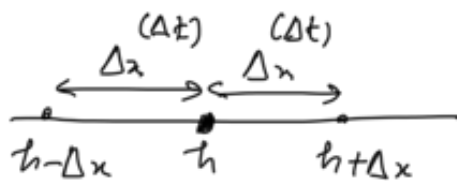


Brownian Motion (BM) process:



$X(t)$  : position of particle at time  $t$ .

$$X_i = \begin{cases} +1 & \text{if the } i^{\text{th}} \text{ step of length } \Delta x \text{ is to the right} \\ -1 & \text{" " " " " " " " " " left} \end{cases}$$

$$X(t) = \Delta x \left( \underline{X_1 + X_2 + \dots + X_{\left[\frac{t}{\Delta t}\right]}} \right)$$

Where  $\lceil \cdot \rceil$ : greatest integer less than or equal to the number  $\lceil 4.4 \rceil = 4$

$X_i$ 's are indep.

$$P(X_i = 1) = P(X_i = -1) = \frac{1}{2}$$

$$E(X_i) = 0 \quad ; \quad V(X_i) = E(X_i^2) = 1$$

$$E(X(t)) = 0$$

$$V(X(t)) = (\Delta x)^2 \sum_{i=1}^{(t/\Delta t)} V(X_i)$$

$$= (\Delta x)^2 \left[ \frac{t}{\Delta t} \right]$$

Let  $\Delta x \rightarrow 0, \Delta t \rightarrow 0$

(i) If  $\Delta x = \Delta t \rightarrow 0$   $\int E(X(t)) = 0$ ,  $V(X(t)) = 0$   
trivial result

(ii) If we let  $\Delta x = \sigma \sqrt{\Delta t}$ ,  $\sigma > 0$   
as  $\Delta t \rightarrow 0$

$$E(X(t)) = 0, \quad V(X(t)) \rightarrow \sigma^2 t$$

Def<sup>n</sup> A SP  $\{X(t), t \geq 0\}$  BM process if

- (i)  $X(0) = 0$  (ii)  $\{X(t), t \geq 0\}$  has stationary indep. increments  
 (iii)  $\forall t > 0, X(t) \sim N(0, \sigma^2 t)$

$\Rightarrow \sigma = 1$  Standard BM / Wiener process

$\{X(t)\}$  BM, then  $W(t) = \frac{X(t)}{\sigma} \sim N(0, t)$  S BM / Wiener process

$\rightarrow W(t) \sim N(0, t)$

density  $f_t(x) = \frac{1}{\sqrt{2\pi t}} e^{-x^2/2t}, -\infty < x < \infty$

Note that

$W(t_1) = x_1, \dots, W(t_n) = x_n \equiv W(t_1) = x_1, W(t_2) - W(t_1) = x_2 - x_1, \dots, W(t_n) - W(t_{n-1}) = x_n - x_{n-1}$

Also  $W(t_1), W(t_2) - W(t_1), \dots, W(t_n) - W(t_{n-1})$  are indep and has stationary increments

$\underbrace{W(t_k) - W(t_{k-1})}_{\sim N(0, t_k - t_{k-1})} \stackrel{\text{def}}{=} W(t_k - t_{k-1})$

Joint density of  $W(t_1), \dots, W(t_n)$  is

$\underline{f(x_1, \dots, x_n)} = f_{t_1}(x_1) f_{t_2-t_1}(x_2-x_1) \dots f_{t_n-t_{n-1}}(x_n-x_{n-1})$

$= \frac{\exp \left\{ -\frac{1}{2} \left[ \frac{x_1^2}{t_1} + \frac{(x_2-x_1)^2}{t_2-t_1} + \dots + \frac{(x_n-x_{n-1})^2}{t_n-t_{n-1}} \right] \right\}}{(2\pi)^{n/2} [t_1(t_2-t_1) \dots (t_n-t_{n-1})]^{1/2}}$

Conditional  $[W(s) | W(t) = B], s < t$   
 density

density  $f(x|B) = f_s(x) f_{t-s}(B-x)$

$$\begin{aligned}
& \sigma^2 \frac{s}{t} \quad \text{---} \quad \frac{f_t(B)}{f_t(B)} \\
& = k_1 \exp \left\{ - \frac{x^2}{2s} - \frac{(B-x)^2}{2(t-s)} \right\} \\
& = k_2 \exp \left\{ -x^2 \left( \frac{1}{2s} + \frac{1}{2(t-s)} \right) + \frac{Bx}{t-s} \right\} \\
& = k_2 \exp \left\{ - \frac{t}{2s(t-s)} \left( x^2 - \frac{2sB}{t} x \right) \right\} \\
& = k_3 \exp \left\{ - \frac{(x - Bs/t)^2}{2s(t-s)/t} \right\}
\end{aligned}$$

For  $s < t$

$$\begin{aligned}
& k_1, k_2, k_3 \text{ mid } \gamma_n \\
& [W(s) | W(t) = B] \sim N \left( \frac{s}{t} B, \frac{s(t-s)}{t} \right) \checkmark \\
& \quad \quad \quad \uparrow \quad \quad \quad \uparrow \\
& \quad \quad \quad E(W(s) | W(t) = B) \quad V(W(s) | W(t) = B)
\end{aligned}$$

Example: In a bicycle race btw two competitors, let  $Y(t)$  : the amt of time (in secs) by which the racer that started in the inside position is ahead when 100% of the race has been completed, and suppose that  $\{Y(t)\}_{0 \leq t \leq 1}$  can be effectively modeled as BM process with variance parameter  $\sigma^2$ .

(a) If the inside racer is leading by  $\sigma$  sec's at the midpoint of the race, what is the prob. that she is the winner?

$$\begin{aligned}
& Y(t) \sim N(0, \sigma^2 t) \\
& \text{Sol } P(Y(1) > 0 | Y(\frac{1}{2}) = \sigma)
\end{aligned}$$

$$= P(\underbrace{Y(1) - Y(\frac{1}{2})}_{> 0 - \sigma} \mid \underbrace{Y(\frac{1}{2}) = \sigma}_{})$$

$$= P(Y(1) - Y(\frac{1}{2}) > -\sigma) \quad | \cdot: \text{midpoint increment of } Y(t)$$

$$= P(Y(\frac{1}{2}) > -\sigma) \quad | \text{Stationary increment of } Y(t)$$

$$= P\left(\frac{Y(\frac{1}{2})}{\sigma/\sqrt{2}} > \frac{-\sigma}{\sigma/\sqrt{2}}\right) = P(Z > -\sqrt{2})$$

$$= 1 - \Phi(-\sqrt{2})$$

$$= \Phi(\sqrt{2}) \approx 0.9213$$

$$\left. \begin{array}{l} Z \sim N(0,1) \\ \Phi(x) = P(Z \leq x) \\ \Phi(x) + \Phi(-x) = 1 \end{array} \right\}$$

(b) If the inside racer wins the race by a margin of  $\sigma$  sec's, what is the prob that she was ahead at the midpoint?

sol

$$\underline{P(Y(\frac{1}{2}) > 0 \mid Y(1) = \sigma) = ?}$$

$$\sigma W(t) = Y(t) \sim N(0, \sigma^2 t)$$

For  $s < t$

$$W(t) \sim N(0, t)$$

$$[W(s) \mid W(t) = c] \sim N\left(\frac{s}{t}c, \frac{s}{t}(t-s)\right)$$

$$[\underline{W(s)} \mid \underline{Y(t) = c}] = [W(s) \mid W(t) = \frac{c}{\sigma}] \sim N\left(\frac{s}{t}\frac{c}{\sigma}, \frac{s}{t}(t-s)\right)$$

$$[Y(s) \mid Y(t) = c] = [\sigma W(s) \mid Y(t) = c] \sim N\left(\frac{s}{t}c, \frac{\sigma^2 s(t-s)}{t}\right)$$

$$[Y(\frac{1}{2}) \mid Y(1) = \sigma] \sim N\left(\frac{\sigma}{2}, \frac{\sigma^2}{4}\right)$$

$$\left( \begin{array}{l} s = \frac{1}{2}, t = 1 \\ c = \sigma \end{array} \right)$$

$$P(Y(\frac{1}{2}) > 0 \mid Y(1) = \sigma) = P(Z > \underline{0 - \sigma/2})$$

$$= P(Z > -1) = 1 - P(Z \leq -1) = 1 - \Phi(-1) \\ = \Phi(1) \approx 0.8413$$

→  $W(t)$  is MG. ?

For  $s < t$   
 Sol  $E(W(t) | W(s), 0 \leq u \leq s)$

$$= E(W(t) - W(s) + W(s) | W(s), 0 \leq u \leq s) \\ = E(W(t) - W(s) | W(s), 0 \leq u \leq s) + E(W(s) | W(s), 0 \leq u \leq s) \\ = \underbrace{E(W(t) - W(s))}_{\text{by independent increment}} + W(s) \\ = 0 + W(s) = W(s) \\ W(t) \text{ MG.}$$

$$| W(t) - W(s) \sim N(0, t-s)$$

Martingale Stopping thm: An important property of MG  $Y(t)$

is that if you continually observe the process and stop at some time  $T$ , then, subject to some technical condition  $E(Y(T)) = E(Y(0))$

$T \rightarrow$  stopping time for MG.

expected value of the stopped MG is equal to its fixed time expectation.

Eg. Let  $T = \min \{t : W(t) = 2 - 4t\}$ , i.e.,  $T$  is the first time that  $W(t) = 2 - 4t$ . Then  $E(T) = ?$

first time that satisfy this condition 2-45. Let  $T = \tau$

sol Using MG stopping time

$$\underline{E(W(T))} = E(W(0)) = 0$$

$$W(T) = 2 - 4T \Rightarrow E(W(T)) = 2 - 4E(T)$$

$$\Rightarrow 2 - 4E(T) = 0 \Rightarrow E(T) = 1/2$$

—X—

Q, let  $Y(t) = W^2(t) - t$ .

$$Y(t) \text{ MG? } E(Y(t)) = ? \quad \text{Ex.}$$

—X—

Geometric BM

$Y(t)$  BM drift  $\mu$ , var-parameter  $\sigma^2$

$$Y(t) \sim N(\mu t, \sigma^2 t),$$

$$X(t) = e^{Y(t)}$$

$\{X(t), t \geq 0\}$  Geometric BM.

For  $s < t$

$$E(X(t) | X(u), 0 \leq u \leq s)$$

$$= E(e^{Y(t)} | Y(u), 0 \leq u \leq s)$$

$$= E(e^{Y(s) + Y(t) - Y(s)} | Y(u), 0 \leq u \leq s)$$

$$= e^{Y(s)} E(e^{Y(t) - Y(s)} | Y(u), 0 \leq u \leq s)$$

$$= X(s) E(e^{Y(t) - Y(s)}) \quad \left\{ \text{indep. increments} \right.$$

$$= X(s) e^{\mu(t-s) + (t-s)\sigma^2/2} \quad \left| \begin{array}{l} \text{Stationary increments} \\ Y(t) - Y(s) \sim N(0, t-s) \end{array} \right.$$

$$= X(s) e^{(t-s)(\mu + \sigma^2/2)}$$

$$\begin{aligned} W &\sim N(0, t-s) \\ E(e^{aW}) &= e^{aE(W) + \frac{1}{2} a^2 \text{Var}(W)} \\ &= e^{\frac{1}{2} a^2 (t-s)} \end{aligned}$$

$$\Rightarrow E(X(t) | X(u), 0 \leq u \leq s) = X(s) e^{(t-s)(\mu + \sigma^2/2)}$$

$$\Rightarrow E(X(t)) = E(X(s)) e^{(t-s)(\mu + \sigma^2/2)} \quad *u$$

Geo. BM is useful in modeling of stock prices over time when you feel the %age changes are I.I.D.

eg Let  $X_n$  : price of some stock at time  $n$ .

It might be reasonable to suppose that

$$\frac{X_n}{X_{n-1}}, n \geq 1, \text{ are I.I.D.}$$

$$\begin{aligned} \text{Let } Y_n &= \frac{X_n}{X_{n-1}} \Rightarrow X_n = Y_n X_{n-1} \\ &= Y_n Y_{n-1} X_{n-2} \\ &\vdots \\ &= Y_n Y_{n-1} \dots Y_1 X_0 \end{aligned}$$

$$\Rightarrow \log X_n = \sum_{i=1}^n \log(Y_i) + \log(X_0)$$

$\log(Y_i), i \geq 1$ , I.I.D.,  $\{\log(X_n)\}$  will, when suitably normalized, approx. BM with a drift, so.

$$e^{\log X_n} = X_n, \quad \{X_n\} \text{ approx. Geo. BM.}$$

$X(t)$  BM with drift  $\mu$ :

$$X(t) \sim N(\mu t, t)$$

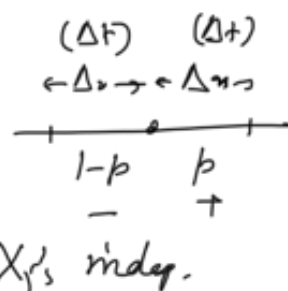
$$; W(t) \sim N(0, t)$$

$$X(t) = W(t) + \mu t$$

BM also be defined as a limit of random walks

Scal  $X(t)$  : position at time  $t$

$$X_i = \begin{cases} 1 & \text{if } i^{\text{th}} \text{ step in +ve direction} \\ -1 & \text{o.w.} \end{cases}$$



$$X(t) = \Delta x (X_1 + \dots + X_{\lfloor t/\Delta t \rfloor})$$

$$E(X(t)) = \Delta x \left\lfloor \frac{t}{\Delta t} \right\rfloor (2p-1)$$

$$V(X(t)) = (\Delta x)^2 \left\lfloor \frac{t}{\Delta t} \right\rfloor (1 - (2p-1)^2)$$

$$E(X_i) = 1 \cdot p + (-1)(1-p) = 2p-1$$

$$V(X_i) = E(X_i^2) - (E(X_i))^2 = 1 - (2p-1)^2$$

If we let  $\Delta x = \sqrt{\Delta t}$  and let  $\Delta t \rightarrow 0$  ,  $p = \frac{1}{2}(1 + \mu\sqrt{\Delta t})$

$$E(X(t)) \rightarrow \mu t$$

$$V(X(t)) \rightarrow t$$

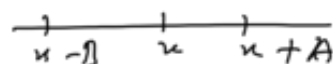
—X—

$$\begin{aligned} & \sqrt{\Delta t} \times \frac{t}{\Delta t} \times \mu \sqrt{\Delta t} \rightarrow \mu t \\ & \Delta t \times \frac{t}{\Delta t} \times (1 - \mu^2 \Delta t) \rightarrow t \end{aligned}$$

Probability that the process will hit A before -B; A, B > 0

Let  $P(x) = P(X(t) \text{ hits A before } -B \mid X(0)=x)$  ,  $-B < 0 < A$

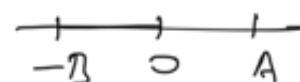
where  $P(x)$  is the prob. that process will hit A before B given that we are now at x.



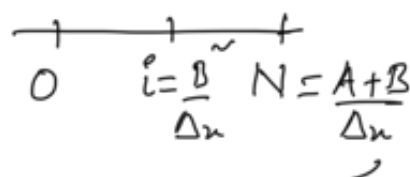
Boundary condition  $P(A) = 1$  ,  $P(-B) = 0$



①



Gambler's ruin problem



$$p = \frac{1}{2}(1 + \mu \Delta x)$$

$$\lim_{\Delta x \rightarrow 0} \left( \frac{1-p}{p} \right)^{1/\Delta x} = \lim_{\Delta x \rightarrow 0} \left( \frac{1 - \mu \Delta x}{1 + \mu \Delta x} \right)^{1/\Delta x}$$

$$= \frac{e^{-\mu}}{e^{\mu}} = e^{-2\mu}$$

$$\frac{1 - \left(\frac{q}{p}\right)^i}{1 - \left(\frac{q}{p}\right)^N}$$

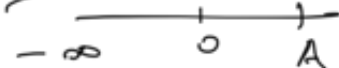
Letting  $\Delta x \rightarrow 0$ , we see that

$$P(\text{up } A \text{ before down } B) = \frac{1 - e^{-2B\mu}}{1 - e^{-2\mu(A+B)}} \quad \text{--- ①}$$

$$= \frac{e^{2B\mu} - 1}{e^{2\mu(A+B)} - 1} e^{2\mu A}$$

Case I If  $\mu < 0$  by letting  $B \rightarrow \infty$

$$P(\text{process ever goes to } A) = e^{2\mu A} \quad \text{--- ②}$$



In this case, the process drift off to  $-\infty$  and its max in exp. is with rate  $(-2\mu)$ .

Case II let  $\mu \rightarrow 0$  in ①

$$P(\text{BM goes up } A \text{ before down } B) = \frac{B}{A+B}$$

T. ...

in general

$$P(x) = \frac{1 - e^{-2\mu(x+B)}}{1 - e^{-2\mu(A+B)}} \\ -x-$$

### Example (Exercising a Stock Option)

Suppose we have the option of buying, at some time in the future, one unit of a stock at a fixed price  $A$ , indep. of current market price. The current market price of the stock is taken to be 0, and we suppose that it changes in accordance with a BM having a negative drift coefficient  $-d$ , where  $d > 0$ . The question is, when, if ever, should we exercise our option?

Sol policy exercise the option when market price is  $x$

$$\hookrightarrow \text{expected gain} = (x-A)P(x),$$

where  $P(x)$  prob. that the process will ever reach  $x$ ,  
 $\mu = -d < 0$ ,  $d > 0$

$$\text{From (2)} \quad P(x) = e^{-2dx}$$

Optimal value of  $x$  is one max.  $(x-A)e^{-2dx} = f(x)$

$$f'(x) = (x-A)e^{-2dx}(-2d) + e^{-2dx} = 0$$

$$\Rightarrow x = A + \frac{1}{2d}$$

$$f''(x) \Big|_{x=A+\frac{1}{2d}} > 0$$

$$x = A + \frac{1}{2d}$$

eg if  $A=100, d=2$

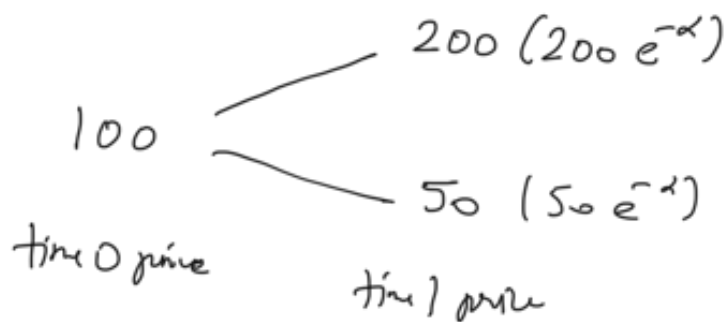
$$x = 100 + \frac{1}{4} = 100.25$$

- x -

## Pricing Stock Option:

example in option pricing?

$\text{amt } V$  at  $t$  is  $V e^{-\alpha t}$   
 $\text{time } 0 \text{ value present value}$   
 $\alpha \rightarrow \text{discount factor}$   
 $e^{-\alpha t}$  discount factor  
Option share of stock at a future time at a fixed price.



Option: buy <sup>unit</sup> of stock costs 150 per share (time 0 price)

$C = ?$  unit cost of an option

We will show unless  $C \leq \frac{50}{3}$ , there will be a combination of purchases that will always result in a +ve gain.

Summary 1. ...

At time 0, we

$$\begin{cases} \text{buy } x \text{ unit of stock} \\ \text{buy } y \text{ " " " option} \end{cases}$$

sell means -ve

value of our holding at time 1

$$\text{value} = \begin{cases} 200x + 50y & \text{if price is } 200 \\ 50x & \text{if price is } 50 \end{cases}$$

let we choose  $y$  str.

$$200x + 50y = 50x \Rightarrow \boxed{y = -3x} \checkmark$$

$$\begin{aligned} \text{gain} &= 50x - (100x - 3xc) \\ &= x(3c - 50) \end{aligned} \quad \left\{ \begin{array}{l} \text{the value of holding} = 50x \\ \text{Original cost} = 100x + cy \\ \begin{array}{l} x \text{ unit stock} \\ \leftarrow -3x \text{ unit option} \end{array} = 100x - 3xc \end{array} \right.$$

$$\left\{ \begin{array}{l} 0 \quad \text{if } 3c = 50 \\ +ve \quad \text{if } 3c > 50 \\ -ve \quad \text{if } 3c < 50 \end{array} \right. \rightarrow \begin{array}{l} \text{only option cost } c \text{ that does} \\ \text{not result in an arbitrage is} \\ \underline{c = 50/3} \end{array}$$

A sure win betting scheme is called  
an arbitrage

eg ①  $c = 20$  (unit cost per option)

$$\underline{x = 1}, \underline{y = -3}$$

$$y = -3x$$

$$\text{initially cost} = 100 - 60 = 40$$

$$\begin{aligned} \text{value of holding at time 1 (} \uparrow 200, \downarrow 50) \\ = 50 \end{aligned}$$

guaranteed profit =  $50 - 40 = 10$  is attained

(2)  $C = 15$

$$x = -1, y = 3$$

$$\text{initial gain} = 100 - 45 = 55$$

$$\text{Value of holding at time 1 is} = -50$$

$$\text{guaranteed profit} = 55 - 50 = 5$$

Arbitrage thm: expt. whose set of possible outcomes  
 $S = \{1, 2, \dots, m\}$ .

$n$  wagers

amnt  $x_i$  is bet on wager  $i$ , then return  $x_i r_i(j)$  is  
earned if the outcome of expt. is  $j$ ,  $j \in S = \{1, 2, \dots, m\}$   
 $i \in \{1, 2, \dots, n\}$

$r_i(\cdot) \rightarrow$  return for unit bet on wager  $i$ .

Betting scheme  $\underline{x} = (x_1, \dots, x_n)$

Outcome of expt. is  $j$ , then return then  $\underline{x} = \sum_{i=1}^n x_i r_i(j)$

$\exists \underline{p} = (p_1, \dots, p_m)$  on  $S = \{1, \dots, m\}$  under which

each wager has expected return 0, or else there  
is a betting scheme that guarantees a positive win.

Arbitrage thm: Exactly one of the following is true:

Either

(i)  $\exists$  a  $\underline{p} = (p_1, \dots, p_m)$  for which  $\sum_{i=1}^n p_i r_i(j) = 0$   
or  $\forall j = 1, \dots, m$

(ii)  $\exists$  a betting scheme  $\pi = (\pi_1, \dots, \pi_n)$  for which

$$\sum_{i=1}^n \pi_i \sigma(i, j) > 0 \quad \forall j = 1, \dots, m.$$

In other words, if  $X$  is the outcome of the expt, then  
 arbitrage then states that either there is a prob.  
 vector  $\underline{p}$  for  $X$  st  $E_{\underline{p}}(\pi_i(X)) = 0 \quad \forall i = 1, \dots, n$   
 or else there is a betting scheme that leads  
 to a sure win.

Example (contd)



time 0

time 1

C

Options: to buy at time 1 at present value

st, no sure win is possible

of 150 per share

two outcomes

two wagers  $\rightarrow$   $\begin{cases} \text{buy/sell stock} \\ \text{buy/sell option} \end{cases}$

no sure win  
by

$$\underline{p} = (p, 1-p)$$

$$\underline{E}(\text{return}) = 0.$$

$$\text{returns from purchasing} = \begin{cases} 200 - 150 = 100, & \text{if price 200 at time 1} \\ 50 - 150 = -100, & \text{if price 50 at time 1} \end{cases}$$

no of stock  $\{ S_0 - 100 = -S_0 \text{ g. } -S_0 - 1 \}$

If  $p \rightarrow$  prob. that price is 200 at time 1, then  
 $E(\text{return}) = 100p - S_0(1-p)$

$$\underline{E(\text{return}) = 0} \Rightarrow \underline{100 = 200p + S_0(1-p)}$$

$$\Rightarrow p = \frac{1}{3}$$

$(p, 1-p) = (\frac{1}{3}, \frac{2}{3})$  for which value yields  
 an expected return 0.

return from purchasing one share of option =  $\begin{cases} S_0 - C & \text{if price is 200} \\ -C & \text{" " " " } S_0 \end{cases}$

expected return when  $p = \frac{1}{3}$  is

$$E(\text{return}) = (S_0 - C) \times \frac{1}{3} - C \times \frac{2}{3} = \frac{S_0}{3} - C$$

$$E(\text{return}) = 0 \Rightarrow C = \frac{S_0}{3}$$

arbitrage for only value of  $C$  for which there will  
 not be a sure win is  $C = S_0/3$ .

—X—

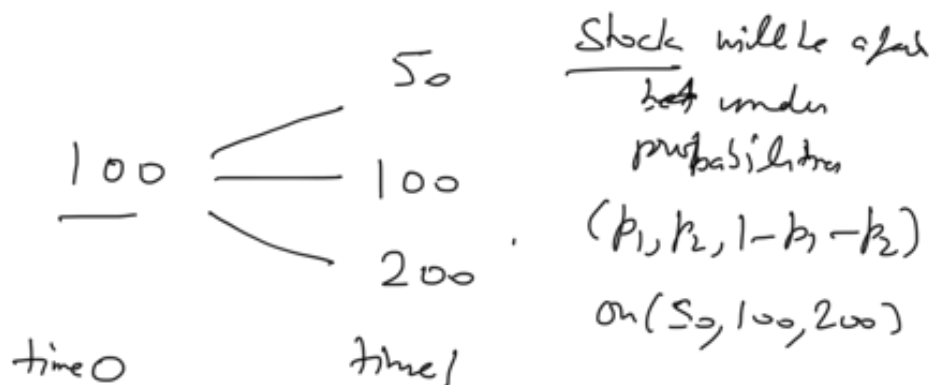
Example 1 The present price of a stock is 100. The price at  
 time 1 will be either 50, 100 or 200. An option to  
 purchasing shares of the stock at time 1 for the  
 (present value) price  $K$  cost  $C$ .

(a) If  $K = 120$ , show that an arbitrage opportunity  
 exists with  $C = 80$ .

unus 4/1 2 > 73

(b) If  $k = 80$ , show that there is not an arbitrage opportunity if  $20 \leq C \leq 40$ .

Sol



(C)

(K)

$$\underline{100 = 50p_1 + 100p_2 + 200(1-p_1-p_2)}$$

$$\Rightarrow 2 = p_1 + 2p_2 + 4(1-p_1-p_2)$$

$$\Rightarrow \underline{3p_1 + 2p_2 = 2} \quad \text{--- (1)}$$

(a)

$$\checkmark \underline{k = 120}$$

(C)

option

return =

$$\left\{ \begin{array}{lll} -C & \checkmark & \text{if } 50 \text{ w.p. } p_1 \\ -C & \checkmark & \text{if } 100 \text{ w.p. } p_2 \\ \underline{80-C} & & \text{if } 200 \text{ w.p. } 1-p_1-p_2 \end{array} \right.$$

$$E(\text{return}) = 0 \Rightarrow -Cp_1 - Cp_2 + (80-C)(1-p_1-p_2) = 0$$

$$\Rightarrow \underline{C = 80(1-p_1-p_2)} \quad \text{--- (2)}$$

$\Rightarrow$  solving (1) & (2)

$$p_1 = \frac{C}{40}, \quad p_2 = \frac{80-3C}{80}$$

$$1-p_1-p_2 = C$$



$$1 \cdot 1 \cdot 2 \cdot \frac{80}{3}$$

$$\Rightarrow \underline{80 \geq 3C} \Leftrightarrow \text{no arbitrage}$$

$$C > \frac{80}{3} \Leftrightarrow \text{arbitrage opportunity occurs.}$$

(b)

$$k=80$$

$$C = 20p_1 + 120(1-p_1-p_2) \quad (2)$$

Solve (1) & (2)

$$p_1 = \frac{C-20}{30}, \quad p_2 = \frac{40-C}{20}$$

$$1-p_1-p_2 = \frac{C-20}{60}$$



$$- \leq p_i \leq 1$$

$$\text{iff } \underline{20 \leq C \leq 40}$$

no arbitrage

—X—

Black - Scholes Option pricing formula:

present price of stock  $X(0) = X_0$  ;  $X(t)$  stock price at time  $t$

stock  $[0, T]$

$\alpha \rightarrow$  discount factor

$$e^{-\alpha t} X(t)$$

Observe  $X(t)$  up to  $\underline{s < t}$

buy (or sell) stock at price  $X(s)$ , then sell (buy) then shares at time  $t$  for price  $X(t)$

purchase  $N$  different options at time 0

Option  $i$  cost  $\underline{C_i}$  per share option purchase share of stock at time  $t_i$  for fixed price  $\underline{k_i}$

$\underline{C_i}$  ? for which there is a purchase  $i=1, \dots, N$

that lead to a sure win.

Use Arbitrage theorem

$\underline{P}$  prob. measure on the set of outcomes

Wagen

$$\begin{array}{ccc} s & & t \\ \downarrow & \searrow & \\ \underline{e^{-\alpha s} X(s)} & & e^{-\alpha t} X(t) \end{array}$$

$\underline{P}$  on  $X(t)$ ,  $0 \leq t \leq T$

$$E_{\underline{P}} [ e^{-\alpha t} X(t) | X(u), 0 \leq u \leq s ] = e^{-\alpha s} X(s) \quad \checkmark$$

$X(t)$  m.s. (1)  $\longleftrightarrow$  (2)

$$\text{worth of option at time } t = \begin{cases} X(t) - k & \text{if } X(t) \geq k \\ 0 & \text{if } X(t) < k \end{cases}$$

$$\text{present value of worth of option} = e^{-\alpha t} (X(t) - k)^+$$

$$E_{\underline{P}} (e^{-\alpha t} (X(t) - k)^+) = C \quad \text{--- (2)}$$

$$C_i = E_{\underline{P}} [ e^{-\alpha t_i} (X(t_i) - k_i)^+ ] , i=1, 2, \dots, N \quad \text{--- (2')}$$

By arbitrage theorem if we can find a prob. measure  $\underline{P}$  on the set of outcomes that satisfies (1), then if  $C$ , the cost of an option to purchase one share at time  $t$  at the fixed price  $k$ , is given by (2), then no arbitrage is possible. On the other hand, if for given prices  $C_i, i=1, 2, \dots, N$ , there is no prob. measure

P that satisfy both ① and equality ②'  
 then a sure win is possible.

P  $X(t)$ ,  $0 \leq t \leq T$

$$\text{Let } \underline{X(t) = x_0 e^{Y(t)} \sim \text{Geo BM}} \\ \underline{Y(t) \sim \text{BM } \mu, \sigma^2}$$

wfgy  $x_u$ , for  $s < t$

$$E(X(t) | X(u), 0 \leq u \leq s) = X(s) e^{\overbrace{(t-s)(\mu + \sigma^2/2)}^{\downarrow \downarrow}}$$

$$\text{Choose } \boxed{\mu + \frac{\sigma^2}{2} = \alpha}$$

$$\Rightarrow E(e^{-\alpha t} X(t) | X(u), 0 \leq u \leq s) = e^{-\alpha s} X(s)$$

$\therefore \Rightarrow$  (1) is satisfied.

Eq (2)  $\Leftrightarrow$   
 satisfied

$$C = \underline{E_P(e^{-\alpha t} (X(t) - k)^+)} \quad \checkmark, \text{ then no arbitrage is possible}$$

$$\text{Since } \underline{X(t) = x_0 e^{Y(t)}}, Y(t) \sim N(\mu t, \sigma^2 t)$$

$$\Rightarrow C e^{\alpha t} = \int_{-\infty}^{\infty} (x_0 e^y - k)^+ \frac{1}{\sqrt{2\pi t \sigma^2}} e^{-\frac{(y - \mu t)^2}{2t\sigma^2}} dy$$

$$C e^{\alpha t} = \int_{\log(k/x_0)}^{\infty} (x_0 e^y - k) \frac{1}{\sqrt{2\pi t \sigma^2}} e^{-\frac{(y - \mu t)^2}{2t\sigma^2}} dy \quad \left| \begin{array}{l} x_0 e^y \geq k \\ \Leftrightarrow y \geq \log(k/x_0) \end{array} \right.$$

$$C e^{\alpha t} = x_0 e^{\mu t} \frac{1}{\sqrt{2\pi}} \int_a^{\infty} e^{w\sigma\sqrt{t}} e^{-w^2/2} dw - k \frac{1}{\sqrt{2\pi}} \int_a^{\infty} e^{-w^2/2} dw, \quad \left| \begin{array}{l} w = \frac{y - \mu t}{\sigma\sqrt{t}} \\ dw = \frac{dy}{\sigma\sqrt{t}} \end{array} \right.$$

$$\text{where } a = \log(k/x_0) - \mu t \quad \therefore (3)$$

$$\begin{aligned}
 & \frac{e^{-\frac{a^2}{2\sigma^2 t}}}{\sigma\sqrt{t}} \\
 \text{Now } & \frac{1}{\sqrt{2\pi}} \int_a^\infty e^{w\sigma\sqrt{t}} e^{-w^2/2} dw = \frac{e^{t\sigma^2/2}}{\sqrt{2\pi}} \int_a^\infty e^{-(w-\sigma\sqrt{t})^2/2} dw \\
 & = e^{t\sigma^2/2} P(N(\sigma\sqrt{t}, 1) \geq a) \\
 & = e^{t\sigma^2/2} P(N(0, 1) \geq a - \sigma\sqrt{t}) \\
 & = e^{t\sigma^2/2} (1 - \Phi(a - \sigma\sqrt{t})) \\
 & = e^{t\sigma^2/2} \Phi(\sigma\sqrt{t} - a) \quad \left| \Phi(x) + \Phi(-x) = 1 \right.
 \end{aligned}$$

$$\therefore (3) \quad C(e^{\alpha t}) = x_0 e^{\mu t + \frac{1}{2}\sigma^2 t} \Phi(\sigma\sqrt{t} - a) - k \Phi(-a)$$

Since  $\mu + \frac{\sigma^2}{2} = \alpha$ , let  $b = -a$

$$\underline{C} = x_0 \Phi(\sigma\sqrt{t} + b) - k e^{-\alpha t} \Phi(b) \quad \text{--- (4)}$$

When  $b = -a = \frac{\mu t - \log(k/x_0)}{\sigma\sqrt{t}} = \frac{\alpha t - \sigma^2 t/2 - \log(k/x_0)}{\sigma\sqrt{t}}$

Optimal price formula (4) depends on  $x_0, t, k, \alpha, \sigma^2$

(4)  $\hookrightarrow$  then no arbitrage is possible.

Black-Scholes Option cost valuation.

(it does not depend on  $\mu$  but only on  $\sigma^2$ )  
drift var-param

Example The current price of a stock is 100. Suppose that the logarithm of the price of the stock at time

according to a BM process with drift coeff  $\mu=2$  and var parameter  $\sigma^2=1$ . Give the Black-Scholes cost of an option to buy the stock at time 10 for a cost of 100 per unit.

Sol  $\mu=2, \sigma^2=1, \alpha = \mu + \frac{\sigma^2}{2} = 2 + \frac{1}{2}$

$$x_0 = 100, t=10, k=100$$

$$b = \frac{\alpha t - \sigma^2 t/2 - \log(k/x_0)}{\sigma \sqrt{t}} =$$

$$C = x_0 \Phi(\sigma \sqrt{t} + b) - k e^{-\alpha t} \Phi(b) =$$

Ex.

— X —

White Noise :

$\{W(t), t \geq 0\}$   $W(H-N)_{0,t}$  SDM,  $f$  has cont derivative on  $[a,b]$

Sto. integral

$$\int_a^b f(t) dW(t) \equiv \lim_{\substack{n \rightarrow \infty \\ \max(t_i - t_{i-1}) \rightarrow 0}} \sum_{i=1}^n f(t_{i-1}) [W(t_i) - W(t_{i-1})]$$

Itô's integral correspond  
—— (1)\*

where  $a = t_0 < t_1 < \dots < t_n = b$  is a partition of  $[a,b]$

$$\sum_{i=1}^n f(t_{i-1}) [W(t_i) - W(t_{i-1})]$$

$$= f(b)W(b) - f(a)W(a) - \sum_{i=1}^n W(t_i) [f(t_i) - f(t_{i-1})]$$

Observe the

$$f(t_n)w(t_n) - f(t_0)w(t_0) - w(t_1)[f(t_1) - f(t_0)] - w(t_2)[f(t_2) - f(t_1)] \\ \dots - w(t_n)[f(t_n) - f(t_{n-1})]$$

$$\boxed{\int_a^b f(t)dw(t) = f(b)w(b) - f(a)w(a) - \int_a^b w(t)df(t)} \quad \checkmark \quad \underline{\underline{\text{Ito's lemma}}}$$

(2)<sup>x</sup>

Assume interchangeability b/w exp and lin<sup>2</sup>

$$E\left(\int_a^b f(t)dw(t)\right) = 0$$

$$V\left(\sum_{i=1}^n f(t_{i-1})(w(t_i) - w(t_{i-1}))\right) \\ = \sum_{i=1}^n f^2(t_{i-1}) \underbrace{\text{Var}(w(t_i) - w(t_{i-1}))}_{t_i - t_{i-1}} \\ = \sum_{i=1}^n f^2(t_{i-1}) (t_i - t_{i-1})$$

$$V\left(\int_a^b f(t)dw(t)\right) = \int_a^b f^2(t)dt = E\left(\int_a^b f(t)dw(t)\right)^2$$

(Ito's isometry)

$\int_a^b f(t)dw(t)$  white noise transformation  
 $\downarrow$   
 white noise

$f$  travel through white noise medium to yield the output  
 (at time  $b$ )  $\int_a^b f(t)dw(t)$   $\int$  it integrate  $f_t$  is non-random

$$W_t \triangleq W(t) \quad \text{---x---} \quad \int_a^b f(t) dW(t) \sim N(0, \int_a^b f^2(t) dt)$$

$$\stackrel{E_j(1)}{=} E\left(\int_0^T W_t dW_t\right) = E\left(\sum_j W_{t_j} (W_{t_{j+1}} - W_{t_j})\right)$$

$$\begin{aligned} E\left(\int_0^t W_s dW_s\right) &= E\left(\frac{W_t^2}{2} - \frac{t}{2}\right) \\ &= \frac{t}{2} - \frac{t}{2} = 0 \end{aligned}$$

$$= \sum_j E(W_{t_j}) E(W_{t_{j+1}} - W_{t_j}) = 0$$

indep. increments

$$\int_0^t \frac{1}{2} d(W_s)^2 = \frac{1}{2} W_t^2$$

Itô's lemma  
\$W\_t\$ is nowhere differentiable  
so usual calculus cannot be applied

Example (2)  
Itô's integral

$$\int_0^t W_s dW_s \approx \sum_j W_{t_j} (W_{t_{j+1}} - W_{t_j})$$

$$= \frac{W_t^2}{2} - \frac{1}{2} \sum_j (W_{t_{j+1}} - W_{t_j})^2 \rightarrow \frac{W_t^2}{2} - \frac{t}{2}$$

$$\left( \stackrel{Ex.}{=} \sum_{k=1}^n a_{k-1} (a_k - a_{k-1}) = \frac{1}{2} a_n^2 - \frac{1}{2} \sum_{k=1}^n (a_k - a_{k-1})^2 \right)$$

$$\sqrt{h} Z \stackrel{d}{=} (W_{t+h} - W_t) \sim N(0, h) \quad Z \sim N(0, 1)$$

$$W_t \sim N(0, t)$$

Quadratic Variation

$$\sum_{j=1}^n (W_{t(j)/h} - W_{t(j-1)/h})^2 \stackrel{d}{=} \sum_{j=1}^n \left( \sqrt{\frac{t}{n}} Z_j \right)^2$$

For BM trajectories

$$= t \times \frac{1}{n} \sum_{j=1}^n Z_j^2 \rightarrow t$$

\$\rightarrow E(Z^2) = 1\$

Thus the paths of the BM are very irregular  
(nowhere differentiable) random paths that nevertheless  
have a very special property that their quadratic

Variation on  $|g(t)| \uparrow$  exactly as the deterministic pt.

$$dW_t dW_t = (dW_t)^2 = dt$$

$$\text{Similarly } dW_t dt = dt dW_t = 0$$

$$dt \cdot dt = (dt)^2 = 0$$

\*\*\*

Example (3) Consider a particle of unit mass that is suspended in a liquid and suppose that, due to the liquid, there is a viscous force that retards the velocity of the particle at a rate proportional to its present velocity. In addition, let us suppose that the velocity instantaneously changes according to a constant multiple of white noise, i.e., if  $V(t)$  <sup>particle's</sup> vel. at  $t$ , suppose that

$$V'(t) = -\beta V(t) + \alpha W'(t),$$

where  $W(t), t \geq 0$  SBM

$$\Rightarrow e^{\beta t} [V'(t) + \beta V(t)] = \alpha e^{\beta t} W'(t)$$

$$\frac{d}{dt} [e^{\beta t} V(t)] = \alpha e^{\beta t} W'(t)$$

$$\Rightarrow e^{\beta t} V(t) = V(0) + \alpha \int_0^t e^{\beta s} W'(s) ds$$

$$V(t) = V(0) e^{-\beta t} + \alpha \int_0^t e^{-\beta(t-s)} W'(s) ds$$



$$V(t) = V(0) e^{-\beta t} + \alpha \int_0^t e^{-\beta(t-s)} dW(s)$$

eq (2)\*

$$V(t) = V(0) e^{-\beta t} + \alpha \left[ W(t) - \int_0^t W(s) \beta e^{-\beta(t-s)} ds \right] \quad |W(0) = 0$$

(Ornstein - Uhlenbeck process)

It has been proposed as model for describing the vel. of a particle immersed in a liquid or gas; and as such is useful in statistical mechanics.

—x—

Multivariate normal dist (MVN):

$$Z_i \sim \text{NID}(\sigma_i^2), \quad i=1, \dots, n$$

$$\text{const } a_{ij}, \quad 1 \leq i \leq m, \quad 1 \leq j \leq n \text{ and } \mu_i, \quad 1 \leq i \leq m$$

$$\text{If } X_i = a_{i1}Z_1 + \dots + a_{in}Z_n + \mu_i, \quad i=1, \dots, m,$$

then the  $m$  r.v's  $X_1, \dots, X_m$  are said to have a MVN.

$$E(X_i) = \mu_i \quad ; \quad V(X_i) = \sum_{j=1}^n a_{ij}^2$$

$$E\left(\sum_{i=1}^m t_i X_i\right) = \sum_{i=1}^m t_i \mu_i$$

$$V\left(\sum_{i=1}^m t_i X_i\right) = \text{Cov}\left(\sum_{i=1}^m t_i X_i, \sum_{j=1}^m t_j X_j\right)$$

$$= \sum_{i=1}^m \sum_{j=1}^m t_i t_j \text{Cov}(X_i, X_j)$$

$$\sum_{i=1}^m t_i X_i \sim N(\cdot, \cdot)$$

joint m.g.f of  $X_1, \dots, X_m$

$$\phi(t_1, \dots, t_m) = E\left(e^{\sum_{i=1}^m t_i X_i}\right)$$

$$= \exp\left\{\sum_{i=1}^m t_i \mu_i + \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m t_i t_j \text{Cov}(X_i, X_j)\right\}$$

which shows that the joint dist of  $X_1, \dots, X_m$  is completely determined from a knowledge of values of  $E(X_i)$  and  $\text{Cov}(X_i, X_j)$ ,  $i, j = 1, \dots, m$ . ⊗

### Gaussian Process

Def S.P.  $X(t), t \geq 0$  is Gaussian or a normal process if  $X(t_1), \dots, X(t_n)$  has MVN  $\forall t_1, \dots, t_n$ .

If  $\{B(t), t \geq 0\}$  BM process, then

$B(t_1), B(t_2), \dots, B(t_n)$  can be expressed as l.c of indep.

$N(\cdot, \cdot)$  w.r.t  $B(t_1), B(t_2) - B(t_1), \dots, B(t_n) - B(t_{n-1})$ .

$$\left. \begin{array}{l} B(t_1) \\ B(t_2) = B(t_2) - B(t_1) + B(t_1) \\ \vdots \end{array} \right\}$$

$\Rightarrow \{B(t), t \geq 0\}$  is a Gaussian process.

Infy ⊗, SBB could also be defined as a Gaussian process.

hence  $E(W(t)) = 0$ , and for  $s < t$

$$\text{Cov}(W(s), W(t)) = \text{Cov}(W(s), W(s) + W(t) - W(s))$$

$$= \underbrace{\text{Cov}(W(s), W(s))}_{\substack{\hookrightarrow \text{Var}(W(s)) \\ \hookrightarrow s}} + \underbrace{\text{Cov}(W(s), W(t) - W(s))}_{\substack{\hookrightarrow 0 \quad \text{indep increment} \\ |W(t) \sim N(0, t)}}$$

$$= s = s \wedge t \quad \quad \quad \underline{\Lambda \rightarrow \infty}$$

A Gaussian SP  $[X(t)]$  is a SBM iff

$$m_X(t) := E(X(t)) = 0 \text{ and } r_X(s, t) := \text{Cov}(X(s), X(t)) = s \wedge t, \quad s, t \geq 0.$$

—X—

Example (4) Find the dist of  $X := \int_0^t s dW_s$

As integrand is non-random

$$X \sim N\left(0, \frac{t^3}{3}\right), \text{ where}$$

$$V\left(\int_0^t s dW_s\right) = E\left(\int_0^t s dW_s\right)^2 = \int_0^t s^2 ds = \frac{t^3}{3}$$

Itô Formula :

$[X_t]_{t \in [0, T]}$  Itô process on  $(\Omega, \mathcal{F}, P)$  with  
BM  $[W_t]_{t \in [0, T]}$  on it) w

$$X_t = X_0 + \underbrace{\int_0^t a_s ds}_{\text{drift coeff}} + \underbrace{\int_0^t b_s dW_s}_{\text{diffusion coeff}} \quad \text{--- (I1)}$$

(I1) has on  $[0, T]$  stochastic differential

$$dX_t = a_t dt + b_t dW_t \quad \text{--- (I2)}$$

## (One-dimensional Itô formula)

$(X_t)_{t \in [0, T]}$  Itô process with (I2),  $f(\cdot)$  twice cont. differentiable. Then

$Y_t := f(X_t), t \in [0, T]$  is also Itô process with stochastic differential

$$dY_t \equiv df(X_t) = \left( f'(X_t) a_t + \frac{1}{2} f''(X_t) b_t^2 \right) dt + f'(X_t) b_t dW_t \quad \text{--- (I3)}$$

See multiplication table \*\*

Taylor's formula for  $f$  with two terms

$$df(X_t) = f'(X_t) dX_t + \frac{1}{2} f''(X_t) (dX_t)^2 \quad \text{--- (I4)}$$

using (I2)

$$dX_t = a_t dt + b_t dW_t$$

$$(dX_t)^2 = dX_t \cdot dX_t = (a_t dt + b_t dW_t)(a_t dt + b_t dW_t)$$

$$= \underbrace{a_t^2 (dt)^2}_{=0} + 2a_t b_t \underbrace{dt dW_t}_{=0} + b_t^2 \underbrace{(dW_t)^2}_{=dt}$$

$$= b_t^2 dt$$

using then in (I4) we get (I3).

Example (5)  $f(x) = \frac{1}{2} x^2$ ,  $X_t = W_t$

$$f'(x) = x, \quad f''(x) = 1$$

using (I4)

$$\begin{aligned} Y_t = df(X_t) &= df(W_t) \\ &= d\left(\frac{1}{2} W_t^2\right) \end{aligned}$$

$$\begin{aligned} dY_t &= d\left(\frac{1}{2} W_t^2\right) = f'(W_t) dW_t + \frac{1}{2} f''(W_t) (dW_t)^2 \\ &= W_t dW_t + \frac{1}{2} dt \end{aligned}$$

$$\Rightarrow \frac{d(W_t^2)}{2} - \frac{1}{2}dt = W_t dV_t$$

Which is in perfect agreement with result of Example (2).

Example (6)  $f(x) = e^x$ ,  $X_t = W_t$

$$f'(x) = f''(x) = e^x$$

$$Y_t = f(X_t) = f(W_t) = e^{W_t}$$

Using (14)

$$dY_t = d(e^{W_t}) = e^{W_t} dW_t + \frac{1}{2} e^{W_t} (dW_t)^2$$

$$= Y_t dW_t + \frac{1}{2} Y_t dt$$

(Univariate Ito process and time variable)

Statement:  $f(t, x)$  cont.  $\partial_t f = \frac{\partial f}{\partial t}$  and be twice cont. differentiable

$$\text{in } x, \quad \partial_x := \frac{\partial}{\partial x}, \quad \partial_{xx} := \frac{\partial^2}{\partial x^2}$$

let  $\{X_t\}$  Ito process (22).

Then  $Y_t := f(t, X_t)$  is also an Ito process with stoch. differential

$$dY_t = \underbrace{\partial_t f(t, X_t) dt + \partial_x f(t, X_t) dX_t + \frac{1}{2} \partial_{xx} f(t, X_t) (dX_t)^2}_{\longrightarrow (I.S.)}$$

$$= \left[ \partial_t f(t, X_t) + a_t \partial_x f(t, X_t) + \frac{1}{2} b_t^2 \partial_{xx} f(t, X_t) \right] dt$$

$$+ b_t \partial_x f(t, X_t) dW_t$$

Example: GBM

$$Z_t = e^{X_t} = Z_0 e^{\mu t + \sigma W_t}, \quad t \geq 0; \quad Z_0 = e^{x_0}$$

$$\mu, \sigma \in \mathbb{R}$$

$$\text{let } Z_0 = 1$$

$$Z_t = f(t, W_t) \quad \text{with } f(t, x) = e^{\mu t + \sigma x}$$

$$\partial_t f = \mu f, \quad \partial_x f = \sigma f, \quad \partial_{xx} f = \sigma^2 f$$

Using (IS)

$$\begin{aligned} dZ_t &= \mu f(t, W_t) dt + \sigma f(t, W_t) dW_t + \frac{\sigma^2}{2} f(t, W_t) \underbrace{(dW_t)^2}_{\rightarrow dt} \\ &= \left( \mu + \frac{\sigma^2}{2} \right) Z_t dt + \sigma Z_t dW_t \end{aligned}$$

Result: (The product rule of Itô calculus):

$(X_t), (Y_t)$  two Itô processes on a common filtered prob. space satisfying

$$dX_t = a_t dt + b_t dW_t$$

$$dY_t = \tilde{a}_t dt + \tilde{b}_t dW_t$$

with common BM  $(W_t)$ .

$Z_t := X_t Y_t$  is also an Itô process with

$$dZ_t \equiv d(X_t Y_t) = Y_t dX_t + X_t dY_t + dX_t dY_t \quad \text{--- (I.6)}$$

$$\begin{aligned} &= Y_t (a_t dt + b_t dW_t) + X_t (\tilde{a}_t dt + \tilde{b}_t dW_t) \\ &\quad + (a_t dt + b_t dW_t)(\tilde{a}_t dt + \tilde{b}_t dW_t) \end{aligned}$$

$$\begin{aligned} &= (Y_t a_t + X_t \tilde{a}_t + b_t \tilde{b}_t) dt \\ &\quad + (Y_t b_t + X_t \tilde{b}_t) dW_t \end{aligned} \quad \left| \begin{array}{l} dt dW_t = 0 = dW_t dt \\ (dt)^2 = 0 \\ (dW_t)^2 = dt \end{array} \right.$$

Sol  $d(X_t Y_t) = (X_t + dX_t)(Y_t + dY_t) - X_t Y_t$   
 now expand

Example:  $Z_t = W_t e^{W_t} = X_t Y_t$

let  $X_t := W_t$ ,  $Y_t := e^{W_t}$

Using (6)  
 $dZ_t = e^{W_t} dW_t + W_t \underline{de^{W_t}} + dW_t de^{W_t}$

$= e^{W_t} dW_t + W_t \left( e^{W_t} dW_t + \frac{1}{2} e^{W_t} dt \right) + dW_t \cdot \left( e^{W_t} dW_t + \frac{1}{2} e^{W_t} dt \right)$   
 using example (6)

$= \left( 1 + \frac{1}{2} W_t \right) e^{W_t} dt + (1 + W_t) e^{W_t} dW_t$

| using multiplication table

## Stochastic Differential Equations: (SDE)

SDE one means an equation involving stochastic differential  
 we consider SDE's with form

$$dX_t = a(t, X_t) + b(t, X_t) dW_t \quad (S1)$$

$t \in [0, T]$ ,  $X_0 = x_0$   
 $\uparrow$   
 non-random  
 initial condition

$a(t, x), b(t, x)$ ,  $t \geq 0, x \in \mathbb{R}$   
 $\uparrow$   
 non-random fn

$(W_t)$  SBRs on  $(\mathcal{F}, \mathcal{H}, \mathbb{P})$

An Itô process  $(X_t)_{t \in [0, T]}$  on  $(\mathcal{H}, \mathcal{H}, \mathbb{P})$  is said  
 to be a sol<sup>n</sup> to SDE (S1) if

$$X_t = x_0 + \int_0^t a(s, X_s) ds + \int_0^t b(s, X_s) dW_s, \quad t \in [0, T]$$

⌊(S2)

(S1) will have a unique sol<sup>n</sup> provided that the  $\mu, \sigma, b$  are regular enough.

SDE rarely admit sol<sup>n</sup> of an analytic closed form  
(one exceptional class <sup>being</sup> linear SDEs <sup>a special case</sup> of Ornstein-Uhlenbeck process)

→ Mathematical Modeling and  
Computation in Finance  
by Oosterlee & Goegele

Example (Ornstein-Uhlenbeck process) is the sol<sup>n</sup> of  
linear SDE with additive noise

$$dX_t = -r X_t dt + \sigma dW_t, \quad X_t|_{t=0} = x_0$$

$$r, \sigma > 0.$$

If we use this to model dynamics of a particle,  
then drift term represents a restoring force that  
prevent the particle from getting too far away from  
the origin. We will see that the distribution of  
the particle position has a limit as time goes to  $\infty$ .

This is a very different behavior from that of the  
BM.

Sol<sup>n</sup> 
$$e^{rt} dX_t + r e^{rt} X_t dt = \sigma e^{rt} dW_t$$

$$\Rightarrow \underline{d}(e^{rt} X_t) = \sigma e^{rt} dW_t$$



$$dt \quad \dots \quad - r w_t$$

$$\Rightarrow e^{rt} X_t - X_0 = \int_0^t \sigma e^{rs} dW_s$$

$$\Rightarrow X_t = e^{-rt} X_0 + \sigma \int_0^t e^{-r(t-s)} dW_s$$

is a sol<sup>n</sup>

$$\text{Let } \Theta_t := \int_0^t e^{-r(t-s)} dW_s$$

$\Theta_t$  is a Gaussian process with (using  $\otimes_2$ )

$$E(\Theta_t) = 0$$

$$E(\Theta_t^2) = E\left(\int_0^t e^{-r(t-s)} dW_s\right)^2$$

$$= \int_0^t e^{-2r(t-s)} ds$$

| using Ito's isometry

$$= e^{-2rt} \int_0^t e^{+2rs} ds$$

$$= e^{-2rt} \left( \frac{e^{2rs}}{2r} \right)_{s=0}^t$$

$$= \frac{e^{-2rt}}{2r} (e^{2rt} - 1) = \frac{1}{2r} (1 - e^{-2rt})$$

$$\underline{X_t \sim N\left(e^{-rt} x_0, \sigma_{r,t}^2\right)}$$

$$\text{where } \sigma_{r,t}^2 = \frac{\sigma^2}{2r} (1 - e^{-2rt})$$

of  $X_0$  Gaussian

$$X_t \rightarrow N\left(0, \frac{\sigma^2}{2r}\right) \quad \text{as } t \rightarrow \infty$$

Vasicek interest rate model:

"mean-reverting property" of Ornstein-Uhlenbeck process (i.e., the tendency of SP's trajectory to keep returning to its "historic av. value") made it a candidate for a mathematical model of the interest rate dynamics.

In this model spot interest rate  $r_t$  is assumed to satisfy the SDE

$$dr_t = a(b - r_t)dt + \sigma dW_t, \quad t > 0; \quad a, b, \sigma, r_0 > 0$$

$$\text{Putting } X_t := r_t - b \quad ; \quad dX_t = dr_t$$

$$dX_t = -aX_t dt + \sigma dW_t, \quad t > 0$$

$$r_t - b \sim N\left(b + e^{-at}(r_0 - b), \sigma_{a,t}^2\right)$$

Using Ornstein-Uhlenbeck process

This model has an obvious deficiency with +ve prob., the interest rate  $r_t$  can assume -ve values, which is undesirable.

The ...

may be fixed in the model in next example

Cox - Ingersell - Ross Interest rate model:

assume

$$dr_t = a(b - r_t)dt + \sigma \sqrt{r_t} dW_t, \quad t > 0$$

$a, b, \sigma, r_0 > 0$

It "freezes" the random

oscillation as  $r_t \rightarrow 0$  and so

the +ve drift term becomes dominating, hence the model will never produce negative interest rate values. Moreover  $r_t$  will never turn into zero provided that  $2ab \geq \sigma^2$ .