

2. Same for $\mathcal{T} = \{0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95, 1.00\}$.

§38. Itô's Formula for Brownian Motion

Here we develop an elementary version of Itô's formula in the context of Brownian motion. Suppose $f(t, b)$ is a continuous function of two variables. Then, as we have discussed, $X_t = f(t, B_t)$ describes a new stochastic process with continuous paths. For the discussion that follows to be rigorous, we impose at this juncture some technical restrictions. For convenience, we restrict attention to the X_t process on a finite time interval $[0, T]$. Additionally, we require that:

- (i) the partial derivatives f_{tt} , f_{tb} , f_{bbb} all exist and are continuous;
(ii) for some $h > 0$, $E \left[(f_{bb}(t, B_t))^2 \right] \leq h$ for all $t \in [0, T]$. (38.1)

Condition (ii) is rather technical, but not terribly onerous. Presently we prove:

THEOREM 38.2 (ITÔ'S FORMULA). *If the function $f(t, b)$ satisfies (38.1), then on the interval $[0, T]$ the process $X_t = f(t, B_t)$ has dynamics given by*

$$dX_t = \left(f_t(t, B_t) + \frac{1}{2} f_{bb}(t, B_t) \right) dt + f_b(t, B_t) dB_t.$$

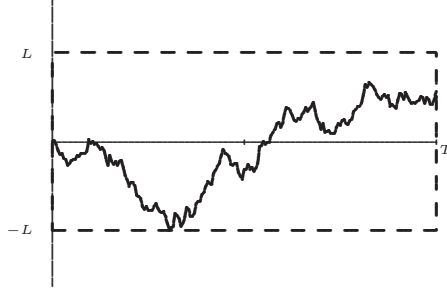
NOTATIONAL REMARK. There is some room for notational confusion here, as X_t denotes the value of the stochastic process X at time t while f_t denotes the partial derivative of f with respect to t . We will use capital letters to denote stochastic processes and lower case letters to denote functions and real variables. This should mitigate any confusion.

EXAMPLE 38.3. In Example 37.8 we have $f(t, b) = b^2 - t$, so $f_t(t, b) = -1$, $f_b(t, b) = 2b$, and $f_{bb}(t, b) = 2$. This gives

$$dX_t = \left(-1 + \frac{1}{2} \cdot 2 \right) dt + 2B_t dB_t = 2B_t dB_t.$$

Here the drift term (M_t in (37.3)) is zero — this is a *zero drift* process.

PROOF OF THEOREM 38.2. For any Brownian path B let $L = \max\{|B_t| : 0 \leq t \leq T\}$. Then the rectangle $\mathcal{R}(T, L) = \{(t, b) : 0 \leq t \leq T \text{ and } |b| \leq L\}$ contains the path. Since f 's derivatives in (38.1) are continuous they are bounded in absolute value in this rectangle (see Figure 38.4). Letting C denote the least such upper bound, we observe that C is a random variable as it depends on ω through the path B that is associated with ω .

Figure 38.4. f 's derivatives are bounded by C in $\mathcal{R}(T, L)$.

Fix $0 \leq u < v \leq T$ and let $\mathcal{T} = \{t_i\}$ be a partition of $[u, v]$. Using standard estimation techniques for functions of two variables (see §45), we get that

$$\begin{aligned} \Delta X_{t_i} &= f(t_{i+1}, B_{t_{i+1}}) - f(t_i, B_{t_i}) \\ &= f_t(t_i, B_{t_i})\Delta t_i + f_b(t_i, B_{t_i})\Delta B_{t_i} + \frac{1}{2}f_{bb}(t_i, B_{t_i})\Delta B_{t_i}^2 \\ &\quad + \text{Error}_i, \end{aligned}$$

where $|\text{Error}_i| \leq C \cdot (\Delta t_i^2 + \Delta t_i|\Delta B_{t_i}| + |\Delta B_{t_i}|^3)$. Here the term $\epsilon(t, \Delta t)$ as defined in (37.3) is given by

$$\begin{aligned} \epsilon(t_i, \Delta t_i) &= \Delta X_{t_i} - \left[\left(f_t(t_i, B_{t_i}) + \frac{1}{2}f_{bb}(t_i, B_{t_i}) \right) \Delta t_i + f_b(t_i, B_{t_i})\Delta B_{t_i} \right] \\ &= \frac{1}{2}f_{bb}(t_i, B_{t_i})\Delta B_{t_i}^2 - \frac{1}{2}f_{bb}(t_i, B_{t_i})\Delta t_i + \text{Error}_i. \end{aligned} \quad (38.5)$$

We will show that, as $\|\mathcal{T}\| \rightarrow 0$,

$$\sum_i \frac{1}{2}f_{bb}(t_i, B_{t_i})\Delta B_{t_i}^2 \xrightarrow{P} \int_u^v \frac{1}{2}f_{bb}(t, B_t) dt, \quad (38.6)$$

and

$$\sum_i |\text{Error}_i| \leq C \cdot \sum_i (\Delta t_i^2 + \Delta t_i|\Delta B_{t_i}| + |\Delta B_{t_i}|^3) \xrightarrow{P} 0. \quad (38.7)$$

Note that the right side of (38.6) is a perfectly legitimate Riemann integral, as, for each ω , the integrand is a continuous function of t . If we combine (38.6) with the fact that

$$\sum_i \frac{1}{2}f_{bb}(t_i, B_{t_i})\Delta t_i \rightarrow \int_u^v \frac{1}{2}f_{bb}(t, B_t) dt \quad \text{as } \|\mathcal{T}\| \rightarrow 0,$$

we see that

$$\left| \sum_i \frac{1}{2} f_{bb}(t_i, B_{t_i}) \Delta B_{t_i}^2 - \sum_i \frac{1}{2} f_{bb}(t_i, B_{t_i}) \Delta t_i \right| \xrightarrow{P} 0 \quad \text{as } \|\mathcal{T}\| \rightarrow 0.$$

($X_m \xrightarrow{P} X$, $Y_m \xrightarrow{P} X \implies |X_m - Y_m| \xrightarrow{P} 0$, see exercises.) This together with (38.7) shows that $\sum_i \epsilon(t_i, \Delta t_i) \xrightarrow{P} 0$, as required (refer to (38.5)).

First we turn our attention to the error terms in (38.7). Note that

$$\sum_i \Delta t_i^2 \leq \|\mathcal{T}\| \sum_i \Delta t_i = \|\mathcal{T}\| \cdot (v - u) \rightarrow 0, \quad \text{as } \|\mathcal{T}\| \rightarrow 0.$$

That was easy. As for the second error term,

$$\begin{aligned} \sum_i \Delta t_i |\Delta B_{t_i}| &\leq \max\{|\Delta B_{t_i}| : 0 \leq i < n\} \cdot \sum_i \Delta t_i \\ &= \max\{|\Delta B_{t_i}|\} \cdot (v - u), \end{aligned}$$

so it will suffice to show that

$$\max\{|\Delta B_{t_i}|\} \rightarrow 0, \quad \text{as } \|\mathcal{T}\| \rightarrow 0. \quad (38.8)$$

But B_t is a continuous function of t . Hence, on any closed and bounded interval $[u, v]$ it is *uniformly continuous* (see Appendix II). That is, for any $\epsilon > 0$ there is a $\delta > 0$ such that $|B_t - B_{t'}| < \epsilon$ whenever $t, t' \in [u, v]$ with $|t - t'| < \delta$. Note that $\delta = \delta(\omega)$ is random because it will depend on the Brownian path $B = B(\omega)$. Now fix any $\epsilon > 0$ and let $\delta > 0$ correspond to that ϵ . Then $\|\mathcal{T}\| < \delta \implies \Delta t_i < \delta \implies |B_{t_i} - B_{t_{i+1}}| < \epsilon$. Because this holds for each individual i , we see that $\|\mathcal{T}\| < \delta \implies \max\{|\Delta B_{t_i}|\} < \epsilon$. This establishes (38.8).

For the third error term, use Lemma 38.9 (stated below) as applied to $H_t = 1$ to get that $\sum_i \Delta B_{t_i}^2 \xrightarrow{P} v - u$ as $\|\mathcal{T}\| \rightarrow 0$. Then, as $\|\mathcal{T}\| \rightarrow 0$,

$$\sum_i |\Delta B_{t_i}^3| \leq \max\{|\Delta B_{t_i}|\} \cdot \sum_i \Delta B_{t_i}^2 \xrightarrow{P} 0,$$

as $X_m \xrightarrow{P} 0$, $Y_m \xrightarrow{P} c \implies X_m Y_m \xrightarrow{P} 0$ (see exercises). Collecting these three error terms yields that

$$\sum_i (\Delta t_i^2 + \Delta t_i |\Delta B_{t_i}| + |\Delta B_{t_i}|^3) \xrightarrow{P} 0,$$

as $\|\mathcal{T}\| \rightarrow 0$. This is enough to get (38.7), for $Y_n \xrightarrow{P} 0 \implies XY_n \xrightarrow{P} 0$ (see, e.g., Theorem 8.6).

Now we turn our attention to establishing (38.6), which is the crux of the matter. We have:

LEMMA 38.9. *If the process H_t satisfies (36.1) and has bounded second moment for $t \in [0, T]$ then*

$$\sum_{i=0}^{n-1} H_{t_i} \Delta B_{t_i}^2 \xrightarrow{P} \int_u^v H_t dt \quad \text{as } \|\mathcal{T}\| \rightarrow 0.$$

Statement (38.6) is simply this lemma as applied to $H_t = \frac{1}{2} f_{bb}(t, B_t)$, which has bounded second moment for $t \in [0, T]$ by virtue of (38.1).

PROOF OF LEMMA 38.9. For partition $\mathcal{T} = \{t_0, \dots, t_n\}$ of $[u, v]$, let

$$\begin{aligned} Z_{\mathcal{T}} &= \sum_i H_{t_i} \Delta B_{t_i}^2 - \sum_i H_{t_i} \Delta t_i \\ &= \sum_i H_{t_i} [\Delta B_{t_i}^2 - \Delta t_i] \\ &= \sum_i H_i M_i, \end{aligned}$$

where $H_i = H_{t_i}$ and $M_i = \Delta B_{t_i}^2 - \Delta t_i$. We will show that $Z_{\mathcal{T}} \xrightarrow{P} 0$ as $\|\mathcal{T}\| \rightarrow 0$. Since

$$\sum_{i=0}^{n-1} H_{t_i} \Delta t_i \rightarrow \int_u^v H_t dt \quad \text{as } \|\mathcal{T}\| \rightarrow 0,$$

the lemma will follow ($X_m - Y_m \xrightarrow{P} 0$, $Y_m \xrightarrow{P} Y \implies X_m \xrightarrow{P} Y$, see exercises). Note that this holds because the left side is a Riemann sum approximation of the integral on the right side. (Again, the integrand is a continuous function of t .) We will show that $E Z_{\mathcal{T}} = 0$ and that $\text{Var } Z_{\mathcal{T}} \rightarrow 0$ as $\|\mathcal{T}\| \rightarrow 0$. Then, by Chebyshev's inequality, $P[|Z_{\mathcal{T}}| \geq \epsilon] \leq \frac{\text{Var } Z_{\mathcal{T}}}{\epsilon^2} \rightarrow 0$, establishing that $Z_{\mathcal{T}} \xrightarrow{P} 0$.

Now $E[\Delta B_{t_i}^2] = 0$, so $E[\Delta B_{t_i}^2] = \text{Var } \Delta B_{t_i} = \Delta t_i$ and $E M_i = 0$. Furthermore, H_i depends on B_t only through time t_i while M_i depends on the Brownian increment on $[t_i, t_{i+1}]$, so H_i and M_i are independent and $E[H_i M_i] = E H_i \cdot E M_i = 0$. By linearity of expectation, $E Z_{\mathcal{T}} = 0$. Regarding the variance, if $0 \leq i < j$, then

$$\begin{aligned} E[H_i M_i H_j M_j] &= E[H_i M_i H_j] \cdot E[M_j] \\ &= E[H_i M_i H_j] \cdot 0 = 0 = E[H_i M_i] \cdot E[H_j M_j]. \end{aligned}$$

The first equality holds because $H_i M_i H_j$ depends on the Brownian path up to time t_j , while M_j depends on the Brownian increment over the interval $[t_j, t_{j+1}]$ — $H_i M_i H_j$ and M_j are therefore independent. We have that $H_i M_i$ and $H_j M_j$ are uncorrelated if $i \neq j$, so

$$\begin{aligned} \text{Var } Z_{\mathcal{T}} &= \sum_i \text{Var } [H_i M_i] = \sum_i E[(H_i M_i)^2] = \sum_i E[H_i^2] E[M_i^2] \\ &\leq h \sum_i \text{Var } [M_i], \end{aligned} \tag{38.10}$$

where h is the hypothesized bound for EH_i^2 . The second equality above holds because $H_i M_i$ is mean 0; the third because H_i^2 and M_i^2 are independent. The inequality uses that M_i is mean 0. Now $\text{Var}[M_i] = \text{Var}[\Delta B_{t_i}^2 - \Delta t_i] = \text{Var}[\Delta B_{t_i}^2]$, and

$$\Delta B_{t_i}^2 \sim (\text{Normal}(0, \Delta t_i))^2 \sim \Delta t_i (\text{Normal}(0, 1))^2,$$

so

$$\text{Var} M_i = \Delta t_i^2 \text{Var}[(\text{Normal}(0, 1))^2] = 2\Delta t_i^2,$$

using that $(\text{Normal}(0, 1))^2$ has the chi-squared distribution with 1 degree of freedom which has variance 2. Then

$$\sum_i \text{Var}[M_i] = \sum_i 2\Delta t_i^2 \leq 2\|\mathcal{T}\| \cdot \sum_i \Delta t_i = 2\|\mathcal{T}\| \cdot (v - u) \rightarrow 0,$$

as $\|\mathcal{T}\| \rightarrow 0$. Combining this with (38.10) gives that $\text{Var} Z_{\mathcal{T}} \rightarrow 0$ as $\|\mathcal{T}\| \rightarrow 0$. This concludes the proof of Lemma 38.9 and Theorem 38.2. \square

REMARK. Lemma 38.9 is sometimes informally paraphrased as “ $dB^2 = dt$.”

EXERCISES

• In problems 1 – 3, verify the assertions made in the proof of Theorem 38.2 and Lemma 38.9.

1. $X_m \xrightarrow{P} X, Y_m \xrightarrow{P} X \implies |X_m - Y_m| \xrightarrow{P} 0.$

2. $X_m \xrightarrow{P} 0, Y_m \xrightarrow{P} c \implies X_m Y_m \xrightarrow{P} 0.$

3. $X_m - Y_m \xrightarrow{P} 0, Y_m \xrightarrow{P} Y \implies X_m \xrightarrow{P} Y.$

• In problems 4 – 7, compute the dynamics of $X_t = f(t, b)$.

4. $f(t, b) = b.$

5. $f(t, b) = tb.$

6. $f(t, b) = tb^2.$

7. $f(t, b) = e^b$ (geometric Brownian motion).

8. Determine a function $g(t)$ so that $f(t, b) = g(t)e^b$ generates a zero drift process.

§39. Application: The Black-Scholes PDE and Formula

Here we study a classic application of Itô’s formula to develop the Black-Scholes formula which values a call option on an underlying stock. It is customary in finance to model the evolution of a stock price as a random process following *geometric Brownian motion*:

$$S_t = s_0 e^{\mu t + \sigma B_t}, \tag{39.1}$$