




## Module 3: Branching process, Application of Markov chains, Markov Processes with discrete and continuous state space

### Lecture 13: Differential Equation for Weiner Process

The Lecture Contains:

-  Kolmogorov Equations
-  Ornstein Uhlenbeck Process
-  Note

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#### Kolmogorov Equations

As usual let us again consider  $\{X(t), t \geq 0\}$  as the **Markov process** in continuous time and continuous state set up such that the following assumptions are considered to be true:

- $P\{|X(t) - X(s)| > \delta | X(t) = x\} = o(t - s), s < t$
- $\lim_{\Delta t \rightarrow 0} \frac{E[X(t + \Delta t) - X(t) | X(t) = x]}{\Delta t} = \lim_{\Delta t \rightarrow 0} \int_{|y-x| \leq \delta} (y - x) p(x, t; y, t + \Delta t) dy = a(x, t)$ , where  $a(x, t)$  is the **drift coefficient**.
- $\lim_{\Delta t \rightarrow 0} \frac{E[(X(t + \Delta t) - X(t))^2 | X(t) = x]}{\Delta t} = \lim_{\Delta t \rightarrow 0} \int_{|y-x| \leq \delta} (y - x)^2 p(x, t; y, t + \Delta t) dy = b(x, t)$ , where  $b(x, t)$  is the **diffusion coefficient**.

Then the corresponding **forward Kolmogorov equation** and **backward Kolmogorov equation** are given by:

$$\begin{aligned} \frac{\partial}{\partial t} p(x_0, t_0; x, t) &= -\frac{\partial}{\partial x} \{a(x, t) p(x_0, t_0; x, t)\} + \frac{1}{2} \frac{\partial^2}{\partial x^2} \{b(x, t) p(x_0, t_0; x, t)\} \\ \frac{\partial}{\partial t} p(x_0, t_0; x, t) \Big|_{t=t_0} &= \\ -a(x, t) \Big|_{x=x_0, t=t_0} \times \frac{\partial}{\partial x} p(x_0, t_0; x, t) \Big|_{x=x_0} - \frac{1}{2} b(x_0, t_0) \Big|_{x=x_0, t=t_0} \times \frac{\partial^2}{\partial x^2} p(x_0, t_0; x, t) \Big|_{x=x_0} \end{aligned}$$

#### Note

- In case  $p(x_0, t_0; x, t) = p(x_0, x; t - t_0)$  then the **Markov process** is **homogeneous** and we have  $a(x, t) = a(x)$  and  $b(x, t) = b(x)$ , i.e., both are **independent** of time  $t$ .
- If the **Markov process** is **additive**, then  $\{X(t) - X(t_0)\}$  depends only on  $t$  and  $t_0$  and not on  $x_0$ , hence  $p(x_0, t_0; x, t) = p(x - x_0; t - t_0)$  and we have  $a(x, t) = a(t)$  and  $b(x, t) = b(t)$ , i.e., both are **independent** of time  $x$ .

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#### Ornstein Uhlenbeck Process

The Wiener process does not provide satisfactory result for the Brownian motion for small values of  $t$ . But for moderate and large values of  $t$  it does provide good results. As alternate model which does good results for small values of  $t$  is the Ornstein Uhlenbeck model. **The main difference being instead of displacement,  $X(t)$ , we consider the velocity,  $U(t) = \frac{dX(t)}{dt}$ .**

Now the Brownian motion of a particle if expresses using the concept of velocity takes the form of  $dU(t) = -\beta U(t)dt + dF(t)$ .

The first term on the right hand side, i.e.,  $-\beta U(t)$  represents the part due to the resistance of the medium in which the particle is, while  $dF(t)$  is the random component and  $F(t)$  is Wiener process with drift  $\mu = 0$  and variance parameter  $\sigma^2$ . To make the derivation simply and simplistic we consider  $\beta U(t)$  and  $F(t)$  are independent.

Now for the Markov process  $\{U(t), t \geq 0\}$  as  $\Delta t \rightarrow 0$ ,  $\{U(t + \Delta t) - U(t)\} = \Delta U(t) \rightarrow 0$ , and we have

$$\begin{aligned} \bullet \lim_{\Delta t \rightarrow 0} \frac{E\{U(t+\Delta t) - U(t) | U(t) = u\}}{\Delta t} &= -\beta u + \lim_{\Delta t \rightarrow 0} \frac{E\{\Delta F(t)\}}{\Delta t} = -\beta u \\ \bullet \lim_{\Delta t \rightarrow 0} \frac{\text{Var}\{U(t+\Delta t) - U(t) | U(t) = u\}}{\Delta t} &= \lim_{\Delta t \rightarrow 0} \frac{(\Delta t)^2}{\Delta t} + \lim_{\Delta t \rightarrow 0} \frac{\text{Var}\{\Delta F(t)\}}{\Delta t} = \sigma^2 \end{aligned}$$

In other words the limit exists hence  $\{U(t), t > 0\}$  is a **diffusion process** and it can be proved that its transition p.d.f, i.e.,  $p(u_0; u, t)$  satisfies the forward **Kolmogorov equation**, with  $a(u, t) = -\beta u$  and  $b(u, t) = \sigma^2$ .

Hence  $p(u_0; u, t)$  satisfies the differential equation  $\frac{\partial p(u_0; u, t)}{\partial t} = \beta \frac{\partial u p(u_0; u, t)}{\partial u} + \frac{1}{2} \sigma^2 \frac{\partial^2 p(u_0; u, t)}{\partial u^2}$ . It can be proved simply by considering the characteristic function that  $p(u_0; u, t)$  is normal with a mean value of  $u_0 e^{-\beta t}$  and variance of  $\sigma^2 \left(1 - \frac{e^{-2\beta t}}{2\beta}\right)$ .

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#### Note

- Thus the process  $\{U(t), t \geq 0\}$  is a **Gaussian process** with mean  $u_0 e^{-\beta t}$  and variance  $\sigma^2 \left(1 - \frac{e^{-2\beta t}}{4\beta}\right)$ .
- Thus the process  $\{U(t), t \geq 0\}$  is a **Markov process** but it does not possess independent increment like the Wiener process.
- As  $t \rightarrow \infty$ , the mean value is 0 and variance is  $\frac{\sigma^2}{2\beta}$ . This implies the distribution of velocity is in statistical equilibrium.
- The **Ornstein-Uhlenbeck process** can be interpreted as a scaling limit of a **discrete process**, in the same way that **Brownian motion** is a scaling limit of **random walks**.

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