

(6)

It follows that

$$I(t_1) \sim N\left(0, \int_0^{t_1} \Delta^2(s) ds\right) \text{ and}$$

$$I(t_2) - I(t_1) \sim N\left(0, \int_{t_1}^{t_2} \Delta^2(s) ds\right)$$

and $I(t_1)$ and $I(t_2) - I(t_1)$ are independent.

$$m(t) = \mathbb{E}[I(t)] = 0.$$

$$\begin{aligned} \text{and } c(t_1, t_2) &= \mathbb{E}[I(t_1)I(t_2)] \\ &= \mathbb{E}[I(t_1)(I(t_2) - I(t_1)) + I^2(t_1)] \\ &= \mathbb{E}[I(t_1)(I(t_2) - I(t_1))] + \mathbb{E}[I^2(t_1)] \\ &= \mathbb{E}[I(t_1)] \mathbb{E}[(I(t_2) - I(t_1))] + \int_0^{t_1} \Delta^2(s) ds. \\ &= \int_0^{t_1} \Delta^2(s) ds. \end{aligned}$$

$$\text{For general case } c(s, t) = \int_0^{s \wedge t} \Delta^2(u) du.$$

Brownian Bridge:-

Defn:- Let $W(t)$ be a Brownian motion. Fix $T > 0$, we define the Brownian bridge from 0 to 0 on $[0, T]$ to be the process

$$X(t) = W(t) - \frac{t}{T} W(T), \quad 0 \leq t \leq T.$$

— Note that $\frac{t}{T} W(T)$ as a function of t is the line from $(0, 0)$ to $(T, W(T))$

$$- X(0) = X(T) = 0$$

(7)

- $X(t)$ is not adapted to the filtration $\mathcal{F}(t)$ generated by the Brownian motion $W(t)$.

For $0 < t_1 < t_2 < \dots < t_n < T$, the random variables

$$X(t_1) = W(t_1) - \frac{t_1}{T} W(T), \quad \dots \quad X(t_n) = W(t_n) - \frac{t_n}{T} W(T).$$

are jointly normal because $W(t_1), \dots, W(t_n), W(T)$ are jointly normal. Hence the Brownian Bridge from 0 to 0 is a Gaussian process.

Its mean function is

$$m(t) = \mathbb{E}[X(t)] = \mathbb{E}[W(t) - \frac{t}{T} W(T)] = 0$$

For $s, t \in (0, T)$ the covariance function is

$$\begin{aligned} C(s, t) &= \mathbb{E}[(W(s) - \frac{s}{T} W(T))(W(t) - \frac{t}{T} W(T))] \\ &= \mathbb{E}[W(s)W(t)] - \frac{t}{T} \mathbb{E}[W(s)W(T)] - \frac{s}{T} \mathbb{E}[W(t)W(T)] \\ &\quad + \frac{st}{T^2} \mathbb{E}[W^2(T)] \\ &= s\wedge t - \frac{ts}{T} - \frac{ts}{T} + \frac{st}{T^2} \cdot T \\ &= s\wedge t - \frac{st}{T}. \end{aligned}$$

Definition:- Let $W(t)$ be a Brownian motion. Fix $T > 0$, $a \in \mathbb{R}$ and $b \in \mathbb{R}$. We define the Brownian bridge from a to b on $[0, T]$ to be the process

$$X^{a \rightarrow b} = a + \frac{(b-a)t}{T} + X(t), \quad 0 \leq t \leq T,$$

where $x(t) = x^{0 \rightarrow 0}$ is the Brownian bridge from 0 to 0. (8)

$$X^{a \rightarrow b}(0) = a \text{ and } X^{a \rightarrow b}(T) = b.$$

Adding a non-random function to a Gaussian process gives us another Gaussian process. The mean function is

$$m^{a \rightarrow b}(t) = \mathbb{E}[X^{a \rightarrow b}(t)] = a + \frac{(b-a)}{T}t$$

covariance function is

$$C^{a \rightarrow b}(s, t) = \mathbb{E}[(X^{a \rightarrow b}(s) - m^{a \rightarrow b}(s))(X^{a \rightarrow b}(t) - m^{a \rightarrow b}(t))]$$

$$= \mathbb{E}[X(s)X(t)]$$

$$= sT - \frac{st}{T}$$

Brownian Bridge as a scaled stochastic Integral:-

We cannot write the Brownian bridge as a stochastic integral of a deterministic integrand because the variance of the Brownian Bridge,

$$\mathbb{E}[X^2(t)] = C(t, t) = t - \frac{t^2}{T} = \frac{(T-t)t}{T}$$

increases for $0 \leq t \leq T/2$ and decreases for $T/2 \leq t \leq T$.

The variance of $I(t) = \int_0^t \Delta(s) ds$ is $\int_0^t \Delta^2(s) ds$ which is non-decreasing in t .

However, we can obtain a process with the same distribution as the Brownian bridge from 0 to 0 as a scaled integral. In particular, consider (9)

$$Y(t) = (T-t) \int_0^t \frac{1}{T-u} dW(u), \quad 0 \leq t \leq T$$

The integral $I(t) = \int_0^t \frac{1}{T-u} dW(u)$ is a Gaussian process for $t \in [0, T]$.

For $0 < t_1 < t_2 < \dots < t_n < T$, the random variables

$$Y(t_1) = (T-t_1)I(t_1), \quad Y(t_2) = (T-t_2)I(t_2), \quad \dots \quad Y(t_n) = (T-t_n)I(t_n)$$

are jointly normal because $I(t_1), \dots, I(t_n)$ are jointly normal. In particular $Y(t)$ is a Gaussian process.

The mean and covariance function of I are $m^I(t) = 0$.

$$C^I(s, t) = \int_0^{s \wedge t} \frac{1}{(T-u)^2} du = \frac{1}{T-(s \wedge t)} - \frac{1}{T} \quad \forall s, t \in [0, T].$$

This means that the mean function for Y is $m^Y(t) = 0$.

To compute the covariance function for Y , we assume for the moment that $0 \leq s \leq t \leq T$. so that

$$C^I(s, t) = \frac{1}{T-s} - \frac{1}{T} = \frac{s}{T(T-s)}.$$

$$\text{Then } C^Y(s, t) = \mathbb{E}[(T-s)(T-t)I(s)I(t)]$$

$$= (T-s)(T-t) \frac{s}{T(T-s)} = \frac{(T-t)s}{T} = s - \frac{st}{T}.$$

In general

$$C^Y(s, t) = s \wedge t - \frac{st}{T} \quad \text{for } s, t \in [0, T]$$

This is the same covariance formula we obtained for the Brownian bridge. Because the mean and covariance function for a Gaussian process completely determine the distribution of the process. We conclude that the process Y has the same distribution as Brownian bridge from 0 to 0 on $[0, T]$.

We now consider the variance

$$\mathbb{E}[Y^2(t)] = C^Y(t, t) = \frac{t(T-t)}{T}$$

Note that as $t \uparrow T$, this variance converges to 0. In other words, as $t \uparrow T$, the random process $Y(t)$, which has mean zero, has a variance that converges to zero. This observation suggests that it makes sense to define $Y(T) = 0$. If we do that, then $Y(t)$ is continuous at $t = T$. We summarize this discussion with the following theorem.

Theorem:- Define the process

$$Y(t) = \begin{cases} (T-t) \int_0^t \frac{1}{T-u} dW(u) & \text{for } 0 \leq t < T \\ 0 & \text{for } t = T. \end{cases}$$

Then $Y(t)$ is a continuous Gaussian process on $[0, T]$ and has mean and covariance functions

$$m^Y(t) = 0, \quad t \in [0, T].$$

$$C^Y(s, t) = st - \frac{st}{T} \text{ for all } s, t \in [0, T].$$

In particular, the process $Y(t)$ has the same distribution as the Brownian bridge from 0 to 0 on $[0, T]$.

Note that $Y(t)$ is adapted to the filtration generated by the Brownian motion $W(t)$

$$\begin{aligned} dY(t) &= \int_0^t \frac{1}{T-u} dW(u) \cdot d(T-t) + (T-t) \cdot d \int_0^t \frac{1}{T-u} dW(u) \\ &= - \int_0^t \frac{1}{T-u} dW(u) \cdot dt + (T-t) \cdot \frac{1}{(T-t)} dW(t) \\ &= - \frac{Y(t)}{(T-t)} dt + dW(t) \end{aligned}$$

Multidimensional Distribution of the Brownian Bridge:-

We fix $a \in \mathbb{R}$ and $b \in \mathbb{R}$ and let $X^{a \rightarrow b}(t)$ denote the Brownian bridge from a to b on $[0, T]$. We also fix $0 = t_0 < t_1 < \dots < t_n < T$. We compute the joint density of $X^{a \rightarrow b}(t_1), \dots, X^{a \rightarrow b}(t_n)$.