

Lesson 6 Applications of the Ito formula

Exponential of a semimartingale

Stochastic exponential of a semimartingale.

Exponential martingales

Levy's theorem. Levy's characterization of Brownian motion.

Dubins-Schwarz theorem

Watanabe's characterization of the Poisson process.

Equivalence of probability measures on filtered spaces.

The Girsanov-Meyer theorem.

Change of measure for Brownian motion

The Ito formula

Let S be a semimartingale, $f \in C^2([0, \infty), \mathbb{R})$.

Then $f(S)$ is also a semimartingale and $\forall t \geq 0$,

$$f(S_t) - f(S_0) = \int_0^t f'(S_{u-}) dS_u + \int_0^t \frac{1}{2} f''(S_{u-}) d[S]_u^c + \sum_{0 \leq s \leq t} \left\{ f(S_u) - f(S_{u-}) - \Delta S_u f'(S_u) \right\}$$

Ito formula : time dependent version

✓ If $f \in C^{1,2}([0, T] \times \mathbb{R}, \mathbb{R})$

(continuously differentiable in t ,
twice continuously differentiable in x)

then for any semimartingale S , $\forall T \geq 0$,

$$f(T, S_T) - f(0, S_0) = \int_0^T \frac{\partial f}{\partial x}(t, S_{t-}) dS_t + \int_0^T \frac{\partial f}{\partial t}(t, S_t) dt$$

$$+ \int_0^T \frac{1}{2} \frac{\partial^2 f}{\partial x^2}(t, S_{t-}) d[S]_t^c$$

$$+ \sum_{0 \leq t \leq T} f(t, S_t) - f(t, S_{t-}) - \Delta S_t \cdot \frac{\partial f}{\partial x}(t, S_{t-})$$

Proof: apply Ito formula to $X = (t, S_t)$ $[t] = 0$, $[t, S] = 0$

Exponential of a semimartingale

X semi-martingale

$$S_t = S_0 e^{X_t}$$

$$f(x) = S_0 e^x$$

$$S_t = S_0 + \int_0^t f'(S_{u-}) dX_u + \frac{1}{2} \int_0^t f''(S_{u-}) d[X]_u^c$$

$$+ S_0 \sum_{0 \leq u \leq t} (e^{X_{u-} + \Delta X_u} - e^{X_{u-}} - e^{X_{u-}} \cdot \Delta X_u)$$

$$= S_0 + \int_0^t S_{u-} dX_u + \frac{1}{2} \int_0^t S_{u-} d[X]_u^c + \sum_{0 \leq u \leq t} S_{u-} (e^{\Delta X_u} - 1 - \Delta X_u)$$

Ex. X Ito process $X_t = X_0 + \int_0^t \sigma_u dW_u + \int_0^t \mu_u du$

$$[X]_t^c = [X]_t^z = \int_0^t \sigma_u^2 du$$

$$S_T = S_0 + \int_0^T S_t \sigma_t dW_t + \int_0^T S_t \mu_t dt + \frac{1}{2} \int_0^T S_t \sigma_t^2 dt$$

$$\text{" } \frac{dS_t}{S_t} = \sigma_t dW_t + \left(\mu_t + \frac{\sigma_t^2}{2} \right) dt \text{ " } \quad dS_t = S_t dX_t + \frac{1}{2} \sigma_t^2 dt$$

Stochastic exponential of a semimartingale "Doléans-Dade" exponential

Let X be a semimartingale with $X_0 = 0$. Then

$$Z_t = \exp\left(X_t - \frac{1}{2}[X]_t\right) \prod_{0 \leq s \leq t} \left(1 + \Delta X_s\right) \exp\left(-\Delta X_s - \frac{(\Delta X_s)^2}{2}\right)$$

$$= \exp\left(X_t - \frac{1}{2}[X]_t^c\right) \prod_{0 \leq s \leq t} (1 + \Delta X_s) e^{-\Delta X_s}$$

is a semimartingale which verifies

$$Z_t = 1 + \int_0^t Z_{u-} dX_u \quad \text{i.e.} \quad dZ_t = Z_{t-} dX_t$$

Z is called the stochastic exponential of X : $Z = \mathcal{E}(X)$

Rem: if X local martingale then $\mathcal{E}(X)$ is also a local martingale.

Proof: Let $V_t^\varepsilon = \prod_{0 \leq s \leq t, |\Delta X_s| > \varepsilon} (1 + \Delta X_s) e^{-\Delta X_s} = \exp\left(\sum_{0 \leq s \leq t, |\Delta X_s| \geq \varepsilon} \ln(1 + \Delta X_s) - \Delta X_s\right)$

$|\ln(1+u) - u| \leq K_\varepsilon u^2$ for $|u| \leq \varepsilon$ so

$\sum_{0 \leq s \leq t} |\ln(1 + \Delta X_s) - \Delta X_s| \leq K \sum_{0 \leq s \leq t} |\Delta X_s|^2 < [X]_t^c < \infty$; $V_t^\varepsilon \xrightarrow{\varepsilon \rightarrow 0} V_t = \prod_{0 \leq s \leq t} e^{-\Delta X_s} (1 + \Delta X_s)$

Let $U_t = X_t - \frac{1}{2} [X]_t^c$. $Z_t = f(U_t, V_t)$ where $f(u, v) = ve^u$

$\frac{\partial f}{\partial u} = \frac{\partial^2 f}{\partial u^2} = f$; $\frac{\partial f}{\partial v}(u, v) = e^u$. Now: $[U]_t^c = [X]_t^c$

$$V_t = \prod_{0 \leq s \leq t} e^{-\Delta X_s} (1 + \Delta X_s) = \exp \left(\underbrace{\sum_{0 \leq s \leq t} \ln(1 + \Delta X_s) - \Delta X_s}_{S_t} \right)$$

S is a pure jump process

$$|\Delta S_t| = |\ln(1 + \Delta X_t) - \Delta X_t| \leq K_\varepsilon |\Delta X_t|^2 \quad \text{for } |\Delta X_t| \leq \varepsilon$$

$$\sum_{\substack{|\Delta X_s| \leq \varepsilon \\ 0 \leq s \leq t}} |\Delta S_u| \leq \sum_{\substack{|\Delta X_s| \leq \varepsilon \\ 0 \leq s \leq t}} K_\varepsilon |\Delta X_s|^2 < [X]_t K_\varepsilon \quad \text{so } \sum_{0 \leq u \leq t} |\Delta S_u| < \infty \text{ a.s.}$$

So $V = e^S$ is a pure jump process of finite variation therefore

$$[V]_t = \sum_{0 \leq s \leq t} (\Delta V_s)^2, \quad [V]_+^c = 0, \quad [V, U]_+^c = 0$$

Applying the Ito formula to $f(U_t, V_t)$ yields :

$$Z_t = 1 + \int_0^t Z_{s-} dU_s + \int_0^t e^{X_s - [X]_s^c} dV_s + \frac{1}{2} \int_0^t Z_{s-} d[U]_s^c$$

$$+ \sum_{0 \leq s \leq t} Z_s - Z_{s-} - \Delta U_s \cdot Z_{s-} - \Delta V_s e^{U_{s-}}$$

$$= 1 + \int_0^t Z_{s-} dX_s - \frac{1}{2} \int_0^t Z_{s-} d[X]_s^c + \frac{1}{2} \int_0^t Z_{s-} d[U]_s^c$$

$$U = X - \frac{1}{2} [X]^c$$

so

$$+ \sum_{0 \leq s \leq t} e^{U_{s-}} \Delta V_s + \sum_{0 \leq s \leq t} Z_s - Z_{s-} - \Delta V_s e^{U_{s-}} - \Delta U_s \cdot Z_{s-}$$

$$\Delta U_s = \Delta X_s$$

$$= 1 + \int_0^t Z_{s-} dX_s + \sum_{0 \leq s \leq t} Z_{s-} (1 + \Delta U_s - 1 - \Delta U_s)$$

since

$$Z_t = Z_{t-} e^{\Delta X_t} e^{-\Delta X_t} = Z_{t-} (1 + \Delta X_t) = Z_{t-} (1 + \Delta U_t) \text{ so } Z_t = 1 + \int_0^t Z_{s-} dX_s$$

Stochastic exponential : properties

(i) If X is continuous $\mathcal{E}(X) = e^{X - \frac{1}{2}[X]}$

(ii) If X is continuous with finite variation $\mathcal{E}(X) = e^X$

(iii) $\Delta \mathcal{E}(X)_t = \mathcal{E}(X)_{t-} \Delta X_t$ a.s.

(iv) $\mathcal{E}(X) > 0$ a.s. $\Leftrightarrow \Delta X > -1$ a.s.

(v) $\mathcal{E}(X)\mathcal{E}(Y) = \mathcal{E}(X+Y + [X, Y])$

(vi) Preservation of local martingale property:

If X is a local martingale then $\mathcal{E}(X)$ is also a local martingale.

$$Z = \mathcal{E}(X) \quad Z_t = 1 + \int_0^t Z_{u-} dX_u = e^{X_t - \frac{1}{2}[X]_t} \prod_{0 \leq s < t} e^{-\Delta X_s} (1 + \Delta X_s)$$

Examples:

$$\checkmark \mathcal{E}(\lambda W) = e^{\lambda W - \frac{\lambda^2 t}{2}}$$

$$\checkmark N \text{ counting process: } N_t = \sum_{n \geq 1} 1_{t \leq T_n} \quad (T_n)_{n \geq 1} \uparrow \text{sequence of stopping times}$$

$$\begin{aligned} \mathcal{E}(N)_t &= e^{N_t} \prod_{0 \leq s \leq t} (1 + \Delta N_s) e^{-\Delta N_s} = e^{N_t} e^{-\sum_{0 \leq s \leq t} \Delta N_s} \prod_{0 \leq s \leq t} (1 + \Delta N_s) \xrightarrow[n \rightarrow \infty]{} \infty \\ &= 2^{N_t} \quad \mathcal{E}(N) = 2^N \quad \text{since } [N]_t^c = 0 \end{aligned}$$

$$\checkmark \text{Itô process: } X_t = \int_0^t \sigma_u dW_u + \int_0^t \mu_u du$$

$$\mathcal{E}(X) = \exp\left(X_t - \frac{1}{2} \int_0^t \sigma_u^2 du\right)$$

$$\checkmark \text{Finite variation process: } X_t = \int_0^t b_s ds + \sum_{0 \leq s \leq t} \Delta X_s \quad \left\{ \begin{array}{l} \sum_{s \leq t} |\Delta X_s| < \infty \\ \Delta X_s > -1 \end{array} \right.$$

$$\mathcal{E}(X) = e^{\int_0^t b_s ds} \prod_{0 \leq s \leq t} (1 + \Delta X_s) = \exp\left(X_t + \sum_{0 \leq s \leq t} \{\ln(1 + \Delta X_s) - \Delta X_s\}\right)$$

$$\text{since } [X]^c = 0$$

Exponential martingales

- If X is a martingale then $\mathcal{E}(X)$ is a **local** martingale.
- If $\Delta X > -1$ then $\mathcal{E}(X)$ is a positive supermartingale, with $\mathcal{E}(X)_0 = 1$.
- ✓ If: $\forall t \geq 0, E(\mathcal{E}(X)_t) = 1$ then $\mathcal{E}(X)$ is a martingale, called the **exponential martingale** associated to X .
- ✓ It is not always easy to show that $E(\mathcal{E}(X)_t) = 1$.
- ✓ One method: write
$$\mathcal{E}(X)_t = \frac{e^{X_t}}{E(e^{X_t})}$$

Proposition: Let M be a continuous local martingale.

If for each t there exists a constant $K_t > 0$, $[M]_t < K_t$ a.s.

Then $\mathbb{P}(\max_{s \leq t} M_s > y) \leq \exp(-y^2/2K_t)$ (*)

and $E(\theta M)$ is a martingale for every $\theta \in \mathbb{R}$.

Corollary: if $H \in L$ is a bounded, left-continuous adapted process on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$ and W a Brownian motion then

$$M_t = e^{\int_0^t H_s dB_s - \frac{1}{2} \int_0^t |H_s|^2 ds} = E\left(\int H dB\right)$$

is a martingale.

Proof: $\mathbb{P}(\max_{s \leq t} M_s > y) \leq \mathbb{P}(\max_{s \leq t} E(\theta M)_s > e^{\theta y - \frac{K_t \theta^2}{2}}) \leq e^{-\theta y + \frac{1}{2} \theta^2 K_t}$

Let $Z(t) = \max_{[0, t]} M$. $E e^{\theta Z(t)} = 1 + \int dy \mathbb{P}(Z(t) > y) \theta e^{\theta y}$

$$\leq 1 + \theta \int e^{\theta y} e^{-y^2/2K_t} dy < \infty$$

$Y = E(\theta M) = \exp(\theta M - \frac{1}{2} \theta^2 [M])$ is a local martingale

so $\exists (T_n)_{n \geq 1}$ stopping times, $T_n \uparrow \infty$ a.s.,

$$E[Y_{T_n \wedge t} | \mathcal{F}_s] = Y_{T_n \wedge s} \quad \forall t \geq s$$

Since $Y_{T_n \wedge t}$ is dominated by $e^{\theta Z(t)}$, $E e^{\theta Z(t)} < \infty$

The dominated convergence theorem applies as $n \rightarrow \infty$:

$$E[Y_t | \mathcal{F}_s] = Y_s \quad \forall t \geq s \quad ; \quad Y \text{ is a martingale.}$$

$$E(\theta M) = \exp(\theta M - \frac{\theta^2}{2} [M])$$

Examples of exponential martingales

✓ $\forall \lambda > 0$, $E(\lambda W)_t = \exp(\lambda W_t - \frac{\lambda^2 t}{2})$ is a martingale.

✓ If N is a Poisson process and $M_t = N_t - \lambda t$

$E(M) = e^{N_t \ln 2 - \lambda t}$ is a martingale

✓ If $\theta \in L$ is a bounded, \mathcal{F}_t -adapted cagled process

$X_t = \int_0^t \theta_s dW_s$ is a square-integrable martingale

$E(X)_t = \exp(\int_0^t \theta_s dW_s - \frac{1}{2} \int_0^t |\theta_s|^2 ds)$ is a martingale

Lévy's theorem or how to recognize a Brownian motion when you meet one

Theorem: A continuous local martingale X is a Brownian if and only if: $\forall t \geq 0 \quad [X]_t = t$

Proof: first note that $E(X_t^2) = E([X]_t) = t < \infty$
so X is a square-integrable martingale.

Apply Ito's formula to $f(t, x) = \exp\left(iux + \frac{u^2 t}{2}\right)$:

$$\underbrace{e^{iuX_t + \frac{u^2 t}{2}}}_{Y_t} = 1 + \int_0^t iu e^{iuX_s + \frac{u^2 s}{2}} dX_s + \int_0^t \frac{u^2}{2} e^{iuX_s + \frac{u^2 s}{2}} ds - \int_0^t \frac{u^2}{2} e^{iuX_s + \frac{u^2 s}{2}} d[X]_s$$
$$= 1 + \int_0^t iu e^{iuX_s + \frac{u^2 s}{2}} dX_s$$

By the martingale preserving property of the stochastic integrals, Y is a local martingale

$$[Y]_t = \int_0^t |u|^2 d[X]_s = |u|^2 t \quad \text{so} \quad E(Y_t^2) = E[Y]_t < \infty$$

so Y is a square-integrable martingale. So $\forall t \geq s$

$$E[Y_t | \mathcal{F}_s] = Y_s \quad \text{which means} \quad E[e^{iu(X_t - X_s)} | \mathcal{F}_s] = e^{-\frac{u^2}{2}(t-s)}$$

so $X_t - X_s \sim N(0, t-s)$ is independent of \mathcal{F}_s

Thus X is a Brownian motion on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$.

Lévy's theorem: original form

• Let M be a continuous local martingale with $M_0 = 0$.

If $M_t^2 - t$ is a local martingale then

M is a Brownian motion.

Proof: By Itô's formula $M_t^2 = \int_0^t 2M_s dM_s + [M]_t$

so $M_t^2 - \int_0^t 2M_s dM_s$ has finite variation

$M_t^2 - [M]_t$ is a continuous local martingale

So $[M]_t - t = M_t^2 - t - (M_t^2 - [M]_t)$ is a continuous local martingale. But $[M]_t - t$ is a process of finite variation so $[M]_t - t = 0$. Thus by the previous theorem

M is Brownian motion.

Lévy's Theorem : multidimensional version

If (X^1, \dots, X^d) are continuous local martingales
with $X_0^i = 0$ and

$$[X^i]_t = t \quad [X^i, X^j] = 0 \quad \forall i \neq j$$

the $X = (X^1, \dots, X^d)$ is a d -dimensional Brownian motion.

Proof: By Lévy's Theorem, X^i is a Brownian motion

compute $E(e^{iu \cdot X_t})$ for $u \in \mathbb{R}^d$ by applying
Ito formula to $e^{iu \cdot X_t}$ for $u \in \mathbb{R}^d$

Dubins - Schwarz Theorem:

Let M be a continuous local martingale on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$
with $M_0 = 0$, $[M]_t \xrightarrow{t \rightarrow \infty} \infty$. Define

$$T_t = \inf \{ u > 0, [M]_u > t \}$$

$\mathcal{G}_t = \mathcal{F}_{T_t}$. Then $B_t = M_{T_t}$ is a Brownian motion

on $(\Omega, \mathcal{F}, (\mathcal{G}_t)_{t \geq 0}, \mathbb{P})$ and $M_t = B_{[M]_t}$ \mathbb{P} -a.s.

Any continuous local martingale is a
time-changed Brownian motion!

Proof : $T_t = \inf \{ u \geq 0, [M]_u > t \}$

$$[M]_\bullet(\omega) : [0, \infty) \rightarrow [0, \infty)$$

$$t \rightarrow [M]_t(\omega)$$

is strictly \uparrow continuous
one-to-one

T_t is \checkmark finite a.s. since $[M]_t \xrightarrow{t \rightarrow \infty} \infty$
 \checkmark a hitting time of a cadlag adapted process so a stopping time.

$$\{ T_t \leq s \} = \{ [M]_s > t \}$$

Define $B_t = M_{T_t}$ and $G_t = \mathcal{F}_{T_t}$.

Then $[B]_t = [M]_{T_t} = t$ by continuity.

The map $T : (0, \infty) \times \Omega \mapsto (0, \infty)$
 $(t, \omega) \mapsto \inf \{ u > 0, [M]_u(\omega) > t \}$

is **continuous, increasing in t** almost surely

and $T \circ [M] = [M] \circ T = \text{Id}$ \mathbb{R} -a.s.

so $B_t = M_{T_t}$ is a.s. continuous and $M_t = B_{[M]_t}$

$\exists (\tau_n)_{n \geq 1}$ \mathbb{F} -stopping times $\tau_n \uparrow \infty$ a.s., M^{τ_n} is a martingale

$U_n = T_0 \wedge \tau_n$ are (G_t) -stopping times, $U_n \uparrow \infty$ a.s.

✓ By the optional sampling theorem: $\forall t \geq s$,

$$E[B_t^{U_n} - B_s^{U_n} | \mathcal{G}_{s \wedge U_n}] = E[M_{T_t}^{\tau_n} - M_{T_s}^{\tau_n} | \mathcal{F}_{T_s \wedge \tau_n}] = M_{T_s}^{\tau_n} - M_{T_s}^{\tau_n} = 0$$

So B is a continuous local martingale, $[B]_t = t$ a.s.

so by **Lévy's theorem**

B is a Brownian motion on $(\Omega, \mathbb{F}, (G_t)_{t \geq 0}, \mathbb{P})$.

And we have shown that $M_t = B_{[M]_t}$.

Example:

X Itô process on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$

$$X_t = \int_0^t \sigma_u dW_u, \quad \sigma \in L \quad \begin{array}{l} \text{adapted left-continuous} \\ \text{stochastic process} \end{array} \quad \int_0^\infty \sigma_t^2 dt = \infty$$

$$[X]_t = \int_0^t \sigma_u^2 du \quad T_t(\omega) = \inf \left\{ u > 0, \int_0^u \sigma_s^2(\omega) ds > t \right\}$$

So: $B_t = X_{T_t}$ is a Brownian motion on $(\Omega, (\mathcal{G}_t)_{t \geq 0}, \mathbb{P})$

where $\mathcal{G}_t = \mathcal{F}_{T_t}$

and $X_t = B_{\int_0^t \sigma_u^2 du}$

(apply to $u = T_t^{-1}(t)$)

In particular: $X \stackrel{d}{=} B_{\int_0^t \sigma_u^2 du}$

Watanabe's Theorem or how to recognize a
Poisson process next time you meet one

Theorem: Let N be a counting process

$$N_t = \sum_{n \geq 1} 1_{t \leq T_n}$$

If $M_t = N_t - \lambda t$ is a local martingale,

then N is a Poisson process with intensity λ .

Proof: Apply Ito's formula to N with $f(x) = e^{i\theta x}$:

$$\begin{aligned}
 e^{i\theta N_t} &= 1 + \sum_{0 \leq s \leq t} (e^{i\theta N_s} - e^{i\theta N_{s-}}) \\
 &= 1 + \int_0^t (e^{i\theta(N_{s-} + 1)} - e^{i\theta N_{s-}}) dN_s \\
 &= 1 + \underbrace{\int_0^t (e^{i\theta(N_{s-} + 1)} - e^{i\theta N_{s-}}) dM_s}_{Z_+} + \int_0^t (e^{i\theta(N_{s-} + 1)} - e^{i\theta N_{s-}}) \lambda ds
 \end{aligned}$$

$M_t = N_t - \lambda t$ local martingale

By the martingale-preserving property of the stochastic integral, Z is a local martingale

$$[Z]_t = \sum_{0 \leq s \leq t} (e^{i\theta(N_{s-} + 1)} - e^{i\theta N_{s-}})^2 \leq 4 N_t$$

$$\text{So: } E(Z_+^2) = E([Z]_t) \leq 2t E(N_t) < \infty$$

so Z is a L^2 -martingale.

$$\forall t \geq s, \quad E[e^{i\theta N_t} | \mathcal{F}_s] = e^{i\theta N_s} + \lambda(e^{i\theta} - 1) \int_s^t E[e^{i\theta N_u} | \mathcal{F}_s] du$$

$$\text{Let } \varphi_t(\theta, s) = E[\exp i\theta(N_t - N_s) | \mathcal{F}_s]$$

$$\varphi_t(\theta, s) = 1 + \lambda(e^{i\theta} - 1) \int_s^t \varphi_u(\theta, s) du \quad \text{so } \varphi_t(\theta, s)$$

$$\text{solves the ODE: } \frac{\partial}{\partial t} \varphi_t(\theta, s) = \lambda(e^{i\theta} - 1) \varphi_t(\theta, s)$$

$$\text{whose solution is } \varphi_t(\theta, s) = \exp[(t-s)\lambda(e^{i\theta} - 1)]$$

Characteristic
function of Poisson distribution ($\lambda(t-s)$)

By iterating, we obtain that for $0 = t_0 < t_1 < \dots < t_k$

$$E\left[\prod_{k=1}^n e^{i\theta_k(N_{t_k} - N_{t_{k-1}})}\right] = \prod_{k=1}^n e^{\lambda(t_k - t_{k-1})(e^{i\theta_k} - 1)}$$

so the increments of N are independent and $\sim \text{Poisson}(\lambda(t_k - t_{k-1}))$

Intensity of a counting process

Consider a counting process $N_t = \sum_{n \geq 1} 1_{t \leq T_n}$ on a filtered probability space $(\Omega, \mathcal{F}, \mathbb{F} = (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$. $(T_n)_{n \geq 1}$ increasing sequence of stopping times

Def: An \mathbb{F} -adapted process $(\lambda_t)_{t \geq 0}$ is

an \mathbb{F} -intensity for N if
$$M_t = N_t - \int_0^t \lambda_u du$$

is a local martingale on $(\Omega, \mathcal{F}, \mathbb{F}, \mathbb{P})$.

• An increasing process $(H_t)_{t \geq 0}$ is called a $(\mathcal{F}_t)_{t \geq 0}$ -hazard process for N if $N-H$ is a local martingale on $(\Omega, \mathcal{F}, \mathbb{F}, \mathbb{P})$.

✓ For the Poisson process this coincides with the usual definition of intensity

✓ **Watanabe:** Any counting process with **constant** intensity is a Poisson process.

Representation of continuous martingales as Brownian stochastic integrals

Let M be a continuous local martingale on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$
such that $t \rightarrow [M]_t$ is absolutely continuous and non-vanishing:

There exists $a: [0, \infty) \times \Omega \rightarrow (0, \infty)$ such that

$$\frac{d}{dt} [M]_t(\omega) = a_t(\omega) > 0 \quad \text{d}t \times \text{d}\mathbb{P} \quad \text{a.e.} \quad (*)$$

Then there exists a Brownian motion B
on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$ such that:

$$M_t = M_0 + \int_0^t \sqrt{a_u} dB_u$$

Define : $B_t = \int_0^t \frac{dM_u}{\sqrt{a_u}}$: B is a continuous local martingale
on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$

$$[B]_t = \int_0^t \frac{d[M]_u}{(\sqrt{a_u})^2} = \int_0^t \frac{a_u}{a_u} du = t \quad \text{so by Lévy's theorem}$$

B is a Brownian motion on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$.

And

$$M_t = M_0 + \int_0^t \sqrt{a_u} dB_u$$

Representation of continuous martingales as

Brownian stochastic integrals: multidimensional version

Let (X^1, \dots, X^d) be continuous local martingales on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$

such that $t \rightarrow [X](t) = \left([X^i, X^j] \right)_{i,j=1 \dots d}(t)$ is absolutely continuous:

$\exists a: [0, \infty) \times \Omega \rightarrow \text{Sym}^+(d)$ adapted such that $\frac{d}{dt} [X](\omega) = a(t, \omega) > 0$

i.e. $\frac{d}{dt} [X^i, X^j](\omega) = a^{ij}(t, \omega)$

Then there exists a Brownian motion (W^1, \dots, W^d) on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$

and an adapted $\mathbb{R}^{d \times d}$ -valued process $(\sigma_t)_{t \geq 0}$ such

that
$$X_t = X_0 + \int_0^t \sigma_u \cdot dW_u$$

Proof: Let $\bar{T} > 0$. Let $\underline{\lambda}_t(\omega) =$ smallest eigenvalue of $a_t(\omega)$

$\underline{\lambda}_t(\omega) > 0$ and $t \rightarrow \underline{\lambda}_t(\omega)$ is caglad

So $\inf_{t \in [0, \bar{T}]} \underline{\lambda}_t(\omega) = \min_{t \in [0, \bar{T}]} \underline{\lambda}_t(\omega) > 0$ a.s.

Therefore there exists a measurable process

$$\sigma : [0, \bar{T}] \times \Omega \rightarrow M_{d \times d}(\mathbb{R})$$

such that $\sigma_t^* \sigma_t(\omega) = a_t(\omega)$ $dt \times dP$ -a.e.

In particular $\det(\sigma_t(\omega)) = \sqrt{\det |a_t(\omega)|} > 0$: $\sigma_t(\omega)$ is a.s. invertible.

Define now: $W_t = \int_0^t \sigma_u^{-1} \cdot dX_u = (W^1, \dots, W^d)$

$$\begin{aligned} [W]_t &= \int_0^t (\sigma_u^{-1}) (\sigma_u^{-1})^* d[X] = \int_0^t \sigma_u^{-1} (\sigma_u^{-1})^* a_u du \\ &= \int_0^t \sigma_u^{-1} (\sigma_u^{-1})^* \sigma_u^* \sigma_u du = t I_d \end{aligned}$$

Each W^i is a continuous local martingale on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$

and $[W^i, W^j] = t \delta_{ij}$ so by

the multidimensional version of Lévy's theorem,

W is a standard d -dimensional Brownian motion

on the same space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$

Furthermore
$$X_t = X_0 + \int_0^t \sigma_u \cdot dW_u$$

W Brownian motion on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$

$$B_t = \int_0^t \underbrace{\operatorname{sgn}(W_u)}_{\sigma_u} dW_u$$

$$\begin{aligned} \operatorname{sgn}(x) &= +1 \quad \text{if } x > 0 \\ &= -1 \quad \text{if } x \leq 0 \end{aligned}$$

$$[B]_t = \int_0^t \sigma_u^2 du = t$$

B is a Brownian motion by Lévy's theorem

B is $(\mathcal{F}_t)_{t \geq 0}$ -adapted but W is not adapted to $(\mathcal{F}_t^B)_{t \geq 0}$.

$$[B, W] = \left[\int_0^t \operatorname{sgn}(W_u) dW_u, \int_0^t dW_u \right] = \int_0^t \operatorname{sgn}(W_u) du$$

= Time spent > 0 during $[0, t]$ - Time spent < 0 by W