

Itô vs. Stratonovich Stochastic Integration

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1 Formal Definition of the Stochastic Integral

Consider a filtered probability space $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, \mathbb{P})$ and a standard Brownian motion B_t . For a partition of the interval $[0, T]$ given by $0 = t_0 < t_1 < \dots < t_n = T$ with mesh size $|\Delta| \rightarrow 0$, we define the stochastic integral of an adapted, square-integrable process G_t as the limit in $L^2(\Omega)$ of the Riemann-Stieltjes sum:

$$S_n = \sum_{i=0}^{n-1} G_{\tau_i} (B_{t_{i+1}} - B_{t_i}). \quad (1.1)$$

The distinction between the two frameworks depends on the choice of the evaluation point $\tau_i \in [t_i, t_{i+1}]$:

- **Itô Integral:** Evaluated at the left-hand endpoint, $\tau_i = t_i$.

$$\int_0^T G_t dB_t := \lim_{|\Delta| \rightarrow 0} \sum_{i=0}^{n-1} G_{t_i} (B_{t_{i+1}} - B_{t_i}) \text{ in } L^2(\Omega).$$

- **Stratonovich Integral:** Evaluated at the midpoint time,

$$\int_0^T G_t \circ dB_t := \lim_{|\Delta| \rightarrow 0} \sum_{i=0}^{n-1} G_{\tau_i} (B_{t_{i+1}} - B_{t_i}) \text{ in } L^2(\Omega), \quad \tau_i = \frac{t_i + t_{i+1}}{2}.$$

2 Examples and Comparison

2.1 Example: Integral of Brownian Motion

Let $G_t = B_t$. We compute $\int_0^T B_t dB_t$ and $\int_0^T B_t \circ dB_t$ using the respective definitions.

Itô Integral: $\tau_i = t_i$.

$$\sum B_{t_i} (B_{t_{i+1}} - B_{t_i}) = \frac{1}{2} \sum (B_{t_{i+1}}^2 - B_{t_i}^2 - (B_{t_{i+1}} - B_{t_i})^2) = \frac{1}{2} B_T^2 - \frac{1}{2} \sum (\Delta B_i)^2.$$

As $\sum (\Delta B_i)^2 \rightarrow T$ in L^2 , we have

$$\int_0^T B_t dB_t = \frac{1}{2} B_T^2 - \frac{1}{2} T.$$

Stratonovich Integral: Use the midpoint-time rule $\tau_i = \frac{t_i + t_{i+1}}{2}$. We decompose the integrand as $B_{\tau_i} = B_{t_i} + (B_{\tau_i} - B_{t_i})$. The sum becomes:

$$\sum_{i=0}^{n-1} B_{\tau_i} \Delta B_i = \sum_{i=0}^{n-1} B_{t_i} \Delta B_i + \sum_{i=0}^{n-1} (B_{\tau_i} - B_{t_i}) \Delta B_i.$$

The first term is the Itô sum, converging to $\int_0^T B_t dB_t = \frac{1}{2} B_T^2 - \frac{1}{2} T$. For the second term (the correction), we write $\Delta B_i = (B_{t_{i+1}} - B_{\tau_i}) + (B_{\tau_i} - B_{t_i})$. Then

$$(B_{\tau_i} - B_{t_i}) \Delta B_i = (B_{\tau_i} - B_{t_i})(B_{t_{i+1}} - B_{\tau_i}) + (B_{\tau_i} - B_{t_i})^2.$$

Note that $Z_i = (B_{\tau_i} - B_{t_i})(B_{t_{i+1}} - B_{\tau_i})$ has mean 0 and variance $\mathbb{E}|Z_i|^2 = \frac{1}{4} \Delta t_i^2$, thus, the first part $\sum_i Z_i$ vanishes in L^2 . The second part is the quadratic variation over the left half-intervals $[t_i, \tau_i]$, summing to $\frac{1}{2} T$. Thus,

$$\int_0^T B_t \circ dB_t = \left(\frac{1}{2} B_T^2 - \frac{1}{2} T \right) + \frac{1}{2} T = \frac{1}{2} B_T^2.$$

2.2 Comparison Table

The choice of τ_i leads to fundamental differences in the resulting calculus.

Property	Itô Calculus	Stratonovich Calculus
Notation	$\int_0^T G_t dB_t$	$\int_0^T G_t \circ dB_t$
Expectation	$\mathbb{E} \left[\int_0^T G_t dB_t \right] = 0$	Generally $\neq 0$
Martingale Property	The integral is a martingale	Not a martingale
Chain Rule	Requires Itô's Lemma	Standard Calculus (Leibniz rule)
Application	Finance, Filtering theory	Physics, Manifold-valued SDEs

Table 1: Key differences between Itô and Stratonovich frameworks.

3 The Itô–Stratonovich Correction

We derive the correction term using the same midpoint-time convention

$$\int_0^t H_s \circ dB_s = \lim_{|\Delta| \rightarrow 0} \sum_{i=0}^{n-1} H_{\tau_i} \Delta B_i, \quad \tau_i = \frac{t_i + t_{i+1}}{2}, \quad \Delta B_i = B_{t_{i+1}} - B_{t_i}.$$

Theorem 3.1 (Itô–Stratonovich Correction, one-dimensional). *Assume $f, g \in C_b^1(\mathbb{R})$ with sufficient growth control so the following integrals are well-defined, and let X solve the Itô SDE*

$$dX_t = f(X_t) dt + g(X_t) dB_t. \quad (3.1)$$

Then

$$\int_0^t g(X_s) \circ dB_s = \int_0^t g(X_s) dB_s + \frac{1}{2} \int_0^t g(X_s) g'(X_s) ds. \quad (3.2)$$

Consequently, (3.1) is equivalent to the Stratonovich SDE

$$dX_t = \left(f(X_t) - \frac{1}{2} g(X_t) g'(X_t) \right) dt + g(X_t) \circ dB_t. \quad (3.3)$$

Proof. Let Π be a partition and $\tau_i = (t_i + t_{i+1})/2$. Consider the difference of Riemann sums:

$$S_{\Pi}^{\circ} - S_{\Pi}^{\text{Ito}} := \sum_{i=0}^{n-1} (g(X_{\tau_i}) - g(X_{t_i})) \Delta B_i.$$

By Taylor expansion,

$$g(X_{\tau_i}) - g(X_{t_i}) = g'(X_{t_i})(X_{\tau_i} - X_{t_i}) + r_i, \quad r_i = o(|X_{\tau_i} - X_{t_i}|).$$

Hence

$$S_{\Pi}^{\circ} - S_{\Pi}^{\text{Ito}} = \sum_i g'(X_{t_i})(X_{\tau_i} - X_{t_i}) \Delta B_i + \sum_i r_i \Delta B_i. \quad (3.4)$$

Under standard moment bounds, $X_{\tau_i} - X_{t_i} = O_{L^2(\mathbb{P})}(\sqrt{\Delta t_i})$.

First, we show that the remainder $R_{\Delta} := \sum_{i=0}^{n-1} r_i \Delta B_i \xrightarrow{\mathbb{P}} 0$. Recall that $r_i = g(X_{\tau_i}) - g(X_{t_i}) - g'(X_{t_i})(X_{\tau_i} - X_{t_i})$. By the Mean Value Theorem, $r_i = (g'(\xi_i) - g'(X_{t_i}))(X_{\tau_i} - X_{t_i})$ for some ξ_i between X_{t_i} and X_{τ_i} . Let $M_{\Delta} = \sup_{|s-t| \leq |\Delta|} |X_s - X_t|$. Since X is continuous, $M_{\Delta} \rightarrow 0$ almost surely as $|\Delta| \rightarrow 0$.

We can bound the magnitude of the remainder sum:

$$|R_{\Delta}| \leq \sum_{i=0}^{n-1} |g'(\xi_i) - g'(X_{t_i})| \cdot |X_{\tau_i} - X_{t_i}| \cdot |\Delta B_i|.$$

Take $K > 0$. Since $g \in C_b^1$ on $[-K, K]$, for any $\varepsilon > 0$, there exists $\delta > 0$ (depending on K) such that $|g'(y) - g'(x)| < \varepsilon$ whenever $|y - x| < \delta$. Let $\Omega_{K,\delta} = \{\sup_{t \in [0, T]} |X_t| \leq K\} \cap \{M_{\Delta} < \delta\}$. On this compact set, g' is uniformly continuous, so we have $|g'(\xi_i) - g'(X_{t_i})| < \varepsilon$. Thus,

$$\mathbb{E}[|R_{\Delta}| \mathbf{1}_{\Omega_{K,\delta}}] \leq \varepsilon \sum_{i=0}^{n-1} \mathbb{E}[|X_{\tau_i} - X_{t_i}| \cdot |\Delta B_i|].$$

By Hölder's inequality and the standard estimate $\mathbb{E}[|X_{\tau_i} - X_{t_i}|^2] \leq C \Delta t$,

$$\mathbb{E}[|X_{\tau_i} - X_{t_i}| \cdot |\Delta B_i|] \leq \sqrt{\mathbb{E}|X_{\tau_i} - X_{t_i}|^2} \sqrt{\mathbb{E}|\Delta B_i|^2} \leq C \Delta t.$$

Therefore, $\mathbb{E}[|R_{\Delta}| \mathbf{1}_{\Omega_{K,\delta}}] \leq \varepsilon C T$. Since ε is arbitrary and $\mathbb{P}(\Omega_{K,\delta}^c)$ can be made arbitrarily small by choosing K large and $|\Delta|$ small, the result follows.

Second, we analyze the main term $\sum_i g'(X_{t_i})(X_{\tau_i} - X_{t_i}) \Delta B_i$. Recall the increment on $[t_i, \tau_i]$:

$$X_{\tau_i} - X_{t_i} = \int_{t_i}^{\tau_i} f(X_s) ds + \int_{t_i}^{\tau_i} g(X_s) dB_s.$$

The drift contribution in (3.4) is negligible: it is of size $O(\Delta t_i) \cdot O(\sqrt{\Delta t_i}) = O((\Delta t_i)^{3/2})$ and sums to $o(1)$. For the martingale term, Taylor expand $g(X_s)$ at t_i and integrate,

$$\int_{t_i}^{\tau_i} g(X_s) dB_s = g(X_{t_i})(B_{\tau_i} - B_{t_i}) + o_P(\sqrt{\Delta t_i}).$$

Together, we have the leading order approximation

$$(X_{\tau_i} - X_{t_i}) \Delta B_i = g(X_{t_i})(B_{\tau_i} - B_{t_i}) \Delta B_i + o_P(\Delta t_i).$$

Write $\Delta B_i = (B_{\tau_i} - B_{t_i}) + (B_{t_{i+1}} - B_{\tau_i})$. Then

$$(B_{\tau_i} - B_{t_i})\Delta B_i = (B_{\tau_i} - B_{t_i})^2 + (B_{\tau_i} - B_{t_i})(B_{t_{i+1}} - B_{\tau_i}).$$

The cross term has mean zero and variance $O((\Delta t_i)^2)$, hence its sum is $o_P(1)$. Moreover $\sum_i \left((B_{\tau_i} - B_{t_i})^2 - \frac{\Delta t_i}{2} \right) \xrightarrow{P} 0$, so

$$(X_{\tau_i} - X_{t_i})\Delta B_i = \frac{1}{2}g(X_{t_i})\Delta t_i + o_P(\Delta t_i).$$

Plugging into (3.4) yields

$$S_{\Pi}^{\circ} - S_{\Pi}^{\text{Itô}} = \frac{1}{2} \sum_i g'(X_{t_i})g(X_{t_i})\Delta t_i + o_P(1) \xrightarrow{P} \frac{1}{2} \int_0^t g'(X_s)g(X_s) ds.$$

Taking limits gives (3.2), and rearranging the drift gives (3.3). \square

To describe the same process X_t in both frameworks, we must adjust the drift. The term

$$\frac{1}{2}g(X_t)g'(X_t)$$

is the **Itô–Stratonovich correction**. Heuristically it arises from the quadratic variation of Brownian motion, i.e. the fact that $(\Delta B_i)^2 \approx \Delta t_i$ at leading order, and it represents the interaction between state-dependent diffusion and noise fluctuations.

4 Chain Rule for the Stratonovich Integral

We state and prove the chain rule (the analogue of the classical Leibniz rule) using the midpoint-time definition

$$\int_0^T H_s \circ dB_s := \lim_{|\Delta| \rightarrow 0} \sum_{i=0}^{n-1} H_{\tau_i} (B_{t_{i+1}} - B_{t_i}), \quad \tau_i = \frac{t_i + t_{i+1}}{2}.$$

Theorem 4.1 (Stratonovich Chain Rule, one-dimensional). *Let X be a continuous semimartingale solving the Stratonovich SDE*

$$dX_t = a(X_t) dt + b(X_t) \circ dB_t, \quad (4.1)$$

where a, b are locally Lipschitz (and of at most linear growth), and let $\varphi \in C_b^2(\mathbb{R})$. Then

$$d\varphi(X_t) = \varphi'(X_t) \circ dX_t = \varphi'(X_t)a(X_t) dt + \varphi'(X_t)b(X_t) \circ dB_t. \quad (4.2)$$

Equivalently, for every $t \in [0, T]$,

$$\varphi(X_t) - \varphi(X_0) = \int_0^t \varphi'(X_s)a(X_s) ds + \int_0^t \varphi'(X_s)b(X_s) \circ dB_s. \quad (4.3)$$

Proof. Fix a partition $0 = t_0 < \dots < t_n = t$ and set $\tau_i = (t_i + t_{i+1})/2$, $\Delta X_i = X_{t_{i+1}} - X_{t_i}$. By Taylor's theorem,

$$\varphi(X_{t_{i+1}}) - \varphi(X_{t_i}) = \varphi'(X_{\tau_i}) \Delta X_i + R_i, \quad (4.4)$$

where the remainder satisfies $|R_i| \leq C|\Delta X_i|^2$, with $C = \|\varphi''\|_\infty$. Summing (4.4) over i gives

$$\varphi(X_t) - \varphi(X_0) = \sum_{i=0}^{n-1} \varphi'(X_{\tau_i})\Delta X_i + \sum_{i=0}^{n-1} R_i. \quad (4.5)$$

For solutions of (4.1) with locally Lipschitz coefficients one has the increment estimate $\Delta X_i = O_{L^2}(\sqrt{\Delta t_i})$. Indeed, writing the equation in Itô form with modified drift $\tilde{a}(x) = a(x) + \frac{1}{2}b(x)b'(x)$, we have

$$X_{t_{i+1}} - X_{t_i} = \int_{t_i}^{t_{i+1}} \tilde{a}(X_s) ds + \int_{t_i}^{t_{i+1}} b(X_s) dB_s.$$

Squaring and taking expectations, using the elementary inequality $(A + B)^2 \leq 2A^2 + 2B^2$,

$$\mathbb{E}[|X_{t_{i+1}} - X_{t_i}|^2] \leq 2\mathbb{E}\left[\left(\int_{t_i}^{t_{i+1}} \tilde{a}(X_s) ds\right)^2\right] + 2\mathbb{E}\left[\left(\int_{t_i}^{t_{i+1}} b(X_s) dB_s\right)^2\right].$$

By Jensen's inequality (for the drift) and Itô isometry (for the diffusion), assuming bounded coefficients for simplicity (or using localization arguments),

$$\mathbb{E}[|X_{t_{i+1}} - X_{t_i}|^2] \leq 2(t_{i+1} - t_i) \int_{t_i}^{t_{i+1}} \mathbb{E}[\tilde{a}^2] ds + 2 \int_{t_i}^{t_{i+1}} \mathbb{E}[b^2] ds \leq C(t_{i+1} - t_i).$$

Taking the square root gives the L^2 estimate of order $O(\sqrt{\Delta t_i})$.

Hence

$$\mathbb{E}\left[\sum_i |R_i|\right] \lesssim \sum_i \mathbb{E}[|\Delta X_i|^2] \lesssim \sum_i \Delta t_i = t,$$

and, more precisely, $\sum_i R_i \rightarrow 0$ in probability as $|\Delta| \rightarrow 0$ (one can localize to ensure boundedness of φ'' on the range of X). Therefore,

$$\varphi(X_t) - \varphi(X_0) = \lim_{|\Delta| \rightarrow 0} \sum_{i=0}^{n-1} \varphi'(X_{\tau_i})\Delta X_i = \int_0^t \varphi'(X_s) \circ dX_s.$$

Finally, substituting $dX_s = a(X_s) ds + b(X_s) \circ dB_s$ and using linearity yields (4.3), and thus (4.2). \square

5 Solution to SDEs: Itô vs. Stratonovich

Example 5.1 (Ornstein–Uhlenbeck Process). *Consider the SDE*

$$dX_t = -\theta X_t dt + \sigma dB_t, \quad X_0 = x_0.$$

The solution is the same under both interpretations, since the diffusion coefficient is constant and the correction term vanishes. The explicit solution is

$$X_t = x_0 e^{-\theta t} + \sigma \int_0^t e^{-\theta(t-s)} dB_s.$$

This process is mean-reverting with mean reverting level 0 and rate θ , and it has stationary distribution $\mathcal{N}(0, \sigma^2/(2\theta))$.

Example 5.2. Consider the Ito SDE

$$dX_t = \alpha X_t dt + \beta X_t^2 dB_t, \quad X_0 = x_0.$$

The Itô solution satisfies

$$X_t = x_0 + \int_0^t \alpha X_s ds + \int_0^t \beta X_s^2 dB_s.$$

The Stratonovich SDE for the process X is

$$dX_t = (\alpha X_t - \beta^2 X_t^3) dt + \beta X_t^2 \circ dB_t.$$

The correction term $-\beta^2 X_t^3$ significantly alters the drift's nonlinearity. This illustrates how the choice of interpretation can lead to qualitatively different dynamics, especially in nonlinear systems with state-dependent noise.