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# Chapter 10 Brownian motion.

Here we consider a Markov process in continuous time, when in addition the state is  $\mathbb{R}$ , i.e. not even countable.

It can be seen as a limit of a symmetric random walk when the step size and the time units decrease.

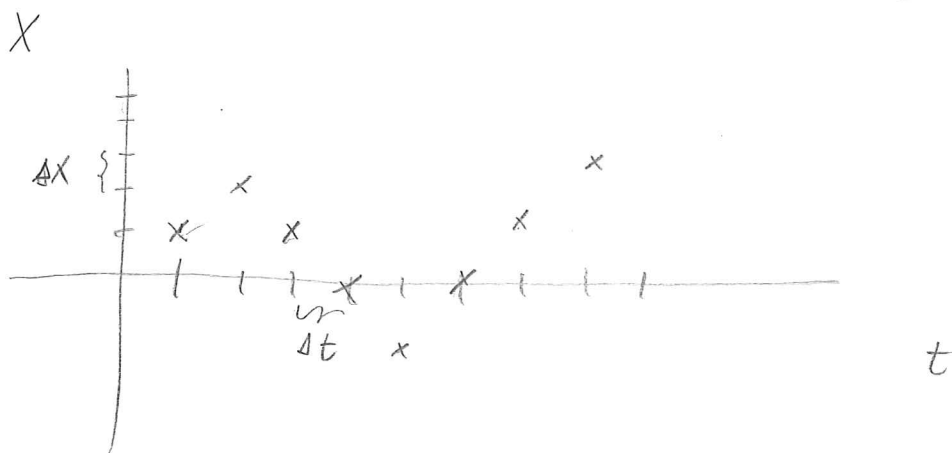
More specifically let  $\Delta t$  be time unit and  $\Delta X$  step size  
 so the position at time  $t$ ,  $X(t)$  is

$$X(t) = \Delta X (X_1 + \dots + X_{\lceil t/\Delta t \rceil}) \quad \left( \lceil \cdot \rceil \text{ integer value} \right)$$

where  $X_i = \begin{cases} +1 & \text{step up size } \Delta X \\ -1 & \text{step down. " "} \end{cases}$

Assume  $X_1, X_2, \dots$  independent  $P(X_i=1) = P(X_i=-1) = \frac{1}{2}$

$$X\left(\frac{s}{\Delta t}\right) - X\left(\frac{s-1}{\Delta t}\right) = \Delta X \cdot X_{\lceil s/\Delta t \rceil} \quad 0 \leq s \leq t$$



Now  $E(X_i) = 0$ ,  $\text{Var}(X_i) = E(X_i^2) = 1$

so  $E[X(t)] = 0$

$\text{Var}(X(t)) = (\Delta X)^2 \cdot \left[ \frac{t}{\Delta t} \right]$

If  $\Delta t, \Delta X \rightarrow 0$ , so that  $\Delta X = \sigma \sqrt{\Delta t}$

$E[X(t)] = 0$   
 $\text{Var}(X(t)) \rightarrow \sigma^2 \cdot t$

The following can be shown to be true.

(i) By the central limit theorem  
 $X(t) \sim N(0, \sigma^2 t)$  approximately  
 since  $X(t)$  sum of independent variables

(ii)  $\{X(t) \ t \geq 0\}$  has independent increments  
 since if  $t_1 < t_2 < \dots < t_n$

$X(t_n) - X(t_{n-1}), X(t_{n-1}) - X(t_{n-2}), \dots, X(t_2) - X(t_1), X(t_1)$   
 are independent depending on disjoint sets of variables.

(iii) The distribution of  $X(t+s) - X(t)$  depends only  
 on  $s$ , i.e. the number of units in  $(s, s+t)$ ,  
 so the  $X(t)$  has stationary increments.

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This motivates the following formal definition

Definition 10.1 A stochastic process  $\{X(t), t \geq 0\}$  is a Brownian motion process / Wiener process.

(i)  $X(0) = 0$

(ii)  $\{X(t), t \geq 0\}$  has stationary independent increments

(iii)  $\forall t > 0, X(t) \sim N(0, \sigma^2 t)$ .

Remark 10.1.1

$\sigma = 1$

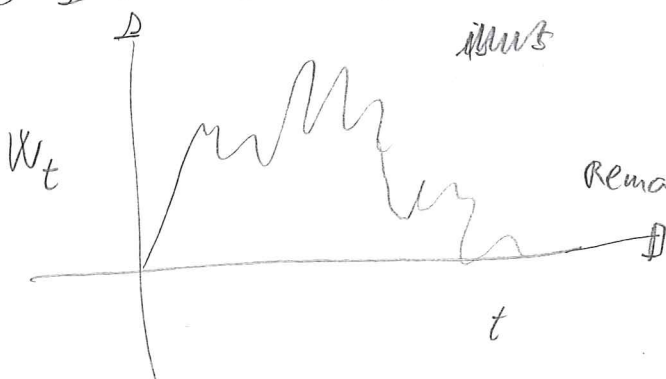
Standard Brownian motion, since

$X(t) \sim N(0, t \cdot \sigma^2)$

thus

$\Rightarrow B(t) = \frac{X(t)}{\sigma} \sim N(0, t)$

assume here now on  $\sigma^2 = 1$



Remark 10.1.2

Application: movement of particles in liquids or gas. Einstein explained movement as result of bombardment of molecules.

Two properties.

$E[X(t+h) - X(t)] = 0$

$E[(X(t+h) - X(t))^2] = h \cdot \sigma^2$

If  $h \rightarrow 0$  this indicates that

$X(t+h) - X(t)$  converges to zero and  $X(t)$  is continuous. This result can be shown rigorously.

$E\left[\frac{X(t+h) - X(t)}{h}\right] = 0$

$E\left[\left(\frac{X(t+h) - X(t)}{h}\right)^2\right] = \frac{\sigma^2 h}{h^2} = \frac{\sigma^2}{h}$

Thus we cannot conclude that  $\frac{X(t+h) - X(t)}{h}$  converges to 0 as  $h \rightarrow 0$ , indicating that  $X(t), t \geq 0$  is not differentiable.

(4)

Remember one dimensional transformation

$$u = g(v) \quad g \text{ strictly increasing}$$

$$F_u(u) = P(u \leq u) = P(g(v) \leq u) \\ = P(v \leq g^{-1}(u)) = F_v(g^{-1}(u))$$

$$\text{so } f_u(u) = f_v(g^{-1}(u)) \cdot \frac{d}{du} g^{-1}(u)$$

In general if  $\underline{u}, \underline{v} \in \mathbb{R}^n$

$$f_{\underline{u}}(\underline{u}) = f_{\underline{v}}(g^{-1}(\underline{u})) \cdot |J| \quad |J| \text{ Jacobian of } g^{-1}$$

$$\text{Let } \underline{u} = \begin{pmatrix} X(t_1) \\ X(t_2) - X(t_1) \\ \vdots \\ X(t_n) - X(t_{n-1}) \end{pmatrix} = \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & 1 \end{pmatrix} \begin{pmatrix} X(t_1) \\ X(t_2) - X(t_1) \\ \vdots \\ X(t_n) - X(t_{n-1}) \end{pmatrix} = G \cdot \underline{v}$$

$$G^{-1} \underline{u} = G^{-1} \begin{pmatrix} X(t_1) \\ X(t_2) - X(t_1) \\ \vdots \\ X(t_n) - X(t_{n-1}) \end{pmatrix} = \begin{pmatrix} 1 & 0 & \dots & 0 \\ -1 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & -1 & 1 \end{pmatrix} \begin{pmatrix} X(t_1) \\ X(t_2) - X(t_1) \\ \vdots \\ X(t_n) - X(t_{n-1}) \end{pmatrix} = \begin{pmatrix} X(t_1) \\ X(t_2) - X(t_1) \\ \vdots \\ X(t_n) - X(t_{n-1}) \end{pmatrix} = \underline{v}$$

$$\text{so } \int (x_1, \dots, x_n) = \int_{t_1}^{t_2} f_{t_1}(x_1) \cdot \int_{t_2-t_1}^{\dots} f_{t_2-t_1}(x_2-x_1) \dots \int_{t_n-t_{n-1}}^{\dots} f_{t_n-t_{n-1}}(x_n-x_{n-1}) \\ = \left(\frac{1}{\sqrt{2\pi}}\right)^n \exp\left(-\frac{1}{2}x_1^2\right) \exp\left(-\frac{1}{2}\frac{(x_2-x_1)^2}{t_2-t_1}\right) \dots \exp\left(-\frac{1}{2}\frac{(x_n-x_{n-1})^2}{t_n-t_{n-1}}\right)$$

so  $(X_1, \dots, X_n)'$  is multivariately distributed