

The above reasoning can be made precise in integral form:  $X_t$  is the solution of an *SDE* if

$$X_t = X_0 + \int_0^t b(X_s) \, ds + \int_0^t \sigma(X_s) \, dB_s.$$

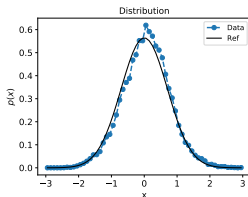
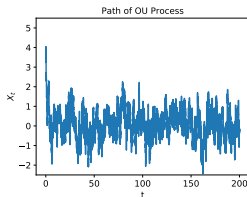
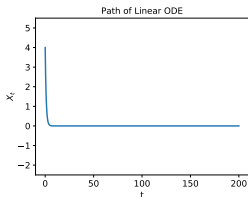
- The second integral is the *Ito stochastic integral*, which can be defined similarly to a Riemann-Stieltjes Integral.
- Given typical Lipschitz-type conditions, local existence and uniqueness can be shown.
- $b$  is called the *drift* field, and  $\sigma$  is the *diffusion* field.





# Examples

1. Brownian Motion itself: just set  $b \equiv 0, \sigma \equiv \text{Id}$ .
2. Ornstein-Uhlenbeck Process on the real line: set  $b(x) = -x$ ,  
 $\sigma = \sqrt{2\beta^{-1}}\text{Id}$ :



Stationary measure is  $\mu \sim \mathcal{N}(0, \sqrt{\beta})$ .

# Examples

- More generally, consider the *overdamped Langevin dynamics*

$$dX_t = -\nabla V(X_t)dt + \sqrt{2\beta^{-1}}dB_t.$$

The scalar function  $V$  is called *potential*. The invariant measure is  $\mu \sim \exp(-\beta V(x))$ , called the *Boltzmann distribution*. In physics,  $\beta$  is related to temperature via  $\beta^{-1} = k_B T$ .

# How to Simulate an SDE

We can simply adapt the Euler Scheme to the SDE world:

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## Algorithm 1 Euler-Maruyama Scheme

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1: procedure EULER-MARUYAMA( $x_0, \Delta_t, m$ )  
2:   for  $k = 0, \dots, m - 1$  do  
3:      $x_{k+1} = x_k + b(x_k)\Delta_t + \sigma(x_k)\mathcal{N}^d(0, \sqrt{\Delta_t})$ .  
4:   end for  
5: end procedure
```

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# Ito's Formula

The chain rule for SDEs: Ito's Formula

## Theorem (Ito's Lemma)

Let  $X_t \in \mathbb{R}^d$  solve the stochastic differential equation  $dX_t = b(X_t)dt + \sigma(X_t)dB_t$ , and let  $f \in C^2(\mathbb{R}^d)$ . Then  $Y_t := f(X_t)$  solves the SDE

$$dY_t = \left[ \nabla f^T(X_t)b(X_t) + \frac{1}{2} \nabla^2 f(X_t) : a(X_t) \right] dt + \nabla f^T(X_t)\sigma(X_t)dB_t,$$

where  $\nabla f \in \mathbb{R}^d$  is the gradient of  $f$ ,  $\nabla^2 f \in \mathbb{R}^{d \times d}$  is the Hessian matrix,  $a := \sigma\sigma^T$  is the covariance matrix of the diffusion, and the colon denotes the Frobenius inner product between matrices:  $A : B = \sum_{i,j} A_{ij}B_{ij}$ .



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# Semigroup

From the Chapman-Kolmogorov equation, we know that the Koopman operators form a semigroup:

## Definition

A family of bounded linear operators  $\mathcal{T}^\tau$ ,  $\tau \geq 0$  on a Banach space  $X$  is called a **strongly continuous semigroup** if:

- (i)  $\mathcal{T}^0 = \text{Id}$ .
- (ii)  $\mathcal{T}^{\tau_1 + \tau_2} = \mathcal{T}^{\tau_1} \mathcal{T}^{\tau_2}$  for all  $0 \leq \tau_1 \leq \tau_2$ .
- (iii)  $\lim_{\tau \rightarrow 0} \mathcal{T}^\tau x = x$  for all  $x \in X$ .

# The Generator

## Definition

Consider the strongly continuous semigroup of Koopman operators  $\mathcal{K}^\tau$  on  $L^2_\mu(\mathbb{X})$ . The generator  $\mathcal{L}$  is a linear operator acting on a function  $f$  by

$$\mathcal{L}f := \lim_{\tau \rightarrow 0} \frac{1}{\tau} (\mathcal{K}^\tau - \text{Id})f,$$

whenever this limit exists. The domain of the generator, that is the set of all  $f$  where the above limit exists, is denoted  $\mathcal{D}(\mathcal{L})$ .

# Generator and Time Evolution

## Theorem

*The generator  $\mathcal{L}$  is defined on a dense subspace  $\mathcal{D}(\mathcal{L})$ . Moreover, we have the differential equation*

$$\frac{d}{d\tau} \mathcal{K}^\tau f = \mathcal{L} \mathcal{K}^\tau f = \mathcal{K}^\tau \mathcal{L} f, \quad f \in \mathcal{D}(\mathcal{L}).$$



# The Generator of an SDE

## Proposition

*Let  $f \in C_0^\infty(\mathbb{R}^d)$  and  $X_t$  solve an SDE with drift  $b$  and diffusion  $\sigma$ . Then  $f \in \mathcal{D}(\mathcal{L})$  and the action of the generator is given by*

$$\mathcal{L}f(x) = b(x) \cdot \nabla f(x) + \frac{1}{2}a(x) : \nabla^2 f(x).$$

## Proof

### Proof.

$$\begin{aligned}\mathcal{L}f(x) &= \lim_{\tau \rightarrow 0} \frac{1}{\tau} \mathbb{E}^x(f(X_\tau) - f(X_0)) \\&= \lim_{\tau \rightarrow 0} \frac{1}{\tau} \mathbb{E}^x \left[ \int_0^\tau \nabla f^T(X_s) b(X_s) + \frac{1}{2} a(X_s) : \nabla^2 f(X_s) \, ds \right] \\&\quad + \mathbb{E}^x \left[ \int_0^\tau \nabla f^T(X_s) \sigma(X_s) \, dB_s \right] \\&= \lim_{\tau \rightarrow 0} \frac{1}{\tau} \mathbb{E}^x \left[ \int_0^\tau \nabla f^T(X_s) b(X_s) + \frac{1}{2} a(X_s) : \nabla^2 f(X_s) \, ds \right] \\&= \nabla f^T(x) b(x) + \frac{1}{2} a(x) : \nabla^2 f(x).\end{aligned}$$

# More about Generators

## Corollary

Let  $f \in C_0^\infty(\mathbb{R}^d)$  and consider the function  $v(\tau, x) = \mathbb{E}^x[f(X_\tau)]$ , with  $X_\tau$  solution of an SDE. Then  $v$  solves the PDE

$$\frac{\partial}{\partial \tau} v(\tau, x) = \mathcal{L}v(\tau, x) = b(x) \cdot \nabla_x v(\tau, x) + \frac{1}{2} a(x) : \nabla_x^2 v(\tau, x).$$

# References

Oksendal, *Stochastic Differential Equations* (2013)

Pazy, *Semigroups of linear operators and applications to partial differential equations* (2012)

Bakry, Gentil, Ledoux, *Analysis and Geometry of Markov Diffusion Operators* (2014)

