



# 1. Kolmogorov's backward/forward eqn.

Let  $X_t$  be an Ito diffusion w/ generator  $A$ . i.e.  $dX_t = b(X_t)dt + \sigma(X_t)dB_t$ ; Lipschitz

$$Af = b \cdot \nabla f + \frac{1}{2} (\sigma \sigma^T) : \text{Hess}(f), \quad \forall f \in C_0^2$$

Recall Dynkin's formula:

$$\mathbb{E}^x[f(X_\tau)] = f(x) + \mathbb{E}^x \left[ \int_0^\tau Af(X_s) ds \right]. \quad \text{for } \tau: \text{stopping time, } \mathbb{E}^x[\tau] < \infty$$

$\xrightarrow{t=\tau}$

$$u(t,x) \leftarrow \mathbb{E}^x[f(X_t)] = f(x) + \mathbb{E}^x \left[ \int_0^t Af(X_s) ds \right]$$

$\Rightarrow$

$$\boxed{\frac{d}{dt} \mathbb{E}^x[f(X_t)] = \mathbb{E}^x[Af(X_t)]} \stackrel{?}{=} A \mathbb{E}^x[f(X_t)] \Rightarrow \partial_t u = Au$$

Theorem 8.1.1 (Kolmogorov's backward eqn.) Let  $f \in C_0^2(\mathbb{R}^n)$ ,  $u(t,x) = \mathbb{E}^x[f(X_t)]$

(a). Then  $u(t, \cdot) \in \text{Dom}(A) \forall t$ ,  $\begin{cases} \partial_t u = Au, & t > 0, x \in \mathbb{R}^n \\ u(0, x) = f(x), & x \in \mathbb{R}^n. \end{cases}$

(b) If  $w(t,x) \in C^{1,2}(\mathbb{R} \times \mathbb{R}^n)$  is bdd & satisfying  $\begin{cases} \partial_t w = Aw, & \text{then } w = \mathbb{E}^x[f(X_t)] \\ w(0, x) = f(x) \end{cases}$

Proof: (a)  $Au(t,x) = \lim_{r \downarrow 0} \frac{\mathbb{E}^x[u(t+r, X_r)] - u(t,x)}{r} = \frac{1}{r} \mathbb{E}^x \left[ \underbrace{\mathbb{E}^{X_r}[f(X_t)] - f(X_r)}_{\mathbb{E}^x[f(X_{t+r}) | \mathcal{F}_r]} - f(X_r) \right]$  Markov.  
 $= \lim_{r \downarrow 0} \frac{1}{r} \mathbb{E}^x[f(X_{t+r}) - f(X_r)]$   $\mathbb{E}^x[f(X_t)] = \mathbb{E}^x[\mathbb{E}^x[f(X_t) | \mathcal{F}_r]]$   
 $= \lim_{r \downarrow 0} \frac{1}{r} [u(t+r, x) - u(t, x)]$   
 $= \partial_t u. \quad \#$

Fix  $(s,x)$

(b)  $\begin{cases} \tilde{A} w = -\partial_t w + Aw = 0 \\ w(0, x) = f(x) \end{cases}$

$\tilde{A}: Y_t = \begin{pmatrix} s-t \\ X_t^{s,x} \end{pmatrix} \quad dY_t = \begin{pmatrix} -dt \\ dX_t \end{pmatrix} = \begin{pmatrix} -1 \\ b(X_t) \end{pmatrix} dt + \begin{pmatrix} 0 \\ \sigma(X_t) \end{pmatrix} dB_t$

By Dynkin's formula,  $\mathbb{E}^{s,x}[w(Y_{t \wedge T_R})] = w(s,x) + \mathbb{E}^{s,x} \left[ \int_0^{t \wedge T_R} \tilde{A} w(Y_r) dr \right] = w(s,x)$

R.A.S.  $\downarrow$   $\hookrightarrow T_R = \inf\{t > 0: |X_t| \geq R\}$ .

$\mathbb{E}^{s,x}[w(Y_t)]$ ,  $\forall t \geq 0$ .

Choosing  $t=s$ :

$w(s,x) = \mathbb{E}^{s,x}[w(Y_s)] = \mathbb{E}[w(\begin{pmatrix} 0 \\ X_s^{s,x} \end{pmatrix})] = \mathbb{E}[f(X_s^{s,x})] = u(s,x). \quad \#$

Remark, semigroup:

$u(t, \cdot) = Q_t f = \mathbb{E}^x[f(X_t)]; \quad \partial_t u = \frac{d}{dt} Q_t f = Q_t (Af) = A(Q_t f)$   
 $\Rightarrow Q_t = e^{At}$  (Need further explanation, b.c.  $A$  is unbounded)

Exe 8.3 (Kolmogorov's forward Equ.) (Fokker-Planck Equ.)

Assume that  $X_t^x$  has a density  $p_t(x, \cdot)$  :  $\mathbb{E}^x[f(X_t)] = \int f(y) p_t(x, y) dy$ ,  $f \in C^2$

If  $p_t(x, \cdot)$  is smooth, then  $\partial_t p_t(x, y) = A_t^* p_t(x, y)$ ,  $\forall x, y$ .

$$A_t^* \phi = - \sum_i \partial_{x_i} (b_i \phi) + \sum_{i,j} \partial_{x_i} \partial_{x_j} (a_{ij} \phi), \quad \forall \phi \in C^2.$$

Proof: By Dynkin's formula:

$$\mathbb{E}^x[f(X_t)] = f(x) + \mathbb{E}^x \left[ \int_0^t A_s f(X_s) ds \right]$$

$$\int_{\mathbb{R}^n} f(y) p_t(x, y) dy = f(x) + \int_{\mathbb{R}^n} \int_0^t A_s f(y) p_s(x, y) ds dy.$$

$$\frac{d}{dt} : \langle f, \partial_t p_t \rangle_{L^2(\mathbb{R}^n)} = \langle A_t f, p_t \rangle = \langle f, A_t^* p_t \rangle. \quad \#$$

How to solve the PDE? Does it have an equilibrium and what is it?  $Au = f$ ? How is it related to invariant measure?

The Resolvent  $(\alpha I - A)^{-1}$

Def: (Resolvent Operator)  $R_\alpha g(x) = \mathbb{E}^x \left[ \int_0^\infty e^{-\alpha t} g(X_t) dt \right]$ ,  $\forall g \in C_b(\mathbb{R}^n)$

(formally:  $\int_0^\infty e^{-\alpha t} e^{At} g dt = \int_0^\infty e^{-(\alpha I - A)t} dt g = (\alpha I - A)^{-1} g$ )

Lemma (Feller cts) Let  $g \in C_b(\mathbb{R}^n)$ . Then  $u(t, x) = \mathbb{E}^x[g(X_t)]$  is cts.

$\Rightarrow R_\alpha g$  is bdd & cts.

Theorem 8.1.5 (a) If  $f \in C_b^2(\mathbb{R}^n)$ , then  $R_\alpha(\alpha - A)f = f$ ,  $\forall \alpha > 0$ .

(b) If  $g \in C_b(\mathbb{R}^n)$ , then  $R_\alpha g \in \text{Dom}(A)$  and  $(\alpha - A)R_\alpha g = g$ ,  $\forall \alpha > 0$ .

Proof, (a) by Dynkin's formula,

$$R_\alpha(\alpha - A)f = \alpha R_\alpha f - R_\alpha A f = \alpha \int_0^\infty e^{-\alpha t} \mathbb{E}^x[f(X_t)] dt - \int_0^\infty e^{-\alpha t} \mathbb{E}^x[A f(X_t)] dt$$

$$= -e^{-\alpha t} u(t, x) \Big|_0^\infty + \int_0^\infty e^{-\alpha t} \partial_t u(t, x) dt - \int_0^\infty e^{-\alpha t} A u dt = f(x).$$

(b). Need to show  $\partial_t \mathbb{E}^x[R_\alpha g(X_t)] = A [ \cdot ]$ :

$$\mathbb{E}^x[R_\alpha g(X_t)] = \mathbb{E}^x \left[ \mathbb{E}^{X_t} \left[ \int_0^\infty e^{-\alpha s} g(X_s) ds \right] \right] \stackrel{\text{Markov}}{=} \mathbb{E}^x \left[ \mathbb{E}^x \left[ \int_0^\infty e^{-\alpha s} g(X_{t+s}) ds \mid \mathcal{F}_t^x \right] \right]$$

$$\frac{d}{dt} \left[ \int_0^\infty e^{-\alpha s} g(X_{t+s}) ds \right] = \int_0^\infty e^{-\alpha s} \partial_t \mathbb{E}^x[g(X_{t+s})] ds = \int_0^\infty e^{-\alpha s} \int_t^{t+s} \mathbb{E}^x[g(X_u)] du ds$$

$$\stackrel{\text{IBP}}{=} \alpha \int_0^\infty e^{-\alpha s} \int_t^{t+s} \mathbb{E}^x[g(X_u)] du ds$$

$$A R_\alpha g = \frac{d}{dt} \mathbb{E}^x[R_\alpha g(X_t)] = \alpha \int_0^\infty e^{-\alpha s} \mathbb{E}^x[g(X_{t+s})] - \mathbb{E}^x[g(X_t)] \Big|_{t=0} ds = \alpha R_\alpha g - g. \quad \#$$

## §8.2 The Feynman-Kac formula

Theorem 8.2.1  $f \in C^0$ ,  $q \in C(\mathbb{R}^n)$  lower bdd. Then

$$(a) \quad \underline{V(t,x) = \mathbb{E}^x \left[ \exp\left(-\int_t^T q(X_s) ds\right) f(X_T)\right]} \text{ solves } \begin{cases} \partial_t u = Av - qv, & t > 0, x \in \mathbb{R}^n \\ v(0,x) = f(x). & x \in \mathbb{R}^n \end{cases}$$

(b) If  $w(t,x) \in C^{1,2}(\mathbb{R}^+ \times \mathbb{R}^n)$  is bdd on  $K \times \mathbb{R}^n$  for each  $K \subseteq \mathbb{R}$  cpt, and  $w$  solves the eqn. then  $w = v$ .

Proof, (a) Let  $Y_t = f(X_t)$ ,  $Z_t = e^{-\int_0^t q(X_s) ds}$ .  $dY_t = A f(X_t) dt + \sigma f(X_t) dB_t$

$$\Rightarrow d(Y_t Z_t) = Y_t dZ_t + Z_t dY_t, \text{ an Ito diffusion.}$$

$$dZ_t = -Z_t q(X_t) dt$$

$$\Rightarrow v(t,x) = \mathbb{E}^x[Y_t Z_t] \text{ is } C^1 \text{ in } t$$

$$\begin{aligned} \text{then, } \frac{1}{t} (\mathbb{E}^x[v(t,x)] - v(t,x)) &= \frac{1}{t} (\mathbb{E}^x[\mathbb{E}^{X_t}(Z_t f(X_t)) - \mathbb{E}^x[Z_t f(X_t)]]) \\ &\stackrel{\text{AV}}{\downarrow} \text{r.b.} = \frac{1}{t} (\mathbb{E}^x[\mathbb{E}^x[f(X_{t+t}) \exp(\int_0^t q(X_s) ds) | \mathcal{F}_t] - \mathbb{E}^x[Z_t f(X_t) | \mathcal{F}_t]]) \\ &= \frac{1}{t} \mathbb{E}^x[Z_{t+t} \exp(\int_0^t q(X_s) ds) f(X_{t+t}) - Z_t f(X_t)] \\ &= \frac{1}{t} \mathbb{E}^x[Z_{t+t} f(X_{t+t}) - f(X_t) Z_t] + \frac{1}{t} \mathbb{E}^x[(e^{\int_0^t q(X_s) ds} - 1) Z_{t+t} f(X_{t+t})] \\ &\stackrel{\text{r.b.}}{=} \mathbb{H}V + qV \quad \text{bdd.} \quad \checkmark \end{aligned}$$

(b). Note that  $\begin{cases} \tilde{A} w(t,x) = -\partial_t w + Aw - qw = 0, & t > 0, x \in \mathbb{R}^n \\ w(0,x) = f(x) & \forall x \in \mathbb{R}^n. \end{cases}$

$$\text{Let } H_t = (s-t, X_t^{q,x}, Z_t) \quad Z_t = Z + \int_0^t q(X_s) ds$$

$$\text{Then } H_t \text{ is an Ito diffusion w generator } A_H \phi(s,x,z) = -\partial_s \phi + A\phi + q(x) \partial_z \phi, \phi \in C^2_0$$

$$\text{For } \phi = e^{-z} w(s,x): \quad A_H \phi = e^{-z} [-\partial_s w_s + Aw - qw] = 0$$

By Dynkin's formula w  $\phi$  and  $\tau_R = \inf\{t > 0: |H_t| \geq R\}$ :

$$\mathbb{E}^{s,x,z} [\phi(H_{t \wedge \tau_R})] = \phi(s,x,z) + \mathbb{E}^{s,x,z} \left[ \int_0^{t \wedge \tau_R} A_H \phi(H_r) dr \right] = 0$$

$$\Rightarrow w(s,x) = \phi(s,x,0) = \mathbb{E}^{s,x,0} [\phi(H_{t \wedge \tau_R})] = \mathbb{E}^x \left[ \exp\left(-\int_0^{t \wedge \tau_R} q(X_r) dr\right) w(s-t, X_{t \wedge \tau_R}) \right]$$

$$\xrightarrow{\text{r.b.}} \mathbb{E}^x \left[ \exp\left(-\int_0^t q(X_r) dr\right) w(s-t, X_t) \right] \quad (\text{w. bdd.})$$

Let  $t=s$ :

$$w(s,x) = \mathbb{E}^x \left[ \exp\left(-\int_0^s q(X_r) dr\right) w(0, X_s^{q,x}) \right] = v(s,x). \quad \#$$

What is the diffusion with the A-q being a generator?

### § 8.3 The Martingale problem.

• Strook & Varadhan (1979): weak solution to SDE & martingale

(\*)  $dX_t = b(X_t)dt + \sigma(X_t)dB_t; X_0 = x. \Leftrightarrow$  generator  $A = b \cdot \nabla + \frac{1}{2} \sigma \sigma^T = Hess$

$$f(X_t) = \underbrace{f(x)} + \int_0^t A f(X_s) ds + \underbrace{\int_0^t \nabla f^T \cdot \sigma(X_s) dB_s}_{\text{an m.b. } \mathcal{F}_t^B \text{ or } \mathcal{F}_t^X}$$

$$\Rightarrow M_t = f(X_t) - \int_0^t A f(X_s) ds = f(x) + \int_0^t \nabla f^T \cdot \sigma(X_s) dB_s \text{ is a m.b. wrt } \mathcal{F}_t^X, \forall f \in C^2(\mathbb{R}^n)$$

That is, the weak solu.  $\{X_t\}$  to (\*) makes  $M_t(f)$  be a m.b. wrt  $\mathcal{F}_t^X \forall f \in C^2$ .

$\downarrow$  Law of  $X_t$   
 a probab. meas.  $\tilde{Q}^x$  on  $((\mathbb{R}^n)^{[0,\infty)}, \mathcal{B}, \tilde{Q}^x)$   $\rightarrow$   $M_t$  is a  $\tilde{Q}^x$ -m.b.  $\forall f \in C^2$ .

Def 8.3.2 (Martingale problem) Let  $L = b \cdot \nabla + a : \nabla^2 = \sum_i b_i \partial_{x_i} + \sum_{ij} a_{ij} \partial_{x_i} \partial_{x_j}$

•  $b_i, a_{ij}$  locally bdd, Borel meas.

• semi-elliptic:  $a(x) \geq 0, \forall x$

We say that a probability meas.  $\tilde{\mathbb{P}}^x$  on the path space  $((\mathbb{R}^n)^{[0,\infty)}, \mathcal{B})$  solves the martingale problem for  $L$  of the process

$$M_t = f(X_t) - \int_0^t Lf(X_r) dr; M_0 = f(x)$$

is a  $\tilde{\mathbb{P}}^x$  martingale wrt.  $\mathcal{B}_t$  for all  $f \in C_0^2(\mathbb{R}^n)$

• The m.b. problem is well-posed if  $\exists!$   $\mathbb{P}^x$ .

Strook & Varadhan: weak solu  $\Leftrightarrow \exists \tilde{\mathbb{P}}^x$  for the m.b. problem.

weak solu. + Markov  $\Leftrightarrow$  well-posed m.b. problem.

Q1: when the weak solu. is NOT Markov?

Q2: when the measure is NOT unique?

### §8.4 Ito process $\Rightarrow$ Ito diffusion

Ito process: (P4)  $dX_t = u(t, \omega) dt + v(t, \omega) dB_t$

Ito diffusion (P4)  $dX_t = b(X_t) dt + \sigma(X_t) dB_t$  (\*)

• If  $X_t$  is an Ito process, then  $\varphi(X_t)$  is also an Ito process.

----- Ito diffusion, ----- . Will  $\varphi(X_t)$  be an Ito diffusion?

Not in general. yes if  $\nabla$

Example 8.4.1 (The Bessel process)  $n \geq 2$

$$R_t = |B_t| = \left( \sum_{i=1}^n B_i(t)^2 \right)^{\frac{1}{2}} \Rightarrow dR_t = \sum_{i=1}^n \frac{B_i dB_i}{R_t} + \frac{n}{2R} dt$$

• This is NOT an SDE in the form of (\*).

• But if  $Y_t = \sum_{i=1}^n \int_0^t \frac{B_i dB_i}{|R|} \sim \tilde{B}_t$  a Bm.

then  $dR_t = \frac{n}{2R_t} dt + dB_t$ , a diffusion

with generator.  $Af(x) = \frac{1}{2} f'' + \frac{n}{2x} f'$

yes.  $V = \frac{B}{|B|}, VV^T = \frac{1}{|B|^2} BB^T = I$

$$\begin{aligned} f(x) &= |x| = (x^2)^{\frac{1}{2}} \\ \nabla g(x) &= \frac{1}{2} (x^2)^{-\frac{1}{2}} \cdot 2x = \frac{x}{|x|} \\ \Delta_i \phi_j &= |x|^{-1} \delta_{ij} - \frac{x_i x_j}{|x|^3} \\ \Delta g &= |x|^{-1} \cdot n - \frac{|x|^2}{|x|^3} = |x|^{-1} (n-1) \end{aligned}$$

(weak uniqueness needs Lipschitz)

Theorem 8.4.2. An Ito process  $dX_t = V dB_t; Y_0 = 0$  w/  $V(t, \omega) \in V^{n \times m}$

$\uparrow$  coincides in law w/ an n-D Bm iff  $VV^T(t, \omega) = I_n, a.a. (t, \omega) \in dt \times dP$

Theorem 8.4.3. Let  $dX_t = b(X_t) dt + \sigma(X_t) dB_t, b \in \mathbb{R}^n, \sigma \in \mathbb{R}^{n \times m}, X_0 = x$

$dY_t = u(t, \omega) dt + v(t, \omega) dB_t, u \in \mathbb{R}^n, v \in \mathbb{R}^{n \times m}, Y_0 = x.$

then  $X_t \stackrel{d}{=} Y_t$  iff  $E[u(t, \cdot) | \mathcal{N}_t] = b(Y_t^x(\omega)); VV^T(t, \omega) = \sigma \sigma^T(Y_t^x(\omega))$  a.a.  $dt \times dP$

Proof: ( $\Leftarrow$ ) Let  $A = b \cdot v + \frac{1}{2}(\sigma \sigma^T)$ : Hess. be the generator of  $X_t$ .  $\forall f \in C_0^2$ , define

$$Hf(t, \omega) := \sum u_i \partial_{x_i} f(Y_t) + \frac{1}{2} \sum_{ij} (VV^T)_{ij} \partial_{x_i x_j} f(Y_t)$$

Then, Ito formula  $f(Y_t) \stackrel{d}{=} f(Y_0) + \int_0^t Hf(r, \omega) dr + \int_0^t v^T \cdot v dB_r$

$$\begin{aligned} \mathbb{E}[f(Y_t) | \mathcal{N}_t] &= f(Y_t) + \int_t^T \mathbb{E}[Hf(r, \omega) | \mathcal{N}_t] dr + 0 \\ &\downarrow \\ &= \mathbb{E}[\mathbb{E}[Hf(r, \omega) | \mathcal{N}_t] | \mathcal{N}_t] \stackrel{(*)}{=} \mathbb{E}[Af(Y_r) | \mathcal{N}_t] \\ &= f(Y_t) + \mathbb{E}[\int_t^T Af(Y_r) dr | \mathcal{N}_t] \end{aligned}$$

Let  $M_t = f(Y_t) - \int_0^t Af(Y_r) dr$ ,

$$\begin{aligned} \Rightarrow \mathbb{E}[M_t | \mathcal{N}_t] &= \mathbb{E}[f(Y_t) - \int_0^t Af(Y_r) dr | \mathcal{N}_t] = f(Y_t) + \mathbb{E}[\int_t^T Af(Y_r) dr | \mathcal{N}_t] - \mathbb{E}[\int_0^T Af(Y_r) dr | \mathcal{N}_t] \\ &= f(Y_t) - \int_0^t Af(Y_r) dr = M_t. \end{aligned}$$

By uniqueness of the solu. to the m.b. problem, we conclude that  $X_t \approx Y_t$ .

$\forall \Rightarrow$ . Assume that  $X_t \approx Y_t$ . Let  $f \in C^2$ . By Ito formula,

$$\begin{aligned} (1) \quad \lim_{h \downarrow 0} \frac{1}{h} (\mathbb{E}^x[f(Y_{t+h}) | \mathcal{N}_t] - f(Y_t)) &= \lim_{h \downarrow 0} \int_t^{t+h} \mathbb{E}[Hf(s, \omega) | \mathcal{N}_t] ds \\ &= \mathbb{E}^x[Hf(t, \omega) | \mathcal{N}_t] = \sum_i \mathbb{E}^x[u_i(t, \omega) \frac{\partial f(Y_t)}{\partial x_i} | \mathcal{N}_t] + \sum_{ij} \mathbb{E}^x[(VV^T)_{ij}(t, \omega) \frac{\partial^2 f(Y_t)}{\partial x_i \partial x_j} | \mathcal{N}_t] \\ (2) &= \sum_i \mathbb{E}^x[u_i(t, \omega) | \mathcal{N}_t] \frac{\partial f(Y_t)}{\partial x_i} + \sum_{ij} \mathbb{E}^x[(VV^T)_{ij}(t, \omega) | \mathcal{N}_t] \frac{\partial^2 f(Y_t)}{\partial x_i \partial x_j}. \end{aligned}$$

On the other hand, since  $X_t \approx Y_t$  &  $X_t$  is a Markov process, so is  $Y_t$ . Hence,

$$\begin{aligned} (1) &= \lim_{h \downarrow 0} \frac{1}{h} (\mathbb{E}^{Y_t}[f(Y_{t+h})] - \mathbb{E}^{Y_t}[f(Y_t)]) = \mathbb{E}^{Y_t}[Hf(0, \omega)] \\ &= \sum_i \mathbb{E}^{Y_t}[u_i(0, \omega) \frac{\partial f(Y_t)}{\partial x_i}] + \frac{1}{2} \sum_{ij} \mathbb{E}^{Y_t}[(VV^T)_{ij}(0, \omega) \frac{\partial^2 f(Y_t)}{\partial x_i \partial x_j}] \\ (2) &= \sum_i \mathbb{E}^{Y_t}[u_i(0, \omega)] \frac{\partial f(Y_t)}{\partial x_i} + \frac{1}{2} \sum_{ij} \mathbb{E}^{Y_t}[(VV^T)_{ij}(0, \omega)] \frac{\partial^2 f(Y_t)}{\partial x_i \partial x_j} \end{aligned}$$

$\mathbb{E}^{Y_t}[F(\omega)g(Y_t)] = \mathbb{E}[F(\omega)g(Y_t) | Y_{s=0} = Y_t]$

Thus (2) = (3),  $\forall f \in C^2$ . Take  $f(x) = x_i$  (use stopping time &  $C^2$  approximation)

$$\mathbb{E}^x[u_i(t, \omega) | \mathcal{N}_t] = \mathbb{E}^{Y_t}[u_i(0, \omega)] \quad \text{a.a.} \quad = b_i(Y_t^x) \quad \forall$$

Take  $f(x) = 2x_i x_j \Rightarrow \mathbb{E}^x[(VV^T)_{ij}(t, \omega) | \mathcal{N}_t] = \mathbb{E}^{Y_t}[(VV^T)_{ij}(0, \omega)] \quad \text{a.a.} \quad = (00^T)_{ij}(Y_t^x)$

Also, since  $X_t \approx Y_t$  their generator are the same, i.e.

$$\downarrow \Delta \quad ??$$

$$VV^T(t, \omega) = (00^T)(Y_t^x)$$

Lemma 8.4.4 Let  $dY_t = u(t, \omega)dt + V(t, \omega)dB_t$ ,  $Y_0 = x$ . as above

there  $\exists$  an  $\mathcal{N}_t$  adapted process  $W(t, \omega)$  st.  $VV^T(t, \omega) = W(t, \omega)$ .

Proof: By Ito's formula,  $g(x) = x_i x_j$ :  $Y_i Y_j(t, \omega) = x_i x_j + \int_0^t (x_i dY_j(s) + Y_j dY_i(s)) + \int_0^t (VV^T)_{ij}(s, \omega) ds$

$$\Rightarrow \int_0^t (VV^T)_{ij}(s, \omega) ds = H_{ij}(t, \omega) = Y_i Y_j(t, \omega) - x_i x_j - \int_0^t ( \quad ) \quad , \quad \mathcal{N}_t \text{ adapted.}$$

$$\Rightarrow (VV^T)_{ij}(t, \omega) = \lim_{h \downarrow 0} \frac{1}{h} (H_{ij}(t+h, \omega) - H_{ij}(t, \omega)) \in \mathcal{N}_t. \quad \#$$

$\triangleleft$  Not on  $u(t, \cdot)$  or  $V(t, \cdot)$ :  $\downarrow$

Remark 1.  $u(t, \cdot)$  may NOT be  $N_t$  meas.. E.g.

$$dY_t = B_t^1 dt + dB_t^2, \quad ,$$



## §8.5 Random time change

Let  $C(t, \omega) \geq 0$  be an  $\mathcal{F}_t$ -adapted process

$$\beta_t := \beta(t, \omega) = \int_0^t C(s, \omega) ds$$

- $\alpha$  (random) time change or time change rate  $C(t, \omega)$
- $\beta_t$  is NDN-decreasing

$$\alpha_t = \inf \{s : \beta_s > t\}$$

- $\alpha_t$  is a right-inverse of  $\beta_t$ ,

$$\beta(\alpha(t, \omega), \omega) = t, \quad \forall \omega, \forall t,$$

- $\alpha_t$  is right-continuous.

- If  $C > 0$ , then  $t \mapsto \beta_t$  is strictly increasing

$$\left\{ \begin{array}{l} t - \alpha_t \text{ is continuous} \\ \alpha_t \text{ is a left-inverse of } \beta_t: \end{array} \right.$$

$$\alpha(\beta(t, \omega), \omega) = t, \quad \forall t$$

- $\omega \mapsto \alpha(t, \omega)$  is an  $\{\mathcal{F}_t\}$ -stopping time. (all the above are deterministic, until here.)

Question: In Theorem 8.4.3.  $X_t$  Ito diffusion,  $Y_t$  Ito process  $X_t \simeq Y_t$ .

When does there exist a time change  $\beta_t$  st  $Y_{\beta_t} \simeq X_t$ ?