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Lump payments of dividends:-

$$0 = t_0 < t_1 < t_2 \dots < t_n < T = t_{n+1}$$

$t_i$  - dividend paying date

at time  $t_i$ , the dividend paid is  $a_i S(t_i)$ ,

$a_i$  is  $F(t_i)$ -mble and  $a_i \in P_{[t_i]}$

The price of the stock is given by

$$S(t_i) = (1 - a_i) S(t_{i-1})$$

$$dS(t) = \alpha(t) S(t) dt + \sigma(t) S(t) \cdot dW(t) \text{ for } t_i \leq t < t_{i+1}$$

If w portfolio process is  $\Delta(t)$  then

$$\begin{aligned} dX(t) &= \Delta(t) dS(t) + r(t) [X(t) - \Delta(t) S(t)] \cdot dt \\ &= \Delta(t) [X(t) \alpha(t) \cdot dt + \sigma(t) S(t) \cdot dW(t)] \\ &\quad + R(t) [X(t) - \Delta(t) S(t)] \cdot dt \\ &= R(t) X(t) dt + \Delta(t) S(t) (R(t) - R(t)) dt \\ &= R(t) X(t) \cdot dt + \Delta(t) S(t) \sigma(t) \left[ \frac{r(t) - R(t)}{\sigma(t)} \cdot dt + dW(t) \right] \\ &= R(t) X(t) \cdot dt + \Delta(t) S(t) \sigma(t) (\Theta(t) \cdot dt + dW(t)) \end{aligned}$$

$$\text{where } \Theta(t) = \frac{\alpha(t) - R(t)}{\sigma(t)}$$

Change the measure to  $\tilde{P}$  so that under  $\tilde{P}$

$$d\tilde{W}(t) = dW(t) + \Theta(t) \cdot dt \text{ is a B.M.}$$

By risk neutral pricing formula,  $D(t) X(t) = \tilde{E} [X(T) D(T) | \mathcal{F}(t)]$   
Consider  $\alpha, R, \sigma, a_i$  are const.

$$= \mathbb{E}[(S(t) - K)^+ D(t) / F(t)]$$

$$\begin{aligned} dS(t) &= \alpha S(t) dt + \sigma S(t) dW(t) \quad \text{for } t_i \leq t < t_{i+1} \\ &= R S(t) dt + \sigma S(t) d\tilde{W}(t) \end{aligned}$$

$$S(t_{i+1}) = S(t_i) \exp \left\{ \sigma (\tilde{W}(t_{i+1}) - \tilde{W}(t_i)) + \left( R - \frac{\sigma^2}{2} \right) (t_{i+1} - t_i) \right\}$$

$$\begin{aligned} S(t_{i+1}) &= (1 - a_{i+1}) (S(t_i)) \\ &= (1 - a_{i+1}) S(t_i) \exp \left\{ \sigma (\tilde{W}(t_{i+1}) - \tilde{W}(t_i)) + \left( R - \frac{\sigma^2}{2} \right) (t_{i+1} - t_i) \right\} \end{aligned}$$

$$\frac{S(t_{i+1})}{S(t_i)} = (1 - a_{i+1}) \exp \left\{ \sigma (\tilde{W}(t_{i+1}) - \tilde{W}(t_i)) + \left( R - \frac{\sigma^2}{2} \right) (t_{i+1} - t_i) \right\}$$

$$\frac{S(T)}{S(0)} = \prod_{i=0}^n \frac{S(t_{i+1})}{S(t_i)}$$

$$= \prod_{i=0}^n (1 - a_{i+1}) \exp \left\{ \sigma \tilde{W}(T) + \left( R - \frac{\sigma^2}{2} \right) T \right\}$$

$$S(T) = S(0) \prod_{i=0}^n (1 - a_{i+1}) \exp \left\{ \sigma \tilde{W}(T) + \left( R - \frac{\sigma^2}{2} \right) T \right\}$$

Price of call at time 0 is  
 $C(0, S(0)) = S(0) \prod_{i=0}^n (1 - a_{i+1}) N(d_+) - e^{-rT} K N(d_-)$

where  $d_{\pm} = \frac{1}{\sigma \sqrt{T}} \left\{ \log \left( \frac{S(0)}{K} \right) + \sum_{i=0}^n \log (1 - a_{i+1}) + \left( r \pm \frac{\sigma^2}{2} \right) T \right\}$

## Stochastic diff eq

$$\text{19/1/24} \quad \frac{dY(t)}{dt} = \alpha(t) Y(t) \cdot dt + \sigma(t) \cdot Y(t) \cdot dW(t)$$

$$\left\{ \begin{array}{l} dX(t) = b(t, X(t)) \cdot dt + \sigma(t, X(t)) \cdot dW(t) \\ X(0) = x \end{array} \right. \quad \text{--- (1)}$$

$$X(t) = X(0) + \int_0^t b(s, X(s)) \cdot ds + \int_0^t \sigma(s, X(s)) \cdot dW(s) \quad \text{--- (2)}$$

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space &  $\{W(t) : t \in [0, T]\}$  be a B.M with "filtrat"  $\mathcal{F}(t) = \sigma\{W(s), 0 \leq s \leq t\}$

Defn: A sol<sup>n</sup> of the eq<sup>n</sup> is a cont stochastic process  $X(t)$ ,  $t \in [0, T]$  with the following properties

①  $X(t)$  is adapted to the filtrat  $\mathcal{F}(t)$ ,  $t \in [0, T]$

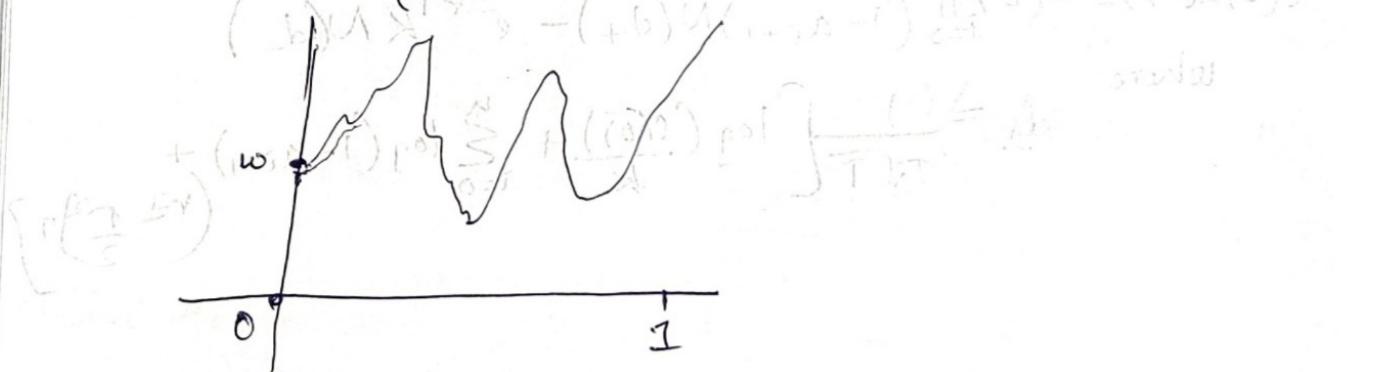
②  $\mathbb{P}(X(0) = x) = 1$

③  $\int_0^T |b(s, X(s))| \cdot ds < \infty$  &  $\mathbb{E} \int_0^T (\sigma(s, X(s)))^2 ds < \infty$

④ It satifies ④

Defn: The SDE above is said to have a unique sol<sup>n</sup> if  $\forall X \neq \tilde{X}$  are 2 sol<sup>n</sup> then

$$\mathbb{P}(X(t) = \tilde{X}(t) : 0 \leq t \leq T) = 1$$



$$\text{P.T} \quad \mathbb{P}(w : X(t) = \tilde{X}(t)) = 1 \quad \forall t \Rightarrow \mathbb{P}(X(t) = \tilde{X}(t) : 0 \leq t \leq T) = 1$$

Thm: Suppose that the coeff  $b(t, x)$ ,  $\sigma(t, x)$  satisfy  
 $|b(t, x) - b(t, y)| + |\sigma(t, x) - \sigma(t, y)| \leq k|x - y|$   
 $|b(t, x)| + |\sigma(t, x)| \leq k(1 + |x|)$  unique  
for some  $+ve$  const  $k$  then the SDE \* has a sol and  
 $E \int_0^T |X(t)|^2 dt < \infty$  (If derivative is not bounded, it is  
not globally lipschitz)

$dx(t) = x^2(t) dt$  (not Lipschitz on  $\mathbb{R}$  but on a compact set)

$$x(0) = 1$$

$$x(t) = \frac{1}{1-t} \quad (\text{This is not a well defined sol at } t=1)$$

$$dx(t) = 3x^{2/3} dt \quad x(t) = \begin{cases} 0 & \text{for } t \leq a \\ (t-a)^3 & \text{for } t > a \end{cases} \quad (\text{Not unique})$$

Gronwall's inequality: let  $f(\cdot)$  be a cont fn  $\Rightarrow$   
 $f(t) \leq c + k \int_0^t f(s) ds$  for  $0 \leq t \leq T$ , where  $c$  is a const  
and  $k$  is a  $+ve$  const then  $f(t) \leq ce^{kt}$ ,  $t \in [0, T]$

$$\text{Pf: } g(t) = c + k \int_0^t f(s) ds \quad t \in [0, T]$$

$$\text{By finding } \dot{g}(t), \quad \dot{g}(t) = k f(t) \quad \forall t \in [0, T] = e^{-kt} k f(t)$$

$$g(t) = c + k \int_0^t f(s) ds \geq f(t) \quad \Rightarrow \quad e^{-kt} (c + k \int_0^t f(s) ds) \leq 0$$

$$\dot{g}(t) \leq k g(t)$$

$$\Rightarrow \dot{g}(t) - k g(t) \leq 0$$

$$e^{-kt} (\dot{g}(t) - k g(t)) \leq 0$$

$$d(e^{-kt} g(t)) \leq 0$$

$$e^{-kt} g(t) \downarrow \quad \text{as } t \geq 0 \quad \text{if } k > 0$$

$$e^{-kt} g(t) \leq g(0) = c$$

$$c \leq g(t) \leq ce^{-kt}$$

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Uniqueness pf: Suppose  $x_1(t), x_2(t)$  two solns of the SDE

$$x_1(t) = x + \int_0^t b(s, x(s)). ds + \int_0^t \sigma(s, x(s)). dw(s)$$

$$x_2(t) = x + \int_0^t b(s, x_2(s)). ds + \int_0^t \sigma(s, x_2(s)). dw(s)$$

$$P(x_1(t) = x_2(t) : t \in [0, T]) = 1$$

$$x_1(t) - x_2(t) = \int_0^t b(s, x_1(s)) - b(s, x_2(s)). ds$$

$$+ \int_0^t (\sigma(s, x_1(s)) - \sigma(s, x_2(s))). dw(s)$$

$$(a+b)^2 \leq 2(a^2 + b^2)$$

$$\mathbb{E} |x_1(t) - x_2(t)|^2 \leq 2 \left[ \mathbb{E} \left| \int_0^t (b(s, x_1(s)) - b(s, x_2(s))). ds \right|^2 \right]$$

$$+ \mathbb{E} \left| \int_0^t (\sigma(s, x_1(s)) - \sigma(s, x_2(s))). dw(s) \right|^2$$

$$\leq 2 \left[ \mathbb{E} \left( \left| \int_0^t (b(s, x_1(s)) - b(s, x_2(s))). ds \right|^2 \right) \right]^{1/2} \quad \text{Ito isometry}$$

Holder inequality on I

$$\int f g \leq \int f \int g \quad q=1$$

$$+ 2 \mathbb{E} \left| \int_0^t (\sigma(s, x_1(s)) - \sigma(s, x_2(s))). dw(s) \right|^2$$

Use Fubini theorem and then Holder inequality

$$\mathbb{E} |x_1(t) - x_2(t)|^2 \leq 2(t+1)K^2 \mathbb{E} \int_0^t |x_1(s) - x_2(s)|^2 ds$$

$$= 2(t+1)K^2 \int_0^t \mathbb{E} |x_1(s) - x_2(s)|^2 ds$$

$$\text{Let } g(t) = \mathbb{E} \{x_1(t) - x_2(t)\}^2$$

$$\text{Then } g(t) \leq 2(t+1)K^2 \int_0^t g(s) ds$$

By Gronwall's inequality

$$0 \leq g(t) \leq 0 \quad \forall t \in [0, T]$$

$$\Rightarrow g(t) = 0 \quad \forall t \in [0, T]$$

$$\mathbb{E} |x_1(t) - x_2(t)|^2 = 0 \quad \forall t \in [0, T]$$

$$\Rightarrow P(X_1(t) = X_2(t)) = 1 \quad \forall t \in [0, T]$$

$$\Rightarrow P(X_1(t) = X_2(t), t \in Q \cap [0, T]) = 1$$

Q - set of rational nos

$$(A, \mathcal{F})$$

$$(A, \mathcal{F}, (A_t)_{t \geq 0}, (X_t)_{t \geq 0}, \mathbb{P})$$

$$X_t = (A_t, \mathcal{F}_t, b)$$

$$\frac{A_t}{(A_t)} \rightarrow \frac{A_t}{(A_t)}$$

$$X_t = (A_t, \mathcal{F}_t, b)$$

$$dS(t) = u(t) S(t) dt + \sigma(t) S(t) dW(t)$$

$$S(0) = S_0$$

$$|u(t)| + |\sigma(t)| \leq K$$

$$(A_t)_{t \geq 0} \times (A_t)_{t \geq 0} \times (A_t)_{t \geq 0} = (A_t)_{t \geq 0}$$

$$\sigma(t) \alpha = \sigma(t) \alpha$$

$$f(x) = \ln S(t) \quad (A_t)_{t \geq 0} \times (A_t)_{t \geq 0} = (A_t)_{t \geq 0}$$

$$d(\ln S(t)) = \frac{1}{S(t)} \cdot dS(t) - \frac{1}{2S^2(t)} \cdot dS(t) \cdot dS(t)$$

$$d(\ln S(t)) = \frac{1}{S(t)} \left( u(t) S(t) dt + \sigma(t) S(t) dW(t) \right)$$

$$\left[ \frac{1}{S(t)} \right] = \frac{1}{S(t)} \left\{ \sigma^2(t) \cdot S^2(t) dt \right\}$$

$$= \left( u(t) - \frac{1}{2} \sigma^2(t) \right) dt + \sigma(t) dW(t)$$

$$S(t) = S(0) \exp \left\{ \int_0^t \left( u(s) - \frac{1}{2} \sigma^2(s) \right) ds + \int_0^t \sigma(s) dW(s) \right\}$$

(Bernt Oksendal SDE)

$$\frac{dX(t)}{dt} = f(t)X(t) + g(t)$$

$$I.F = e^{-\int_0^t f(s) \, ds} = h(t)$$

$$h(t) \cdot \frac{dX(t)}{dt} - f(t) \cdot h(t)X(t) = g(t) \cdot h(t)$$

$$d(h(t)X(t)) = g(t)h(t)$$

$$h(t)X(t) - x = \int_0^t g(s) \cdot h(s) \, ds$$

$$X(t) = \frac{x}{h(t)} + \frac{\int_0^t g(s) \cdot h(s) \, ds}{h(t)}$$

Linear Stochastic DE:

$$dX(t) = (\phi(t)X(t) + \theta(t)) \cdot dW(t) + (f(t)X(t) + g(t)) \cdot dt$$

$$X(0) = x$$

$$I.F \quad H(t) = e^{-\gamma(t)}$$

$$\gamma(t) = \int_0^t \phi(s) \, dW(s) + \int_0^t f(s) \, ds - \frac{1}{2} \int_0^t \phi^2(s) \, ds$$

$$d(H(t)X(t)) = H(t) \, dX(t) + X(t) \, dH(t) + dX(t) \, dH(t)$$

$$\begin{aligned} dH(t) &= -e^{-\gamma(t)} \, d\gamma(t) + \frac{1}{2} e^{-\gamma(t)} \, \phi(t) \, dW(t) \\ &= -H(t)f(t) \, dt - H(t)\phi(t) \, dW(t) + H(t)\phi^2(t) \, dt \end{aligned}$$

$$dX(t) \, dH(t) = -H(t)\phi(t)(\phi(t)X(t) + \theta(t)) \, dt$$

$$d(X(t)H(t)) = H(t) \left[ \theta(t) \, dW(t) + g(t) \, dt - \theta(t)\phi(t) \, dt \right]$$

$$X(t) = x e^{\gamma(t)} + \int_0^t e^{\gamma(t)-\gamma(s)} \theta(s) \, dW(s)$$

$$+ \int_0^t e^{\gamma(t)-\gamma(s)} (g(s) - \theta(s)\phi(s)) \, ds$$

$$\{ (X(t), W(t)) \}_{t \geq 0} \sim \mathcal{N} \left( \mathbb{E}[X(t)] = x e^{\int_0^t f(s) \, ds}, \text{Var}[X(t)] = \int_0^t \phi^2(s) \, ds \right)$$

Example:-  $dX(t) = uX(t)dt + \sigma dW(t)$

$$X(0) = x_0$$

$$f(t) = u, g(t) = 0, \phi(t) = 0, \theta(t) = \sigma$$

$$Y = ut$$

$$X(t) = x_0 e^{ut} + \int_0^t e^{u(t-s)} \sigma dW(s) \quad (\text{OR})$$

$$dX(t) - uX(t).dt = \sigma dW(t)$$

$$d(e^{-ut} X(t)) = \sigma e^{-ut} dW(t)$$

$$X(t)e^{-ut} - x_0 = \int_0^t \sigma e^{-us} dW(s)$$

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Give an example where  $P(X_T = Y_T) = 1 \forall t \in [0, T]$  but  $P(X_t = Y_t, t \in [0, T]) = 1$  is false.

Consider the SDE

$$dX(t) = b(t, X(t)).dt + \sigma(t, X(t)).dW(t) \quad (1)$$

Let  $h(y)$  be a Borel mble f<sup>n</sup>

$$g(t, x) = \mathbb{E}[h(X(T)) | X(t) = x]$$

$$\therefore \mathbb{E}^{t,x}[h(X(T))]$$

Thm:- Assume that  $\mathbb{E}^{t,x}[h(X(T))] < \infty \forall t \in [0, T]$ , where  $X(\cdot)$  is the sol<sup>n</sup> of the SDE (1). Then for  $t \in [0, T]$

$$\mathbb{E}[h(X(T)) | F(t)] = g(t, X(t))$$

Corollary: The sol<sup>n</sup> of SDE's are Markov processes.

Thm:- (Feynman-Kac) Consider the SDE

$$dX(t) = b(t, X(t)).dt + \sigma(t, X(t)).dW(t)$$

Let  $h(y)$  be a Borel mble f<sup>n</sup>. Define

$$g(t, x) = \mathbb{E}^{t,x}[h(X(T))]$$

Then  $g(t, x)$  satisfies the PDE  

$$g_t(t, x) + b(t, x) g_x(t, x) + \frac{1}{2} \sigma^2(t, x) g_{xx}(t, x) = 0$$
  
 and the terminal condition

$$g(T, x) = h(x)$$

$$g(T, x) = \mathbb{E}[h(X(T))]$$

Pf:-

Terminal condition is obvious.

$$g(T, x) = \mathbb{E}[h(X(T)) \mid X(T) = x] = h(x)$$

$$g(t, X(t)) = \mathbb{E}[h(X(T)) \mid \mathcal{F}(t)] \text{ is a martingale}$$

Let  $0 \leq s \leq t \leq T$ . Then

$$g(s, X(s)) = \mathbb{E}[h(X(T)) \mid \mathcal{F}(s)]$$

$$\mathbb{E}[g(t, X(t)) \mid \mathcal{F}(s)] = g(s, X(s))$$

As  $g$  is smooth enough to apply Ito's lemma,

$$\begin{aligned} dg(t, X(t)) &= g_t(t, X(t)).dt + g_x(t, X(t)).dX(t) \\ &\quad + \frac{1}{2} g_{xx}(t, X(t)).dX(t).dX(t) \\ &= g_t(t, X(t)).dt + g_x(t, X(t)) \left\{ b(t, X(t)).dt + \sigma(t, X(t)) \right. \\ &\quad \left. + \frac{1}{2} g_{xx}(t, X(t)) \sigma^2(t, X(t)).dt \right\} \end{aligned}$$

As  $g$  is a martingale,  $dt$  term = 0.

Thm:- Discounted Feynman Kac

$$g(t, x) f(t, x) = \mathbb{E}^{t, x} \left[ e^{-r(T-t)} h(X(T)) \right]$$

then  $f_t(t, x) + b(t, x) f_x(t, x) + \frac{1}{2} \sigma^2(t, x) f_{xx}(t, x) = r f(t, x)$

Pf:-  $f(t, x) = e^{-r(T-t)} g(t, x)$

$$\begin{aligned} \mathbb{E}[f(t, X(t)) \mid \mathcal{F}(t)] &= \mathbb{E}[e^{-r(T-t)} h(X(T)) \mid \mathcal{F}(t)] \\ &\neq f(t, X(t)) \end{aligned}$$

$$e^{-rt} f(t, X(t)) = \mathbb{E}[e^{-r(T-t)} h(X(T)) | \mathcal{F}(t)] \\ = \mathbb{E}[e^{-rT} h(X(T)) | \mathcal{F}(t)]$$

$$0 \leq s < t \leq T$$

$$\mathbb{E}[e^{-rs} f(s, X(s)) | \mathcal{F}(s)]$$

$$= \mathbb{E}[e^{-rT} h(X(T)) | \mathcal{F}(s)] | \mathcal{F}(s)$$

$$= \mathbb{E}[e^{-rT} h(X(T)) | \mathcal{F}(s)]$$

$$= e^{-rs} f(s, X(s))$$

$\Rightarrow e^{-rt} f(t, X(t))$  is a martingale.

$$\xrightarrow{\text{Ito product rule}} d(e^{-rt} f(t, X(t))) = -re^{-rt} f(t, X(t)).dt + e^{-rt} df(t, X(t)) \\ + d(e^{-rt}) df(t, X(t)) = 0$$

$$= -re^{-rt} f(t, X(t)).dt + e^{-rt} \left\{ f_t(t, X(t)).dt + f_x(t, X(t)) \frac{dx(t)}{dt} \right. \\ \left. + \frac{1}{2} f_{xx}(t, X(t)).dx(t) \right\}$$

$$= e^{-rt} \left\{ -rf(t, X(t)) + f_t(t, X(t)) \right. \\ \left. + b(t, X(t)) f_x(t, X(t)) \right\}$$

$$= (r - \frac{1}{2}\sigma^2)x + (r - \sigma b)t + \mathbb{E}[f(t, X(t))]$$

$$= \mathbb{E}[f(t, X(t))]$$

$$C(t, x) = \mathbb{E}[e^{-r(T-t)} (X(T) - K)^+]$$

$$dC(t) = rC(t).dt + \sigma C(t).dW(t)$$

$$b(t, x) = \underline{rx} \quad \text{since risk neutral measure}$$

$$\sigma(t, x) = \sigma x$$

The PDE for  $C(t, x)$  is

$$C_t(t, x) + rx C_x(t, x) + \frac{1}{2} r^2 x^2 C_{xx}(t, x) = rC(t, x)$$

$$C(T, x) = (x - K)^+$$

2.11.3  
↳ Multidimensional Feynman-Kac Thm:-

Let  $W(t) = (W_1(t), W_2(t))$  be a 2-D B.M.

$$dX_1(t) = \beta_1(t, X_1(t), X_2(t)) dt + \gamma_{11}(t, X_1(t), X_2(t)) dW_1(t) \\ + \gamma_{12}(t, X_1(t), X_2(t)) dW_2(t)$$

$$dX_2(t) = \beta_2(t, X_1(t), X_2(t)) dt + \gamma_{21}(t, X_1(t), X_2(t)) dW_1(t) \\ + \gamma_{22}(t, X_1(t), X_2(t)) dW_2(t)$$

Let  $h(x_1, x_2)$  be a Borel measurable f

$$g(t, x_1, x_2) = \mathbb{E} [h(X_1(t), X_2(t)) | X_1(t) = x_1, X_2(t) = x_2] \\ = \mathbb{E}^{t, x_1, x_2} [h(X_1(t), X_2(t))]$$

$$f(t, x_1, x_2) = \mathbb{E}^{t, x_1, x_2} [e^{-r(T-t)} h(X_1(T), X_2(T))]$$

Then

$$g_t(t, x_1, x_2) + \beta_1(t, x_1, x_2) g_{x_1}(t, x_1, x_2) + \beta_2(t, x_1, x_2) g_{x_2}(t, x_1, x_2) \\ + \left[ \frac{1}{2} (\gamma_{11}^2 + \gamma_{12}^2) g_{x_1 x_1} + \frac{1}{2} (\gamma_{21}^2 + \gamma_{22}^2) g_{x_2 x_2} + (\gamma_{11} \gamma_{21} + \gamma_{12} \gamma_{22}) g_{x_1 x_2} \right] (t, x_1, x_2)$$

$$\left[ f_t + \beta_1 f_{x_1} + \beta_2 f_{x_2} + \frac{1}{2} (\gamma_{11}^2 + \gamma_{12}^2) f_{x_1 x_1} + \frac{1}{2} (\gamma_{21}^2 + \gamma_{22}^2) f_{x_2 x_2} \right. \\ \left. + (\gamma_{11} \gamma_{21} + \gamma_{12} \gamma_{22}) f_{x_1 x_2} \right] (t, x_1, x_2) = r f(t, x_1, x_2)$$

$$g(t, x_1, x_2) = \mathbb{E} [h(X_1(T), X_2(T)) | X_1(t) = x_1, X_2(t) = x_2] = \mathbb{E}^{t, x_1, x_2} [h(X_1(T), X_2(T))]$$

$$f(t, x_1, x_2) = \mathbb{E}^{t, x_1, x_2} \left[ e^{-r(T-t)} h(X_1(T), X_2(T)) \right]$$

Vasicek model

$$dR(t) = (\alpha - \beta R(t)) dt + \sigma dW(t), R(0) = r_0 \quad \alpha, \beta, \sigma \text{ are const}$$

$$R(t) = H(t) = e^{\beta t} \quad \text{Let } X(t) = \int_0^t e^{\beta s} dW(s)$$

$$R(t) = r_0 e^{-\beta t} + \frac{\alpha}{\beta} (1 - e^{-\beta t}) + \sigma e^{-\beta t} \int_0^t e^{\beta s} dW(s)$$

$$\therefore f(t, x) = e^{-\beta t} r_0 + \frac{\alpha}{\beta} (1 - e^{-\beta t}) + \sigma e^{-\beta t} x$$

$$R(t) \sim N\left(x_0 e^{-\alpha t} + \frac{\alpha}{\beta} (1 - e^{-\alpha t}), \frac{\sigma^2}{2\beta} (1 - e^{-2\alpha t})\right)$$

$$X(t) = x_0 + \int_0^t \alpha X(s) ds + \int_0^t \sigma dW(s)$$

$$\mathbb{E}[X(t)] = x_0 + \alpha \int_0^t \mathbb{E}[X(s)], ds$$

$$\text{Let } g(t) = \mathbb{E}[X(t)]$$

$$g(t) = x_0 + \alpha \int_0^t g(s), ds$$

$$\frac{d}{dt} g(t) = \alpha g(t)$$

$$\therefore g(t) = x_0 e^{\alpha t}$$

$$\text{Var}(X(t)) = \mathbb{E}[X^2(t)] - (\mathbb{E}[X(t)])^2$$

$$d(X^2(t)) = 2X(t) \cdot dX(t) + \frac{1}{2} (2 dX(t) \cdot dX(t))$$

$$= 2X(t) [\alpha X(t) \cdot dt + \sigma dW(t)] + \sigma^2 dt$$

$$\therefore d(X^2(t)) = (2\alpha(X(t))^2 + \sigma^2) \cdot dt + 2X(t) \sigma dW(t)$$

$$X^2(t) = x_0^2 + \int_0^t (2\alpha X^2(s) + \sigma^2) \cdot ds + \int_0^t 2X(s) \cdot dW(s)$$

$$\mathbb{E}[X^2(t)] = x_0^2 + 2\alpha \int_0^t \mathbb{E}[X^2(s)], ds + \sigma^2 t$$

$$\text{Let } f(t) = \mathbb{E}[X^2(t)]$$

$$\text{Then } f(t) = x_0^2 + 2\alpha \int_0^t f(s), ds + \sigma^2 t$$

$$\frac{d}{dt} f(t) = 2\alpha f(t) + \sigma^2 \quad \text{and} \quad f(0) = x_0^2$$

$$\frac{d}{dt} \ln \left( \frac{2\alpha f(t) + \sigma^2}{2\alpha x_0^2} \right) = \frac{2\alpha}{2\alpha x_0^2}$$

$$f(t) = e^{2\alpha t} \left[ 2\alpha x_0^2 + \frac{\sigma^2}{2\alpha} \right]$$

$$\therefore f(t) = \frac{\sigma^2}{2\alpha} (e^{2\alpha t} - 1) + x_0^2 e^{2\alpha t}$$

$$(x_0^2 + \frac{\sigma^2}{2\alpha}) e^{2\alpha t} = f(t)$$

$$\frac{du}{dt} = \frac{1}{2} \frac{\partial^2 u}{\partial x^2} - K(x)u$$

30/1/24

Gaussian process:-

Def:- A Gaussian process  $X(t), t \geq 0$  is a stochastic process such that for arbitrary time pts

$0 < t_1 < t_2 < t_3 < \dots < t_n$  the r.v.s  $X(t_1), X(t_2), \dots, X(t_n)$  are jointly normally distributed.

it has A r.v.s  $\bar{x} = (x_1, x_2, \dots, x_n)$  is jointly normal if joint density

$$f_x(\bar{x}) = \frac{1}{\sqrt{(2\pi)^n |C|}} \exp\left\{(\bar{x} - \mu)^T C^{-1} (\bar{x} - \mu)^T\right\}$$

( $\bar{x} = (x_1, x_2, \dots, x_n)$ ,  $\mu = (\mu_1, \mu_2, \dots, \mu_n)$ ,  $C$  - cov matrix)

We denote mean of  $X(t)$  by  $m(t)$  & cov of  $X(t)$  w/  $X(s)$  by  $C(t,s)$

$$m(t) = \mathbb{E}\{X(t)\}, C(t,s) = \mathbb{E}\{(X(t) - m(t))(X(s) - m(s))\}$$

Eg:- ①  $W(t), t \geq 0$  B.M is a Gaussian process

$(W(t_1), W(t_2) - W(t_1), W(t_3) - W(t_2), \dots, )$  is jointly normal as each of them are independent of one another.

If  $\bar{x} = (x_1, x_2, \dots, x_n)$  is jointly normal &  $Y = Ax^T$ , also a jointly normal vector  $A = (a_{ij})$

Here  $A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 1 & \dots & 1 \end{bmatrix}$

$$m(t) = \mathbb{E}[W(t)] = 0$$

$$\text{& } C(s,t) = \mathbb{E}[W(s)W(t)] = \mathbb{E}[W(s)(W(t) - W(s)) + (W(s))^2] \\ = s \cdot 1 = \min(s, t)$$

Ex:  $I(t) = \int_0^t \Delta(s) dW(s)$  where  $\Delta(t)$  is non-random. Then  
 $I(t), t \geq 0$  is a Gaussian process.  
 $(I(t) \sim N(0, \int_0^t \Delta^2(s) ds))$

ff:  $I(t_1), I(t_2) - I(t_1), \dots, I(t_n) - I(t_{n-1})$

For a fixed  $u$ , set

$$M_u(t) = \exp \left\{ u \int_0^t \Delta(s) dW(s) - \frac{1}{2} \int_0^t u^2 \Delta^2(s) ds \right\}$$

Ex:  $M_u(t)$  is a martingale

$$\text{H.W. } dM_u(t) = \dots$$

Q  $0 < t_1 < t_2 < T$  with  $t_1, t_2$  and  $(A, B)$  two disjoint intervals. Show that  $M_{u_1}(t_2) | \mathcal{F}(t_1)$  is a martingale.

$$M_{u_2}(t_1) = \mathbb{E}[M_{u_2}(t_2) | \mathcal{F}(t_1)]$$

$$(\mathbb{E}[e^{u_1 I(t_1) + u_2 (I(t_2) - I(t_1))}] \text{ both sides are in } (A, B) \text{ and } (B, C) \text{ respectively})$$

$$\frac{M_{u_1}(t_1)}{M_{u_2}(t_1)} \cdot M_{u_2}(t_1) = \frac{M_{u_1}(t_1)}{M_{u_2}(t_1)} \mathbb{E}[M_{u_2}(t_2) | \mathcal{F}(t_1)]$$

$$M_{u_1}(t_1) = \mathbb{E}\left[M_{u_2}(t_2) \frac{M_{u_1}(t_1)}{M_{u_2}(t_1)} \mid \mathcal{F}(t_1)\right]$$

$$= \mathbb{E}\left[\exp\{u_1 I(t_1) + u_2 (I(t_2) - I(t_1))\}\right]$$

Expect on both sides  $\exp\left\{-\frac{1}{2} u_1^2 \int_0^{t_2} \Delta^2(s) ds - \frac{1}{2} u_2^2 \int_{t_1}^{t_2} \Delta^2(s) ds\right\}$

$$1 = \mathbb{E}\left[\exp\{u_1 I(t_1) + u_2 (I(t_2) - I(t_1))\}\right] \quad | \mathcal{F}(t_1)$$

$$\exp\left\{-\frac{1}{2} u_1^2 \int_0^t \Delta^2(s) ds - \frac{1}{2} u_2^2 \int_t^{t_2} \Delta^2(s) ds\right\}$$

$$= \exp\left\{\frac{1}{2} u_1^2 \int_0^{t_1} \Delta^2(s) \cdot ds\right\} \exp\left\{\frac{1}{2} u_2^2 \int_{t_1}^{t_2} \Delta^2(s) \cdot ds\right\}$$

$$= \mathbb{E}\left[e^{u_1 I(t_1)}\right] \mathbb{E}\left[e^{u_2 (I(t_2) - I(t_1))}\right]$$

For  $I(t) = \int_0^t \Delta(s) \cdot dW(s)$

$$\text{Let } u(t) = \mathbb{E}[I(t)] = 0$$

$$C(s, t) = \mathbb{E}[I(s) I(t)]$$

$$= \mathbb{E}[I(s)(I(t) - I(s)) + I(s)]$$

$$= 0 \times 0 + \int_0^s \Delta^2(u) \cdot du = \int_0^s \Delta^2(u) \cdot du$$

### Brownian Bridge

Defn: Let  $W(t)$  be a B.M. Fix  $T > 0$ , we define the Brownian Bridge from  $0$  to  $0$  (i.e.  $X(0) = 0$  and  $X(T) = 0$ ) to the process  $X(t) = W(t) - \frac{t}{T} W(T), t \in [0, T]$

(Note that  $X(t)$  is not adapted to the same filtration as  $W(t)$ )  
This is a Gaussian process.

$$\mathbb{E}[X(t) X(s)] = \mathbb{E}[W(t) W(s) - \frac{t}{T} W(T) W(s) - \frac{s}{T} W(T) W(t) + \frac{ts}{T^2} W(T) W(T)]$$

$$= \mathbb{E}[W(t) W(s)] - \frac{t}{T} \mathbb{E}[W(T) W(s)] - \frac{s}{T} \mathbb{E}[W(T) W(t)] + \frac{ts}{T^2} \mathbb{E}[W(T) W(T)]$$

$$= \mathbb{E}[W(t) W(s)] - \frac{ts}{T^2} \mathbb{E}[W(T) W(T)]$$

$$= \mathbb{E}[W(t) W(s)] - \frac{ts}{T^2} \mathbb{E}[W(T)^2]$$

$$= \mathbb{E}[W(t) W(s)] - \frac{ts}{T^2} \mathbb{E}[W(T)^2]$$

### Brownian Bridge:

Defn: let  $W(t)$  be a B.M. Fix  $T > 0$ , we define the Brownian bridge from 0 to 0 on  $[0, T]$  to be the process  $X(t) = W(t) - \frac{t}{T} W(T)$ ,  $t \in [0, T]$ .  
This is a Gaussian process.

2/2  
 $X(t) = W(t) - \frac{t}{T} W(T), \quad \forall t \in T$

where  $W(t)$  is a B.M.

$$X(0) = 0 = X(T)$$

$X(t)$  is a Gaussian process

$$0 < t_1 < t_2 < \dots < t_n < T$$

$X(t_1), X(t_2), \dots, X(t_n)$  - jointly normal

To prove that  
 $X(t)$  is a Gaussian, we need to show it's

$$X(t_1) = W(t_1) - \frac{t_1}{T} W(T), \quad X(t_2) = W(t_2) - \frac{t_2}{T} W(T), \dots$$

$$\dots, X(t_n) = W(t_n) - \frac{t_n}{T} W(T)$$

all of them are jointly normal

$$X(t_1) = W(t_1) - \frac{t_1}{T} W(T), \quad X(t_2) = W(t_2) - \frac{t_2}{T} W(T), \dots$$

$$\dots \quad X(t_n) = W(t_n) - \frac{t_n}{T} W(T)$$

$W(t_1), W(t_2), \dots, W(T)$  jointly normal

$\Rightarrow X(t_1), \dots, X(T)$  jointly normal

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

$$C(s, t) = E[X(s) X(t)] = E[(W(s) - \frac{s}{T} W(T))(W(t) - \frac{t}{T} W(T))]$$

$$= E[W(s)W(t) - \frac{ts}{T} W(T)W(s) - \frac{s}{T} W(t)W(T) + \frac{st}{T^2} W(T)^2]$$

$$= s \wedge t - \frac{ts}{T} - \frac{ts}{T} + \frac{st}{T^2} T$$

$$= s \wedge t - \frac{st}{T}$$

$s \wedge t = \min(s, t)$

Defn: Let  $W(t)$  be a B.M. Fix  $T > 0$ ,  $a, b \in \mathbb{R}$ . Define  
 the Brownian Bridge from  $a$  to  $b$  on  $[0, T]$  to be the process

$[0, T]$  to be the process

$$X^{a \rightarrow b}(t) = a + \frac{(b-a)}{T} t + Y(t), \quad t \in [0, T]$$

where  $Y(t)$  is a Brownian bridge from

$$0 \text{ to } 0 \quad X^{a \rightarrow b}(0) = a, \quad X^{a \rightarrow b}(T) = b$$

$$M^{a \rightarrow b}(t) = a + \frac{(b-a)}{T} t \quad (\text{use } E[X(t)] = 0)$$

$$C^{a \rightarrow b}(s, t), \quad E \left[ (X^{a \rightarrow b}(s) - M^{a \rightarrow b}(s)) (X^{a \rightarrow b}(t) - M^{a \rightarrow b}(t)) \right]$$

$$= E \left[ X(s) X(t) \right]$$

(same covariance as Brownian bridge)

$$= t s - \frac{s t}{T}$$

Hence  $Y(t)$  is Gaussian,  $f(t)$  - some deterministic

func not random,  $Y(t)f(t) \rightarrow$  Gaussian

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< Notes

$$\rightarrow I(t) = \int_0^t \Delta(s) dW(s)$$

$$C_{I(t), t} = t - \frac{t^2}{T} = \frac{t(T-t)}{T}$$

$$C_I^T(t, t) = \int_0^t \Delta^2(s) ds$$

$$Y(t) = (T-t) \int_0^t \frac{1}{T-u} dW(u), 0 \leq t \leq T$$

$$\Sigma(t) = \int_0^t \frac{1}{T-u} dW(u)$$

$$0 < t_1 < t_2 < \dots < t_n < T$$

$$Y(t_1) = (T-t_1) I(t_1), \dots, Y(t_n) = (T-t_n) I(t_n)$$

gaussian  
deterministic

$Y(t_1), \dots, Y(t_n)$  - jointly normal

$$M^I(t) = E[I(t)] = 0, M^Y(t) = E[Y(t)] = 0$$

t.s

$$C_I^T(t, t) = \int_0^t \frac{1}{(T-u)^2} du$$

$$C^T(s, t) = \int_0^{t \wedge s} \frac{1}{(T-u)^{\alpha}} du \\ = \frac{1}{T - (s \wedge t)} - \frac{1}{T}, \quad s, t \in [0, T]$$

$$0 \leq s \leq t < T$$

$$C^Y(s, t) : E\left[(T-s) I(s) (T-t) I(t)\right] \\ = (T-s)(T-t) E\left[I(s) I(t)\right] \\ = (T-s)(T-t) \left[ \frac{1}{T-s} - \frac{1}{T} \right] \\ = \frac{(T-t)s}{T} = s - \frac{st}{T}$$

$$C^Y(s, t) : s \wedge t - \frac{st}{T} \quad \text{for } s, t \in [0, T]$$

$$C^Y(t, t), \quad t - \frac{t^2}{T}, \quad t \frac{(T-t)}{T}$$


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< Notes

$$C^Y(s,t) = \delta(t-s) \quad \text{for } s,t \in [0,T]$$

$$C^Y(\zeta_t), \quad t = \frac{\tau}{T}, \quad \frac{t(T-t)}{T}$$

as  $t \rightarrow T$ ,  $C^*(C^*, t) \rightarrow 0$

$$\rightarrow Y(t) = \begin{cases} (\tau - t) \int_0^t \frac{1}{\tau-u} dW(u) & , 0 \leq t < \tau \\ 0 & , t = \tau \end{cases}$$

$\gamma(t)$  is a continuous Gaussian process on  $[0, T]$

has mean & covariance func<sup>n</sup>:

$$m^y(t) = 0, \quad C^y(t, s) = t \wedge s - \frac{st}{T}$$

V2/2F

$X^{a \rightarrow b}(t)$  = Brownian bridge from  $a$  to  $b$

$0 \leq t_0 < t_1 < \dots < t_n \leq T$

$X^{a \rightarrow b}(t_1), \dots, X^{a \rightarrow b}(t_n)$

$$m^{a \rightarrow b}(t) = a + \frac{(b-a)t}{T} = \frac{(T-t)a}{T} + \frac{bt}{T}$$

$$C^{a \rightarrow b}(t, s) = s \frac{1}{T} t - \frac{s}{T}$$

For  $0 \leq s \leq t \leq T$ ,

$$\text{Let } T_j = T - t_j \text{ and } T_0 = T$$

$$z_j = \frac{X^{a \rightarrow b}(t_j)}{T_j} - \frac{X^{a \rightarrow b}(t_{j-1})}{T_{j-1}}$$

$X^{a \rightarrow b}(t_1), \dots, X^{a \rightarrow b}(t_n)$  are jointly normal

$\Rightarrow z_1, \dots, z_n$  are jointly normal

$$\begin{aligned} E[z_j] &= \frac{1}{T_j} E[X^{a \rightarrow b}(t_j)] - \frac{1}{T_{j-1}} E[X^{a \rightarrow b}(t_{j-1})] \\ &= a \left( \frac{1}{T_j} - \frac{1}{T_{j-1}} \right) + \frac{b-a}{T} \left( \frac{t_j}{T_j} - \frac{t_{j-1}}{T_{j-1}} \right) \end{aligned}$$

=  $a$

$$\begin{aligned} \Rightarrow \text{Var}(z_j) &= \frac{1}{T_j^2} C^{a \rightarrow b}(t_j, t_j) + \frac{1}{T_{j-1}^2} C^{a \rightarrow b}(t_{j-1}, t_{j-1}) \\ &\quad - \frac{2}{T_j T_{j-1}} C^{a \rightarrow b}(t_j, t_{j-1}) \\ &= \frac{t_j - t_{j-1}}{T_j T_{j-1}} \end{aligned}$$

$$\begin{aligned} \text{Cov}(Z_i, Z_j) &= \frac{1}{T_j - T_i} C^{a \rightarrow b}(t_i, t_j) = \frac{1}{T_i T_{j-1}} C^{a \rightarrow b}(t_i, t_{j-1}) \\ &\quad + \frac{1}{T_{j-1} T_j} C^{a \rightarrow b}(t_{j-1}, t_j) \\ &\quad + \frac{1}{T_{j-1} T_j} \delta C^{a \rightarrow b}(t_{j-1}, t_{j-1}) \\ &= 0 \end{aligned}$$

$Z_1, Z_2, \dots, Z_n$  are independent ( $\text{as } Z_1, Z_2, \dots, Z_n$  are jointly normal  $\Rightarrow \text{Cov}(Z_i, Z_j) = 0$  for  $i \neq j$ )

$$f_{Z_1, \dots, Z_n}(z_1, \dots, z_n) = \exp \left\{ -\frac{1}{2} \sum_{j=1}^n \left( \frac{z_j - b(t_j - t_{j-1})}{\sqrt{\frac{t_j - t_{j-1}}{T_j T_{j-1}}}} \right)^2 \right\} \times$$

$$z_j = \frac{x_j}{T_j} - \frac{x_{j-1}}{T_{j-1}}$$

$$\prod_{j=1}^n \frac{1}{\sqrt{2\pi} \sqrt{\frac{t_j - t_{j-1}}{T_j T_{j-1}}}}$$

$$\frac{\partial z_j}{\partial x_j} = \frac{1}{T_j}$$

$$\frac{\partial z_j}{\partial x_{j-1}} = -\frac{1}{T_{j-1}}$$

$$J = \begin{bmatrix} \frac{1}{T_1} & 0 & \cdots & 0 \\ -\frac{1}{T_1} & \frac{1}{T_2} & \cdots & 0 \\ 0 & 0 & \ddots & \vdots \\ 0 & \cdots & \cdots & \frac{1}{T_n} \end{bmatrix}$$

$$f_x^{a \rightarrow b}(x_1) \dots f_x^{a \rightarrow b}(x_n)(x_1, \dots, x_n) = \sqrt{\frac{T}{T-t_n}} \prod_{j=1}^n \frac{1}{\sqrt{2\pi} \sqrt{\frac{t_j - t_{j-1}}{T_j T_{j-1}}}}$$

$$\exp \left\{ -\frac{1}{2} \sum_{j=1}^n \frac{(x_j - x_{j-1})^2}{\frac{t_j - t_{j-1}}{T_j T_{j-1}}} - \frac{(b - x_n)^2}{2(T - t_n)} - \frac{(b - a)^2}{2T} \right\}$$

$$= \frac{p(T-t_n, x_n, b)}{p(T, a, b)} \prod_{j=1}^n p(t_j - t_{j-1}, x_{j-1}, x_j)$$

$$\text{where } p(\tau, \alpha, \gamma) = \frac{1}{\sqrt{2\pi}\tau} \exp \left\{ -\frac{(\gamma - \alpha)^2}{2\tau} \right\}$$

The joint density of  $w(t_1), \dots, w(t_n), w(T)$

$$f_{w(t_1) \dots w(T)}(x_1, \dots, x_n, b) = p(T-t_1, x_n, b) \prod_{j=1}^n p(t_j - t_{j-1}, x_{j+1}, x_j)$$

where  $w(0) = a$

$$p(t_1 - t_0, a, x_1) = p(t_1, a, x_1)$$

$$p(t_2 - t_1, x_1, x_2) =$$

Corollary:- The density of  $M^{a \rightarrow b}(T)$  is

$$f_{M^{a \rightarrow b}(T)}(y) = \frac{2(2y - b - a)}{T} e^{-\frac{2}{T}(y-a)(y-b)} \quad y \geq \max\{a, b\}$$

$$\text{Pf: } M(t) = \max_{0 \leq s \leq t} W(s)$$

The conditional distribution of  $M(t)$  given  $W(t) = w$  is

$$f_{M(t)/W(t)}(m/w) = \frac{2(2m - w)}{T} \exp\left\{-\frac{2m(m-w)}{T}\right\} \quad w \leq m, w \geq$$

- Define  $M^{0 \rightarrow w}(T) = \max_{0 \leq t \leq T} X^{0 \rightarrow w}(t)$

$$f_{M^{0 \rightarrow w}(T)}(m) = f_{\frac{m}{W(T)}}($$