

Lecture #13: Calculating Wiener Integrals

Now that we have defined the Wiener integral of a bounded, piecewise continuous deterministic function in $L^2([0, \infty))$ with respect to Brownian motion as a normal random variable, namely

$$\int_0^t g(s) dB_s \sim \mathcal{N}\left(0, \int_0^t g^2(s) ds\right),$$

it might seem like we are done. However, as our ultimate goal is to be able to integrate random functions with respect to Brownian motion, it seems useful to try and develop a *calculus* for Wiener integration. The key computational tool that we will develop is an integration-by-parts formula. But first we need to complete the following exercise.

Exercise 9.1. Verify that the Wiener integral is a linear operator. That is, show that if $\alpha, \beta \in \mathbb{R}$ are constants, and g and h are bounded, piecewise continuous functions in $L^2([0, \infty))$, then

$$\int_0^t [\alpha g(s) + \beta h(s)] dB_s = \alpha \int_0^t g(s) dB_s + \beta \int_0^t h(s) dB_s.$$

Theorem 9.2. Let $g : [0, \infty) \rightarrow \mathbb{R}$ be a bounded, continuous function in $L^2([0, \infty))$. If g is differentiable with g' also bounded and continuous, then the integration-by-parts formula

$$\int_0^t g(s) dB_s = g(t)B_t - \int_0^t g'(s)B_s ds$$

holds.

Remark. Since all three objects in the above expression are random variables, the equality is interpreted to mean that the distribution of the random variable on the left side and the distribution of the random variable on the right side are the same, namely

$$\mathcal{N}\left(0, \int_0^t g^2(s) ds\right).$$

Also note that the second integral on the right side, namely

$$\int_0^t g'(s)B_s ds, \tag{9.1}$$

is the Riemann integral of a function of Brownian motion. Using the notation of the final remark of Lecture #11, we have $h(B_s) = g'(s)B_s$. In Exercise 9.5 you will determine the distribution of (9.1).

Proof. We begin by writing

$$\sum_{j=1}^n g(t_{j-1})(B_{t_j} - B_{t_{j-1}}) = \sum_{j=1}^n g(t_{j-1})B_{t_j} - \sum_{j=1}^n g(t_{j-1})B_{t_{j-1}}. \tag{9.2}$$

Since g is differentiable, the mean value theorem implies that there exists some value $t_j^* \in [t_{j-1}, t_j]$ such that

$$g'(t_j^*)(t_j - t_{j-1}) = g(t_j) - g(t_{j-1}).$$

Substituting this for $g(t_{j-1})$ in the previous expression (9.2) gives

$$\begin{aligned} \sum_{j=1}^n g(t_{j-1})B_{t_j} - \sum_{j=1}^n g(t_{j-1})B_{t_{j-1}} &= \sum_{j=1}^n g(t_j)B_{t_j} - \sum_{j=1}^n g'(t_j^*)(t_j - t_{j-1})B_{t_j} - \sum_{j=1}^n g(t_{j-1})B_{t_{j-1}} \\ &= \sum_{j=1}^n [g(t_j)B_{t_j} - g(t_{j-1})B_{t_{j-1}}] - \sum_{j=1}^n g'(t_j^*)(t_j - t_{j-1})B_{t_j} \\ &= g(t_n)B_{t_n} - g(t_0)B_{t_0} - \sum_{j=1}^n g'(t_j^*)B_{t_j}(t_j - t_{j-1}) \\ &= g(t)B_t - \sum_{j=1}^n g'(t_j^*)B_{t_j}(t_j - t_{j-1}) \end{aligned}$$

since $t_n = t$ and $t_0 = 0$. Notice that we have established an equality between random variables, namely that

$$\sum_{j=1}^n g(t_{j-1})(B_{t_j} - B_{t_{j-1}}) = g(t)B_t - \sum_{j=1}^n g'(t_j^*)B_{t_j}(t_j - t_{j-1}). \quad (9.3)$$

The proof will be completed if we can show that the distribution of the limiting random variable on the left-side of (9.3) and the distribution of the limiting random variable on the right-side of (9.3) are the same. Of course, we know that

$$\sum_{j=1}^n g(t_{j-1})(B_{t_j} - B_{t_{j-1}}) \rightarrow I_t = \int_0^t g(s) dB_s \sim \mathcal{N}\left(0, \int_0^t g^2(s) ds\right)$$

from our construction of the Wiener integral in last lecture. Thus, we conclude that

$$g(t)B_t - \sum_{j=1}^n g'(t_j^*)B_{t_j}(t_j - t_{j-1}) \rightarrow I_t \sim \mathcal{N}\left(0, \int_0^t g^2(s) ds\right)$$

in distribution as well. We now observe that since g' is bounded and piecewise continuous, and since Brownian motion is continuous, the function $g'(t)B_t$ is necessarily Riemann integrable. Thus,

$$\lim_{n \rightarrow \infty} \sum_{j=1}^n g'(t_j^*)B_{t_j}(t_j - t_{j-1}) = \int_0^t g'(s)B_s ds$$

in distribution as in Lecture #11. In other words, we have shown that the distribution of

$$\int_0^t g(s) dB_s$$

and the distribution of

$$g(t)B_t - \int_0^t g'(s)B_s ds$$

are the same, namely

$$\mathcal{N}\left(0, \int_0^t g^2(s) ds\right)$$

and so the proof is complete. □

Example 9.3. Suppose that $t > 0$. It might seem obvious that

$$B_t = \int_0^t dB_s.$$

However, since Brownian motion is nowhere differentiable, and since we have only defined the Wiener integral as a normal random variable, this equality needs a proof. Since $B_t \sim \mathcal{N}(0, t)$ and since

$$\int_0^t dB_s \sim \mathcal{N}\left(0, \int_0^t 1^2 ds\right) = \mathcal{N}(0, t),$$

we conclude that

$$B_t = \int_0^t dB_s$$

in distribution. Alternatively, let $g \equiv 1$ so that the integration-by-parts formula implies

$$\int_0^t dB_s = g(t)B_t - \int_0^t g'(s)B_s ds = B_t - 0 = B_t.$$

Example 9.4. Suppose that we choose $t = 1$ and $g(s) = s$. The integration-by-parts formula implies that

$$\int_0^1 s dB_s = B_1 - \int_0^1 B_s ds.$$

If we now write

$$B_1 = \int_0^1 dB_s$$

and use linearity of the stochastic integral, then we find

$$\int_0^1 B_s ds = B_1 - \int_0^1 s dB_s = \int_0^1 dB_s - \int_0^1 s dB_s = \int_0^1 (1 - s) dB_s.$$

Since

$$\int_0^1 (1 - s) dB_s$$

is normally distributed with mean 0 and variance

$$\int_0^1 (1 - s)^2 ds = \frac{1}{3},$$

we conclude that

$$\int_0^1 B_s ds \sim \mathcal{N}(0, 1/3).$$

Thus, we have a different derivation of the fact that we proved in Lecture #11.

Exercise 9.5. Show that

$$\int_0^1 g'(s)B_s ds = \int_0^1 [g(1) - g(s)] dB_s$$

where g is any antiderivative of g' . Conclude that

$$\int_0^1 g'(s)B_s ds \sim \mathcal{N}\left(0, \int_0^1 [g(1) - g(s)]^2 ds\right).$$

In general, this exercise shows that for fixed $t > 0$, we have

$$\int_0^t g'(s)B_s ds \sim \mathcal{N}\left(0, \int_0^t [g(t) - g(s)]^2 ds\right).$$

Exercise 9.6. Use the result of Exercise 9.5 to establish the following generalization of Example 9.4. Show that if $n = 0, 1, 2, \dots$ is a non-negative integer, then

$$\int_0^1 s^n B_s ds \sim \mathcal{N}\left(0, \frac{2}{(2n+3)(n+2)}\right).$$