

1 Preliminaries

Consider a Wiener process $B_t \in \mathbb{R}$.

Choose some partition of $[0, t]$ such that for some $n \in \mathbb{N}$,

$$0 = t_0 \leq t_1 \leq \dots \leq t_n = t$$

And define

$$\begin{aligned}\Delta t_k &= t_k - t_{k-1} \\ W_k &= B_{t_k} - B_{t_{k-1}} (= \Delta B_k)\end{aligned}$$

By the independent increment property of the Wiener process and the Gaussian distribution of each increment, we have

$$W_k \sim N(0, \Delta t_k)$$

Such that

$$\mathbb{E}(W_k) = 0 \tag{1.1}$$

$$\mathbb{E}(W_k^2) = \Delta t_k \tag{1.2}$$

And since the Moment Generating Function for the distribution of W_k is

$$M(s) = \exp\left(\frac{\Delta t_k}{2} s^2\right)$$

We have

$$\mathbb{E}(W_k^4) = M^{(4)}(0) = 3(\Delta t_k)^2 \tag{1.3}$$

Furthermore,

$$\sum_{k=1}^n \mathbb{E}(W_k^2) = \sum_{k=1}^n \Delta t_k = t$$

2 Part (a)

2.1 We first want to show that $\mathbb{E} \left[\left(\left[\sum_{k=1}^n W_k^2 \right] - t \right)^2 \right] = 2 \sum_{k=1}^n (\Delta t_k)^2$.

Since $t = \sum_{k=1}^n \Delta t_k$, and $\mathbb{E}(W_k^2) = \Delta t_k$, we have

$$\begin{aligned} \mathbb{E} \left[\left(\left[\sum_{k=1}^n W_k^2 \right] - t \right)^2 \right] &= \mathbb{E} \left[\left(\sum_{k=1}^n [W_k^2 - \Delta t_k] \right)^2 \right] \\ &= \mathbb{E} \left[\left(\sum_{k=1}^n [W_k^2 - \mathbb{E}(W_k^2)] \right)^2 \right] \\ &= \mathbb{E} \left[\sum_{k=1}^n (W_k^2 - \mathbb{E}(W_k^2))^2 \right] + \mathbb{E} \left(\sum_{k=1}^n \sum_{j \neq k}^n [W_k^2 - \mathbb{E}(W_k^2)] [W_j^2 - \mathbb{E}(W_j^2)] \right) \end{aligned}$$

Claim: $\mathbb{E} \left(\sum_{k=1}^n \sum_{j \neq k}^n [W_k^2 - \mathbb{E}(W_k^2)] [W_j^2 - \mathbb{E}(W_j^2)] \right) = 0$

Since for all $j \neq k$, W_k and W_j are independently determined random variables, it must also be the case that W_k^2 and W_j^2 are independently determined as well, in which case $\mathbb{E}(W_k^2 W_j^2) = \mathbb{E}(W_k^2) \mathbb{E}(W_j^2)$, therefore

$$\begin{aligned} \mathbb{E}([W_k^2 - \mathbb{E}(W_k^2)] [W_j^2 - \mathbb{E}(W_j^2)]) &= \mathbb{E}(W_k^2 W_j^2 - W_k^2 \mathbb{E}(W_j^2) - W_j^2 \mathbb{E}(W_k^2) + \mathbb{E}(W_k^2) \mathbb{E}(W_j^2)) \\ &= \mathbb{E}(W_k^2 W_j^2) - 2\mathbb{E}(W_j^2) \mathbb{E}(W_k^2) + \mathbb{E}(W_k^2) \mathbb{E}(W_j^2) \\ &= \mathbb{E}(W_j^2) \mathbb{E}(W_k^2) - \mathbb{E}(W_j^2) \mathbb{E}(W_k^2) \\ &= 0 \end{aligned}$$

We would also then get

$$\begin{aligned} \mathbb{E} \left(\sum_{k=1}^n \sum_{j \neq k}^n [W_k^2 - \mathbb{E}(W_k^2)] [W_j^2 - \mathbb{E}(W_j^2)] \right) &= \sum_{k=1}^n \sum_{j \neq k}^n \mathbb{E}([W_k^2 - \mathbb{E}(W_k^2)] [W_j^2 - \mathbb{E}(W_j^2)]) \\ &= \sum_{k=1}^n \sum_{j \neq k}^n 0 \end{aligned}$$

Then

$$\begin{aligned} \mathbb{E} \left[\left(\left[\sum_{k=1}^n W_k^2 \right] - t \right)^2 \right] &= \mathbb{E} \left[\sum_{k=1}^n (W_k^2 - \mathbb{E}(W_k^2))^2 \right] \\ &= \sum_{k=1}^n \mathbb{E}[(W_k^2 - \mathbb{E}(W_k^2))^2] \\ &= \sum_{k=1}^n (\mathbb{E}[W_k^4] - \mathbb{E}(W_k^2)^2) \\ &= \sum_{k=1}^n (3\Delta t_k^2 - \Delta t_k^2) \\ &= 2 \sum_{k=1}^n (\Delta t_k)^2 \end{aligned}$$

Let $Y^{(n)}(t, \omega) := \sum_{k=1}^n W_k^2(\omega)$. Then this result implies that

$$\text{Var} \left(Y^{(n)}(t, \cdot) \right) = 2 \sum_{k=1}^n (\Delta t_k)^2 \approx O(\Delta t_k)$$

And

$$\lim_{\Delta t_k \rightarrow 0} \text{Var} \left(Y^{(n)}(t, \cdot) \right) = 0$$

2.2 Want to show that $\langle B, B \rangle_t^{(2)}(\omega) = t$, a.s.

Let $Y^{(n)}(t, \omega) := \sum_{k=1}^n W_k^2(\omega)$, taking expectations on both sides,

$$\mathbb{E} \left(Y^{(n)}(t, \cdot) \right) = \sum_{k=1}^n \mathbb{E}(W_k) = t$$

And from above result, we have

$$\lim_{\Delta t_k \rightarrow 0} \text{Var} \left(Y^{(n)}(t, \cdot) \right) = 0$$

Therefore as the mesh of the partition approaches 0, i.e. as $\max_k \Delta t_k \rightarrow 0$, we see that $Y(t, \omega)$ converges in distribution to a deterministic variable with value t . Therefore,

$$\langle B, B \rangle_t^{(2)}(\omega) = \lim_{\Delta t_k \rightarrow 0} Y^{(n)}(t, \omega) = t, \text{ almost surely}$$

2.3 Part (b)

All continuous finite variation processes have zero quadratic variation.

If the quadratic variation of a continuous process is finite, then the total variation is not finite, hence infinite.

B_t is continuous, and has a finite quadratic variation of t .

Illustrative demonstration

$$\langle B, B \rangle_t(\omega) = \lim_{\Delta t_k \rightarrow 0} \sum_{t_k \leq t} |W_k|.$$

$$\begin{aligned} \mathbb{E}(|W_k|) &= \int_{-\infty}^{\infty} \frac{|x|}{\sqrt{2\pi\Delta t_k}} \exp\left(-\frac{x^2}{2t}\right) dx \\ &= \sqrt{\frac{2\Delta t_k}{\pi}} \end{aligned}$$

$$\text{Var}(|W_k|) = \Delta t_k$$

Let $\Delta t_k = \frac{t}{n}$ for some $n \in \mathbb{N}$. As $\Delta t_k \rightarrow 0$, we have $n \rightarrow \infty$, and

$$\begin{aligned} \lim_{\Delta t_k \rightarrow 0} \sum_{t_k \leq t} \mathbb{E}|W_k| &= \lim_{n \rightarrow \infty} n \cdot \mathbb{E}(|W_k|) \\ &= \lim_{n \rightarrow \infty} \sqrt{\frac{2}{\pi}} \sqrt{tn} \\ &= \infty \end{aligned}$$

$$\lim_{\Delta t_k \rightarrow 0} \text{Var} \left(\sum_{t_k \leq t} |W_k| \right) = t$$

We might (loosely) say that $\langle B, B \rangle_t(\omega)$ is a normally distributed (by CLT) stochastic variable with a very very large (infinite) expected value and variance that is very very small relative to the expected value (finite variance). The probability of $\langle B, B \rangle_t(\omega)$ taking on a small value (finite value) is vanishingly small.