

- Today:
- Multidimensional Ito
 - Lévy's Theorem.
 - Change of measure / Girsanov's.

Multivariate Ito.

$X_t = (X_t^1, \dots, X_t^d) \rightarrow d$ dimensional Ito process

$f(t, X_1, \dots, X_d) = f(t, \bar{X})$
↙ twice cont. differentiable
↑ once cont. differentiable.

↪ i.e. $\partial_{ij} f$ exists for all $i, j \in \{1, \dots, d\}$.

Then

$$df(t, X_t) = \partial_t f(t, X_t) dt + \sum_{i=1}^d \partial_i f(t, X_t) dX_t^i + \frac{1}{2} \sum_{i,j=1}^d \partial_{ij} f(t, X_t) d[X_t^i, X_t^j]$$

$$\text{Ex } \begin{cases} dX_t = \mu_1 X_t dt + \sigma_1 X_t dW_t^1 \\ dY_t = \mu_2 Y_t dt + \sigma_2 Y_t dW_t^2 \end{cases}$$

$$d[W_t^1, W_t^2] = \rho dt \quad (\rho \in [-1, 1] \text{ constant}).$$

Define $Z_t = \frac{X_t}{Y_t}$

(i) Find dZ_t .

$$f(x, y) = \frac{x}{y}$$

$$\partial_x f = \frac{1}{y} \quad \partial_y f = -\frac{x}{y^2}$$

$$\partial_{xy} f = \partial_{yx} f = -\frac{1}{y^2} \quad \partial_{xx} f = 0 \quad \partial_{yy} f = \frac{2x}{y^3}$$

$$d f(X_t, Y_t) = \frac{dX_t}{Y_t} + \frac{-X_t}{Y_t} \frac{dY_t}{Y_t} - \frac{1}{Y_t^2} d[X, Y]_t + \frac{1}{2} \frac{2X_t}{Y_t} \frac{d[Y, Y]_t}{Y_t^2}$$

$$= \frac{X_+}{Y_+} (\mu_1 dt + \sigma_1 dw_+^1) - \frac{X_+}{Y_+} (\mu_2 dt + \sigma_2 dw_+^2) \\ - \frac{1}{Y_+^2} \sigma_1 \sigma_2 X_+ X_+ \underbrace{d[W^1, W^2]}_{\rho dt} + \frac{X_+}{Y_+} \sigma_2^2 dt$$

$$= \frac{X_+}{Y_+} \left[(\mu_1 - \mu_2 - \rho \sigma_1 \sigma_2 + \sigma_2^2) dt + \sigma_1 dw_+^1 - \sigma_2 dw_+^2 \right]$$

(ii) Compute $d[Z, Z]_+$.

$$d[Z, Z]_+ = \left[Z_+ ((\dots) dt + \sigma_1 dw_+^1 - \sigma_2 dw_+^2), Z_+ ((\dots) dt + \sigma_1 dw_+^1 - \sigma_2 dw_+^2) \right] \\ = [Z_+ (\sigma_1 dw_+^1 - \sigma_2 dw_+^2), Z_+ (\sigma_1 dw_+^1 - \sigma_2 dw_+^2)].$$

~~we~~ we will use bilinearity:

aside: T, U, V processes.

$$d[T+U, v]_t = d[T, v]_t + d[U, v]_t$$

$$d[z, z]_t = [z_t \sigma_1 dw_t^1, z_t (\sigma_1 dw_t^1 - \sigma_2 dw_t^2)] +$$

$$- [z_t \sigma_2 dw_t^2, z_t (\sigma_1 dw_t^1 - \sigma_2 dw_t^2)]$$

$$= [z_t \sigma_1 dw_t^1, z_t \sigma_1 dw_t^1] - [z_t \sigma_1 dw_t^1, z_t \sigma_2 dw_t^2]$$

$$- [z_t \sigma_2 dw_t^2, z_t \sigma_1 dw_t^1] + [z_t \sigma_2 dw_t^2, z_t \sigma_2 dw_t^2]$$

$$= z_t^2 \sigma_1^2 dt - 2z_t^2 \rho \sigma_1 \sigma_2 dt + z_t^2 \sigma_2^2 dt$$

$$= z_t^2 (\sigma_1^2 - 2\rho \sigma_1 \sigma_2 + \sigma_2^2) dt$$

if $\rho=1$: $z_t^2 (\sigma_1 - \sigma_2)^2$ so always positive!

$$\text{If } Y_t = b_t dt + \sum_{i=1}^d \sigma_i dX_t^i$$

where X_t^i Ito processes.

$$\begin{aligned} d[Y_t, Y_t] &= d\left[\sum_{i=1}^d \sigma_i X_t^i, \sum_{j=1}^d \sigma_j X_t^j \right]_+ \\ &= \sum_{i=1}^d \sum_{j=1}^d \sigma_i \sigma_j d[X_t^i, X_t^j]_+ \end{aligned}$$

Lévy's I

Lévy's Theorem:

Let $M = (M^1, \dots, M^d)$ be a continuous d -dimensional martingale with $M_0 = (M_0^1, M_0^2, \dots, M_0^d) = \vec{0}$

$$\text{If } [M_i, M_j]_t = t \mathbb{1}_{\{i=j\}}.$$

then M is a d -dimensional Brownian Motion.

pf $M_0 = 0$ ✓

continuous paths ✓

Remains to check (i) $M_t - M_s \sim \mathcal{N}(0, (t-s)I_d)$. $s \leq t$.

(ii) $M_t - M_s \perp \mathcal{F}_s$.

use MGF's:

If $X \stackrel{||}{=} (X_1, \dots, X_d)$ is a d -dimensional RV.

then $M_X(\lambda) = \mathbb{E}[e^{X \cdot \lambda}] = \mathbb{E}[e^{\lambda_1 X_1 + \dots + \lambda_d X_d}]$,

(λ is a vector here).

we will compute $\mathbb{E}[e^{(M_t - M_s) \cdot \lambda} | \mathcal{F}_s]$.

$$f(x_1, \dots, x_d) = e^{\sum_{i=1}^d x_i \lambda_i}$$

$$\partial_i f = \lambda_i f$$

$$\partial_{ij} f = \lambda_i \lambda_j f \quad (\partial_{ii} f = \lambda_i^2 f)$$

$$\begin{aligned} d f(M_t) &= \sum_{i=1}^d \lambda_i f(M_t) dM_t^i + \frac{1}{2} \sum_{i,j=1}^d \lambda_i \lambda_j f(M_t) d[M_t^i, M_t^j]_t \\ d(e^{M_t \cdot \lambda}) &= \sum_{i=1}^d \lambda_i f(M_t) dM_t^i + \frac{1}{2} \underbrace{\sum_{i=1}^d \lambda_i^2}_{\|\lambda\|^2} f(M_t) dt \end{aligned}$$

$$e^{M_t \cdot \lambda} = e^{M_s \cdot \lambda} + \int_s^t \lambda_i f(M_u) dM_u^i + \int_s^t \frac{1}{2} \|\lambda\|^2 f(M_u) du.$$

$$\mathbb{E} \left[e^{M_t \cdot \lambda} - e^{M_s \cdot \lambda} \mid \mathcal{F}_s \right] = 0 + \int_s^t \frac{1}{2} \|\lambda\|^2 \mathbb{E} \left[e^{M_u \cdot \lambda} \mid \mathcal{F}_s \right] du.$$

divide both sides by $e^{M_s \cdot \lambda}$

$$\mathbb{E} \left[e^{(M_t - M_s) \cdot \lambda} - 1 \mid \mathcal{F}_s \right] = \frac{1}{2} \|\lambda\|^2 \int_s^t \mathbb{E} \left[e^{(M_u - M_s) \cdot \lambda} \mid \mathcal{F}_s \right] du.$$

define $g(t) := \mathbb{E} \left[e^{(M_t - M_s) \cdot \lambda} \mid \mathcal{F}_s \right]$, $t \geq s$:

$$g(t) = 1 + \frac{1}{2} \|\lambda\|^2 \int_s^t g(u) du.$$

$$\left\{ \begin{array}{l} g'(t) = \frac{1}{2} \|\lambda\|^2 g(t) \\ g(s) = 1 \end{array} \right.$$

$$\hookrightarrow g(t) = e^{\frac{1}{2} \|\lambda\|^2 (t-s)}.$$

$$\mathbb{E} \left[e^{(M_t - M_s) \cdot \lambda} \mid \mathcal{F}_s \right] = e^{\frac{1}{2} \|\lambda\|^2 (t-s)} \quad (*)$$

\hookrightarrow MGF of $N(0, (t-s)I_d)$

\hookrightarrow will show why.

$$\Rightarrow M_t - M_s \sim N(0, (t-s)I_d)$$

Notice in $(*)$ RHS is non-random. With some work
 work one can show that $M_t - M_s \perp \mathcal{F}_s$.

Warning

In general if I have a RV X and a σ -algebra \mathcal{F} with

$\mathbb{E}[X \mid \mathcal{F}] = \text{constant}$ this does not imply

$X \perp \mathcal{F}$

If $(X_1, \dots, X_d) \sim N(0, (t-s)\mathbf{I})$

in particular X_i is indep of X_j when $i \neq j$.

$$\begin{aligned} M_x(x) &= \mathbb{E}\left[e^{\sum_{i=1}^d \lambda_i X_i} \right] = \mathbb{E}\left[\prod_{i=1}^d e^{\lambda_i X_i} \right] = \prod_{i=1}^d \mathbb{E}[e^{\lambda_i X_i}] \\ &= \prod_{i=1}^d e^{\frac{1}{2} \lambda_i^2 (t-s)} = e^{\frac{1}{2} \sum_{i=1}^d \lambda_i^2 (t-s)} = e^{\frac{1}{2} \|x\|^2 (t-s)} \quad \square \end{aligned}$$

Ex: Take $p \in [0, 1]$ and independent BM's B, W

$$M_t = \sqrt{1-p} W_t + \sqrt{p} B_t$$

Actually M_t is a (1-dim) BM!

pf $M_0 = 0$ ✓ continuous ✓

just need to verify that $[M, M]_t = t$

$$[M, M]_t = [\sqrt{1-p} W_t, \sqrt{1-p} W_t] + 2[\sqrt{p} B_t, \sqrt{1-p} W_t] + [\sqrt{p} B_t, \sqrt{p} B_t]$$

$$= (1-p)t + 0 + p^2 t$$

$$= t$$

So by Lévy M_t is a BM. \square .

If \mathbb{P} is a prob measure. and Z RV s.t.

$Z > 0$ a.s. and $\mathbb{E}[Z] = 1$ then we can

define a new prob measure $\tilde{\mathbb{P}}$ given

$$\tilde{\mathbb{P}}(A) = \mathbb{E}[Z \mathbb{1}_A].$$

\hookrightarrow under \mathbb{P} .

or we write $d\tilde{\mathbb{P}} = Z d\mathbb{P}$ (means same as line above).

and \tilde{P} is equivalent IP.

$$\text{i.e. } P(A) = 0 \iff \tilde{P}(A) = 0 \quad \text{and} \quad \tilde{P}(A) = 1 \iff P(A) = 1$$

"IP and \tilde{P} agree on what is possible or not possible, but may disagree on how likely things are!"

Ex Suppose $X \sim \mathcal{N}(0,1)$ under P .

define $d\tilde{P} = \underbrace{e^{\alpha X + \beta}}_Z dP$.

α is given to you.

Goal: find $\beta, \gamma \in \mathbb{R}$ s.t. $X + \gamma \sim \mathcal{N}(0,1)$ under \tilde{P} .

Sol'n $z > 0$ ✓

$$\mathbb{E}[z] = e^\beta \mathbb{E}[e^{\alpha X}] = e^{\beta + \frac{1}{2}\alpha^2} \stackrel{\text{set}}{=} 1$$

$$\rightarrow \boxed{\beta = -\frac{1}{2}\alpha^2}$$

Now we need $X_t + \sigma \sim N(0, 1)$ under $\tilde{\mathbb{P}}$.

$$\tilde{\mathbb{P}}(X + \sigma \leq x) = \tilde{\mathbb{P}}(X \leq x - \sigma) = \int_{-\infty}^{x - \sigma} z f_X(y) dy.$$

↳ standard normal
PDR.

$$\int \mathbb{1}_{\{X \leq x - \sigma\}} d\tilde{\mathbb{P}}$$

||

$$\int \mathbb{1}_{\{X \leq x - \sigma\}} z d\mathbb{P}.$$

$$= \int_{-\infty}^{\infty} \mathbb{1}_{\{Y \leq x - \sigma\}} z f_X(y) dy.$$

$$= \int_{-\infty}^{x-\gamma} e^{2y - \frac{1}{2}\alpha^2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y^2} dy.$$

$$= \int_{-\infty}^{x-\gamma} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y-\alpha)^2} dy.$$

set $w = y - \alpha$.

$$\int_{-\infty}^{x-\gamma-\alpha} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}w^2} dw.$$

$$= N(x-\gamma-\alpha).$$

need ~~to~~ this to equal $N(x)$.

Happens $\Leftrightarrow \gamma = -\alpha$.

\therefore If $Z = e^{2X - \frac{\alpha^2}{2}}$ then $X - \alpha$ is $N(0, 1)$ under \tilde{P} .

~~Let~~ $X \sim N(0,1)$ under \mathbb{P} .

and $X \sim N(\alpha, 1)$ under $\tilde{\mathbb{P}}$.

~~Let~~ i.e. we changed the mean, but not the variance.

1-D Girsanov:

$$\text{let } \tilde{W}_t = W_t + \int_0^t b(s) ds.$$

$$Z_t = e^{-\int_0^t b(s) dW_s - \frac{1}{2} \int_0^t b^2 ds}.$$

If $\mathbb{E}[Z_t] = 1$ then

\tilde{W}_t is a BM under $\tilde{\mathbb{P}}$ where $d\tilde{\mathbb{P}} = Z_t d\mathbb{P}$.

this looks similar to what we just did!

$$\text{if } \alpha = -\int_0^t b(s) dW_s, \quad \mathbb{P} = \frac{1}{2} [\alpha, \alpha].$$

Notice Girsanov changes the drift, similar to how the example changed the mean.

But the volatility is not affected.