

## 2. Stochastic processes

**Stochastic process**: collection of random variables  $X(t)$

↳ **Markov process**:  $P(X(t_i) | X(t_{i-1}), X(t_{i-2}), \dots) = P(X(t_i) | X(t_{i-1}))$

Goal: Find probability that  $X$  takes a value  $x$  at time  $t$ ,  $P(x, t)$

1) Consider **specific realisations** of  $X(t)$  } Pool realisations of  
 $\dot{x} = f(x, t) + \xi(t)$  }  $X(t)$  to obtain  $P(x, t)$

2) Directly consider time evolution of **probability density**  $P(x, t)$

$$\frac{d}{dt} P(x, t) = F(P, x, t)$$

## 2.1 Langevin approach (stochastic differential equations)

General form of **stochastic differential equation**:

$$\dot{x} = a(x,t) + b(x,t) \xi(t)$$

deterministic  
part

stochastic  
part

Two classes of SDEs: 1) additive noise:  $b = \text{const}$

2) multiplicative noise:  $b = b(x)$

In differential form:  $dx = a(x,t) dt + b(x,t) dW(t)$

$$\begin{aligned} \hookrightarrow dW(t) &= \xi(t) dt \\ W(t) &= \int_0^t \xi(t) dt \end{aligned}$$

Formal solution:

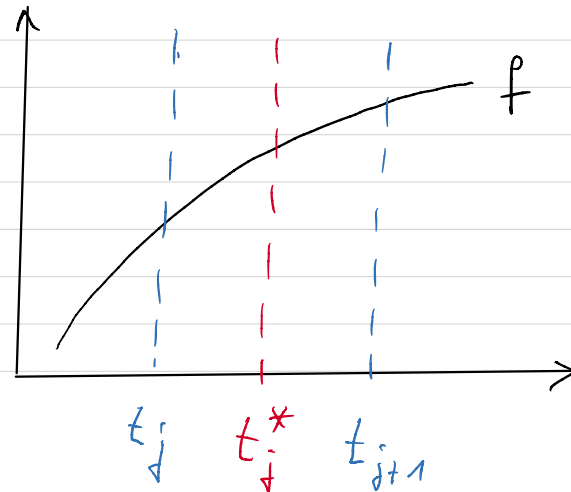
$$x(t) = x(0) + \int_{t_0}^t a(x,s) ds + \int_{t_0}^t b(x,s) dW_s$$

What is the second integral?

Partition  $\Pi_n$  of time domain into  $n$  intervals:

$$\int_{t_0}^t f(s) dW_s = \lim_{|\Pi_n| \rightarrow 0} \sum_{j=1}^n f(t_j^*) (W_{t_{j+1}} - W_{t_j})$$

Stochastic integral is defined as **weighted sum**, where the weights are random variables.



The choice of  $t_j^*$  is important!

Example 1: left point  $t_j^* = t_j$

$$\begin{aligned} & \left\langle \sum_{j=1}^n W_{t_j} (W_{t_{j+1}} - W_{t_j}) \right\rangle \\ &= \sum_{j=1}^n \langle W_{t_j} (W_{t_{j+1}} - W_{t_j}) \rangle \\ &= \sum_{j=1}^n \langle W_{t_j} \rangle \langle W_{t_{j+1}} - W_{t_j} \rangle \\ &= 0 \end{aligned}$$

Example 2:  $t_j^* = t_{j+1}$   $f(t) = W_t$

$$\begin{aligned} & \left\langle \sum_{j=1}^n W_{t_{j+1}} (W_{t_{j+1}} - W_{t_j}) \right\rangle \\ &= \sum_{j=1}^n \langle (W_{t_{j+1}} - W_{t_j})^2 \rangle \\ &= \sum_{j=1}^n (t_{j+1} - t_j) = t - t_0 \end{aligned}$$

Two common choices are:

1) Ito integral:  $t_j^* = t_j$

2) Stratonovich integral:  $t_j^* = (t_{j+1} - t_j)/2 + t_j$

this lecture

Chain rule in stochastic calculus:

$$df(x(t)) \stackrel{\text{Taylor}}{=} \frac{\partial f}{\partial t} dt + \frac{\partial f}{\partial x} dx + \frac{1}{2} \frac{\partial^2 f}{\partial x^2} dx^2 + \dots$$

Substitute

$$\text{LV for } dx \quad = \frac{\partial f}{\partial t} dt + \frac{\partial f}{\partial x} (a dt + b dW) + \frac{1}{2} \frac{\partial^2 f}{\partial x^2} (a^2 dt^2 + 2ab dt dW + b^2 dW^2) + \dots$$

Use  $dx(t) \approx \sqrt{dt}$   
(SD of Brownian motion)

$$= \left( \frac{\partial f}{\partial t} + a \frac{\partial f}{\partial x} + \frac{b^2}{2} \frac{\partial^2 f}{\partial x^2} \right) dt + b \frac{\partial f}{\partial x} dW + \dots$$

Ito's formula

## Example (Langevin)

Consider the unhindered spread of an epidemic.



Deterministically, the concentration of infected people follows  $\dot{x} = a x$

The rate of spreading itself is subject to fluctuations,  $a = \mu + \sigma \xi(t)$

Stochastic dynamics in differential form:

$$dx = \mu x dt + \sigma x dW(t)$$

Divide by  $x$ ,  $\frac{dx}{x} = \mu dt + \sigma dW(t)$

Apply Ito's formula with  $f(x) = \log(x)$ ,

$$dy = d(\log(x)) = \left[ \mu - \frac{\sigma^2}{2} \right] dt + \sigma dW$$

$$\frac{dx}{x} - \frac{\sigma^2}{2} dt$$

$$\Rightarrow \frac{dx}{x} = d(\log x) + \frac{1}{2} \sigma^2 dt$$

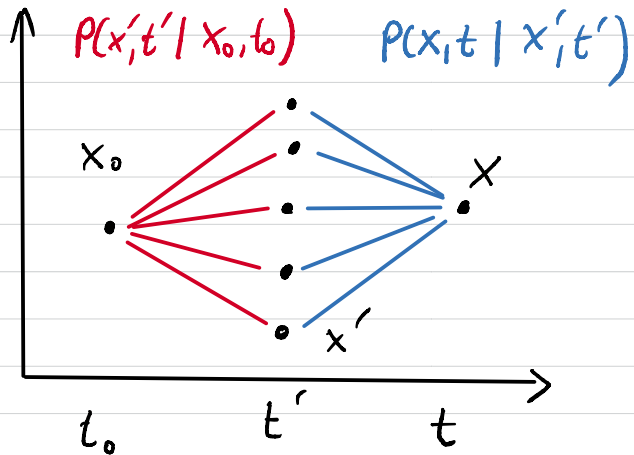
Integrating, and using that  $\int_0^t \frac{dx}{x} = -\mu t - \sigma W(t)$ , we get

$$\log \frac{x}{x_0} = \int_0^t \frac{dx}{x} - \frac{1}{2} \sigma^2 t = \mu t + \sigma W(t) - \frac{1}{2} \sigma^2 t$$

$$\Rightarrow X(t) = x_0 e^{(\mu - \frac{1}{2} \sigma^2) t + \sigma W_t}$$

### 3.2. Einstein approach

Probability of ending up in  $x$  at time  $t$  when starting at  $x_0$  at  $t_0$ :  $P(x, t | x_0, t_0)$



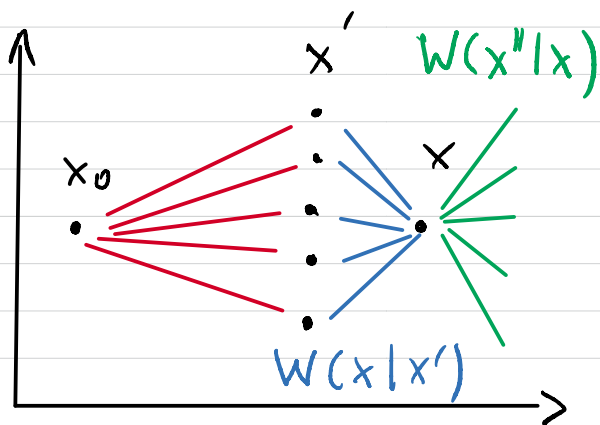
$P(x, t | x_0, t_0)$  is obtained by **summing up contributions of different paths** leading from  $x_0$  to  $x$ :

$$P(x, t | x_0, t_0) = \int p(x, t | x', t') p(x', t' | x_0, t_0) dx'$$

Chapman-Kolmogorov equation

Goal: what is the time evolution of  $p(x, t)$ ,  $\frac{d}{dt} p(x, t) = ?$

gain of probability in  $x$  is counteracted by loss to other states.



$$\frac{d}{dt} p(x, t) = \int W(x | x') p(x', t) dx' + \int W(x'' | x) p(x, t) dx''$$

Master  
equation

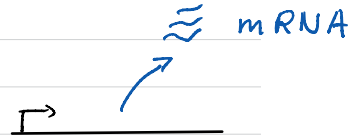
flux into state  $x$

flux out of state  $x$



## Example (Master equation)

Gene expression: Genes are read out by special molecules and **transcribed into mRNA** molecules. These are then translated to proteins which perform biological functions.



What is the probability that  $m$  mRNA molecules are produced in a time interval  $t$ ?

$$\frac{d}{dt} p(m, t) = \lambda [p(m-1, t) - p(m, t)]$$

Introduce a **characteristic function**  $G(s, t) = \langle e^{i s n} \rangle = \sum_n P(m, t) e^{i s n}$

Substituting into Master equation,  $\partial_t G(s, t) = \lambda [e^{i s} - 1] G(s, t)$

$$\Rightarrow G(s, t) = e^{\lambda t [e^{i s} - 1]} \Rightarrow P(m, t) = \frac{(\lambda t)^m}{m!} e^{-\lambda t} \quad \text{Poisson distribution}$$

## Fokker Planck equation

Taylor expand around  $x$  in  $\Delta x = x - x'$ :

$$\partial_t P(x,t) = \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \partial_x^n \alpha_n(x) P(x,t)$$

Kramers -  
Moyal expansion

with moments of the transition probabilities

$$\alpha_n(x) = \int d\Delta x W(x + \Delta x | x) \Delta x^n.$$

Truncate at second order

$$\partial_t P(x,t) = -\partial_x \alpha_1(x) p(x,t) + \frac{1}{2} \partial_x^2 \alpha_2(x) p(x,t)$$

Fokker -  
Planck  
equation

drift term:  $\partial_t \langle x \rangle = \langle \alpha_1 \rangle$

diffusion term

## Example (Fokker-Planck equation)

Fokker-Planck equation for the Poisson process.

Introduce rescaled variable  $x = \frac{m}{N}$  with  $p(x,t) dx = p(m,t) dm$ .

Fokker-Planck approximation to the Master equation:

$$\partial_t p(x,t) = -\frac{\lambda}{N} \partial_x p(x,t) + \frac{\lambda}{2N^2} \partial_x^2 p(x,t)$$

$$\Rightarrow p(x,t) = \frac{N}{\sqrt{2\pi\lambda t}} e^{-\frac{1}{2\lambda t} (Nx - t\lambda)^2}$$

FP and exact solution deviate in the tails.

