

Brownian Motion

An Undergraduate Introduction to Financial Mathematics

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We have already seen that the limiting behavior of a **discrete random walk** yields a derivation of the **normal probability density function**.

Today we explore some further properties of the discrete random walk and introduce the concept of **stochastic processes**.

Assumptions:

- Current value of security is $S(0)$.
- At each “tick” of a clock S may change by ± 1 .
- $P(S(n+1) = S(n) + 1) = 1/2$ and
 $P(S(n+1) = S(n) - 1) = 1/2$.

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If $X_i = \begin{cases} +1 & \text{with probability } 1/2, \\ -1 & \text{with probability } 1/2 \end{cases}$ then

$$S(N) = S(0) + X_1 + X_2 + \cdots + X_N$$

Further Assumptions

- X_i and X_j are independent when $i \neq j$.
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Then

$$S(n) = S(0) + k - (n - k) = S(0) + 2k - n$$

and

$$P(S(n) = S(0) + 2k - n) = \binom{n}{k} \left(\frac{1}{2}\right)^n.$$

Spatial Homogeneity

Define $T(i) = S(i) - S(0)$ for $i = 0, 1, \dots, n$ then

- $T(0) = 0$,
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Question: what states can be visited in n steps?

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Lemma

For the random walk $S(i)$ with initial state $S(0) = 0$,

- 1 $P(S(n) = m) = 0$ if $|m| > n$,
- 2 $P(S(n) = m) = 0$ if $n + m$ is odd,
- 3 $P(S(n) = m) = \binom{n}{(n+m)/2} \left(\frac{1}{2}\right)^n$, otherwise.

Theorem

For the random walk $S(i)$ with initial state $S(0) = 0$,

$$E[S(n)] = 0 \quad \text{and} \quad \text{Var}(S(n)) = n.$$

Mean and Variance of Random Walk (2 of 2)

Proof.

$$\begin{aligned} E[S(n)] &= E[S(0)] + E[X_1] + E[X_2] + \cdots + E[X_n] \\ &= 0 \end{aligned}$$

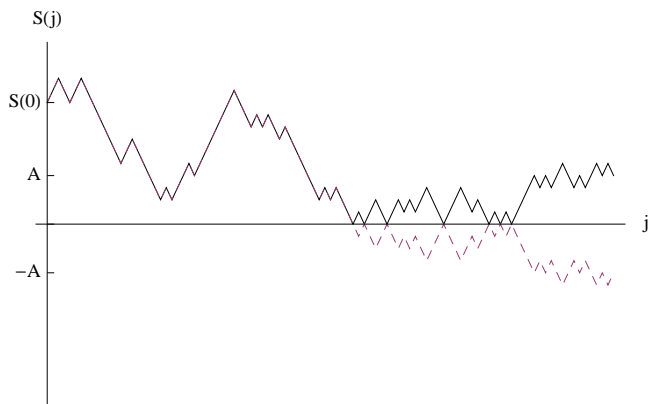
since $E[X_i] = 0$ for $i = 1, 2, \dots, n$. If X_i and X_j are independent when $i \neq j$ we have

$$\text{Var}(S(n)) = \text{Var}(S(0)) + \sum_{i=1}^n \text{Var}(X_i) = n.$$



Reflections of Random Walks (1 of 2)

Consider a random walk for which $S(k) = 0$ for some k .



Reflections of Random Walks (2 of 2)

If $S(k) = 0$ then define another random walk $\hat{S}(j)$ by

$$\hat{S}(j) = \begin{cases} S(j) & \text{for } j = 0, 1, \dots, k \\ -S(j) & \text{for } j = k + 1, k + 2, \dots, n. \end{cases}$$

Reflections of Random Walks (2 of 2)

If $S(k) = 0$ then define another random walk $\hat{S}(j)$ by

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Since UP/DOWN steps occur with equal probability,

$$P(S(n) = A) = P(\hat{S}(n) = -A).$$

Random walks have no “memory” of how they arrive at a particular state. Only the current state influences the next state.

$$P(S(n) = A) = P(\hat{S}(n) = -A)$$

$$\begin{aligned}P(S(k) = 0)P(T(n-k) = A) &= P(\hat{S}(k) = 0)P(\hat{T}(n-k) = -A) \\ &= P(S(k) = 0)P(\hat{T}(n-k) = -A)\end{aligned}$$

$$P(T(n-k) = A) = P(\hat{T}(n-k) = -A)$$

Theorem

If $\{S(j)\}_{j=0}^n$ is an unbiased random walk with initial state $S(0) = i$ and if $|A - i| \leq n$ and $|A + i| \leq n$ then

$$P(S(n) = A | S(0) = i) = P(S(n) = -A | S(0) = i).$$

Theorem

If $\{S(j)\}_{j=0}^n$ is an unbiased random walk with initial state $S(0) = i$ and if $|A - i| \leq n$ and $|A + i| \leq n$ then

$$P(S(n) = A | S(0) = i) = P(S(n) = -A | S(0) = i).$$

These probabilities are 0 if $n + A - i$ is odd (and consequently $n - A - i$ is odd).

Absorbing Boundary Conditions

Remark: so far we have considered only random walks which were free to wander unrestricted.

What if there is a state A such that if $S(k) = A$ then $S(n) = A$ for all $n \geq k$? Such a state is called an **absorbing boundary condition**.

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Example

A gambler going broke and unable to borrow money has encountered an absorbing boundary condition.

Suppose random walk $S(i)$ has an absorbing boundary condition at 0. If $0 < S(0) < A$,

- 1 what is the probability that the state of the random walk crosses the threshold value of A before it hits the boundary at 0?

Suppose random walk $S(i)$ has an absorbing boundary condition at 0. If $0 < S(0) < A$,

- 1 what is the probability that the state of the random walk crosses the threshold value of A before it hits the boundary at 0?
- 2 what is the expected value of the number of steps which will elapse before the state of the random variable first crosses the A threshold?

Answer to First Question (1 of 2)

Define $S_{\min}(n) = \min\{S(k) : 0 \leq k \leq n\}$ which can be thought of as the smallest value the random walk takes on.

The probability the state of the random walk crosses the threshold value of A before it hits the boundary at 0 is then

$$P(S(n) = A \wedge S_{\min}(n) > 0 \mid S(0) = i).$$

Answer to First Question (2 of 2)

Lemma

Suppose a random walk $S(k) = S(0) + \sum_{i=1}^k X_i$ in which the X_i for $i = 1, 2, \dots$ are independent, identically distributed random variables taking on the values ± 1 , each with probability $p = 1/2$. Suppose further that the boundary at 0 is absorbing, then if $A, i > 0$,

$$\begin{aligned} f_{A,i}(n) &= P(S(n) = A \wedge S_{\min}(n) > 0 \mid S(0) = i) \\ &= \left[\binom{n}{(n+A-i)/2} - \binom{n}{(n-A-i)/2} \right] \left(\frac{1}{2}\right)^n, \end{aligned}$$

provided $|A - i| \leq n$, $|A + i| \leq n$, and $n + A - i$ is even.

Consider a random walk with no boundary, that is, the random variable $S(n)$ has an initial state of $S(0) = i > 0$ and $S(k)$ is allowed to wander into negative territory (and back) arbitrarily. In this situation

$$\begin{aligned} & P(S(n) = A \mid S(0) = i) \\ &= P(S(n) = A \wedge S_{\min}(n) > 0 \mid S(0) = i) \\ &\quad + P(S(n) = A \wedge S_{\min}(n) \leq 0 \mid S(0) = i) \end{aligned}$$

by the Addition Rule.

Proof (2 of 3)

Now consider the probability on the left-hand side of the equation.

$$P(S(n) = A | S(0) = i)$$

It possesses no boundary condition and by the spatial homogeneity of the random walk

$$P(S(n) = A | S(0) = i) = P(T(n) = A - i)$$

where $\{T(j)\}_{j=0}^n$ is an unbiased random walk with initial state $T(0) = 0$. Hence $P(T(n) = A - i) = 0$ unless $n + A - i$ is even and $|A - i| \leq n$, in which case

$$P(S(n) = A | S(0) = i) = \binom{n}{(n + A - i)/2} \left(\frac{1}{2}\right)^n.$$

On the other hand if the random walk starts at a positive state i and finishes at $-A < 0$ then it is certain that $S_{\min}(n) \leq 0$.

Consequently

$$\begin{aligned} P(S(n) = A \wedge S_{\min}(n) \leq 0 \mid S(0) = i) &= P(S(n) = -A \mid S(0) = i) \\ &= \binom{n}{(n-A-i)/2} \left(\frac{1}{2}\right)^n \end{aligned}$$

provided $|A + i| \leq n$ and $n - A - i$ is even. Finally

$$\begin{aligned} P(S(n) = A \wedge S_{\min}(n) > 0 \mid S(0) = i) \\ = \binom{n}{(n+A-i)/2} \left(\frac{1}{2}\right)^n - \binom{n}{(n-A-i)/2} \left(\frac{1}{2}\right)^n. \end{aligned}$$

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$$\begin{aligned}f_{16,10}(50) &= P(S(50) = 16 \wedge m_{50} > 0 \mid S(0) = 10) \\&= \left[\binom{50}{28} - \binom{50}{12} \right] 2^{-50} \\&\approx 0.0787178\end{aligned}$$

Stopping Times

Define $\Omega_A = \min\{n \mid S(n) = A\}$ which is the first time that the random walk $S(n) = A$. This is called the **stopping time**.

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Suppose $A = 0$, then $\Omega_0 = n$ if and only if $S(0) = i > 0$, $S(n-1) = 1$, $m_{n-1} > 0$ and $X_n = -1$.

$$\begin{aligned} P(\Omega_0 = n \mid S(0) = i) &= P(X_n = -1 \wedge S(n-1) = 1 \wedge m_{n-1} > 0 \mid S(0) = i) \\ &= \frac{1}{2} P(S(n-1) = 1 \wedge m_{n-1} > 0 \mid S(0) = i) \\ &= \frac{1}{2} f_{1,i}(n-1). \end{aligned}$$

Thus by spatial homogeneity

$$P(\Omega_A = n \mid S(0) = i) = \frac{1}{2} f_{1,(i-A)}(n-1)$$

We can analyze the stopping time by think of the random walk as having two boundaries, one at 0 and another at A .

$p_{i \rightarrow A}$: any random walk $\{S(j)\}$ in the discrete interval $[0, A]$ starting at $i > 0$, terminating at A , and which avoids 0.

$P_{p_{i \rightarrow A}}$: the probability that the random walk starting at $S(0) = i$ follows $p_{i \rightarrow A}$.

$\mathcal{P}_A(i)$: the probability that a random walk which starts at $S(0) = i$ will achieve state $S = A$ while avoiding the state $S = 0$.

Determination of $\mathcal{P}_A(i)$

$$\begin{aligned}\mathcal{P}_A(i) &= \sum_{p_{i \rightarrow A}} P_{p_{i \rightarrow A}} \\ &= P(S(1) = i - 1 \mid S(0) = i) \mathcal{P}_A(i - 1) \\ &\quad + P(S(1) = i + 1 \mid S(0) = i) \mathcal{P}_A(i + 1) \\ &= \frac{1}{2} \mathcal{P}_A(i - 1) + \frac{1}{2} \mathcal{P}_A(i + 1)\end{aligned}$$

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This implies

$$\mathcal{P}_A(i - 1) - 2\mathcal{P}_A(i) + \mathcal{P}_A(i + 1) = 0.$$

Theorem

Suppose $S(k) = S(0) + \sum_{i=1}^k X_i$ where the X_i for $i = 1, 2, \dots$ are independent, identically distributed random variables taking on the values ± 1 , each with probability $p = 1/2$. Suppose further that the boundaries at 0 and A are absorbing, then if $0 \leq S(0) = i \leq A$

- 1 the probability that the random walk achieves state A without achieving state 0 is $\mathcal{P}_A(i) = i/A$,
- 2 the probability that the random walk achieves state 0 without achieving state A is $\mathcal{P}_0(i) = 1 - i/A$.

Suppose $\mathcal{P}_A(i) = \alpha + \beta i$ where α and β are constants.
Substituting into the difference equation yields

$$\alpha + \beta(i - 1) - 2(\alpha + \beta i) + \alpha + \beta(i + 1) = 0$$

so $\mathcal{P}_A(i)$ solves the difference equation.

Since $\mathcal{P}_A(0) = 0$, then $\alpha = 0$.

Since $\mathbf{P}_A(A) = 1$, then $\beta = 1/A$.

Consequently $\mathcal{P}_A(i) = i/A$.

Simpler Question

Question: what is the expected exit time through either boundary $A > 0$ or 0 ?

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We make the following definitions:

- B : the set of boundary points, $B = \{0, A\}$.
- $\omega_{p_{i \rightarrow B}}$: the exit time of the random walk which starts at $S(0) = i$, where $0 \leq i \leq A$ and which follows path $p_{i \rightarrow B}$.
- $\Omega_B(i)$: the expected value of the exit time for a random walk which starts at $S(0) = i$, where $0 \leq i \leq A$.

$$\begin{aligned}\Omega_B(i) &= \sum_{\rho_{i \rightarrow B}} P_{\rho_{i \rightarrow B}} \omega_{\rho_{i \rightarrow B}} \\ &= \frac{1}{2} (1 + \Omega_B(i - 1)) + \frac{1}{2} (1 + \Omega_B(i + 1))\end{aligned}$$

Since the path from $i \rightarrow B$ can be decomposed into paths from $(i - 1) \rightarrow B$ and $(i + 1) \rightarrow B$ with the addition of a single step, the expected value of the exit time of a random walk starting at i is one more than the expected value of a random walk starting at $i \pm 1$.

$$\Omega_B(i-1) - 2\Omega_B(i) + \Omega_B(i+1) = -2$$

for $i = 1, 2, \dots, A-1$, while $\Omega_B(0) = 0 = \Omega_B(A)$.

System of Equations

$$\Omega_B(i-1) - 2\Omega_B(i) + \Omega_B(i+1) = -2$$

for $i = 1, 2, \dots, A-1$, while $\Omega_B(0) = 0 = \Omega_B(A)$.

Try a solution of the form $\Omega_B(i) = ai^2 + bi + c$ and determine the coefficients a , b , and c .

Theorem

Suppose $S(k) = S(0) + \sum_{i=1}^k X_i$ where the X_i for $i = 1, 2, \dots$ are independent, identically distributed random variables taking on the values ± 1 , each with probability $p = 1/2$. Suppose further that the boundaries at 0 and A are absorbing, then if $0 \leq S(0) = i \leq A$ the random walk intersects the boundary ($S = 0$ or $S = A$) after a mean number of steps given by the formula

$$\Omega_B(i) = i(A - i).$$

Example

Suppose an unbiased random walk takes place on the discrete interval $\{0, 1, 2, \dots, 10\}$ for which the boundaries at 0 and 10 are absorbing. As a function of the initial condition i , find the expected value of the exit time.

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i	0	1	2	3	4	5	6	7	8	9	10
$\Omega_B(i)$	0	9	16	21	24	25	24	21	16	9	0

Main Question: Conditional Exit Time

Remark: now we are in a position to answer the original question of the determining the expected value of the exit time for a random walk which exits through state A while avoiding the absorbing boundary at 0 .

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$$\Omega_A(i) = \frac{\sum_{p_{i \rightarrow A}} P_{p_{i \rightarrow A}} \omega_{p_{i \rightarrow A}}}{\sum_{p_{i \rightarrow A}} P_{p_{i \rightarrow A}}} = \frac{\sum_{p_{i \rightarrow A}} P_{p_{i \rightarrow A}} \omega_{p_{i \rightarrow A}}}{\mathcal{P}_A(i)}$$

Decomposing the Walk (1 of 2)

$$\begin{aligned}\Omega_A(i) &= 1 + \frac{\frac{1}{2}\Omega_A(i-1)\mathcal{P}_A(i-1) + \frac{1}{2}\Omega_A(i+1)\mathcal{P}_A(i+1)}{\mathcal{P}_A(i)} \\ &= \mathcal{P}_A(i) + \frac{1}{2}\Omega_A(i-1)\mathcal{P}_A(i-1) + \frac{1}{2}\Omega_A(i+1)\mathcal{P}_A(i+1)\end{aligned}$$

$$\Omega_A(i)\frac{i}{A} = \frac{i}{A} + \frac{i-1}{2A}\Omega_A(i-1) + \frac{i+1}{2A}\Omega_A(i+1)$$

$$2i\Omega_A(i) = 2i + (i-1)\Omega_A(i-1) + (i+1)\Omega_A(i+1)$$

Decomposing the Walk (2 of 2)

The last equation is equivalent to

$$(i - 1)\Omega_A(i - 1) - 2i\Omega_A(i) + (i + 1)\Omega_A(i + 1) = -2i.$$

Decomposing the Walk (2 of 2)

The last equation is equivalent to

$$(i - 1)\Omega_A(i - 1) - 2i\Omega_A(i) + (i + 1)\Omega_A(i + 1) = -2i.$$

Assuming $\Omega_A(i) = ai^2 + bi + c$, determine the coefficients a , b , and c .

Theorem

Suppose $S(k) = S(0) + \sum_{i=1}^k X_i$ where the X_i for $i = 1, 2, \dots$ are independent, identically distributed random variables taking on the values ± 1 , each with probability $p = 1/2$. Suppose further that the boundary at 0 is absorbing. The random walk that avoids state 0 will stop the first time that $S(n) = A$. The expected value of the stopping time is

$$\Omega_A(i) = \frac{1}{3} (A^2 - i^2), \quad \text{for } i = 1, 2, \dots, A.$$

Remark: If the random walk starts in state 0, since this state is absorbing the expected value of the exit time is infinity.

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i	1	2	3	4	5	6	7	8	9	10
$\Omega_{10}(i)$	33	32	$\frac{91}{3}$	28	25	$\frac{64}{3}$	17	12	$\frac{19}{3}$	0

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Assumptions:

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- Size of a step is $\sqrt{t/n}$.

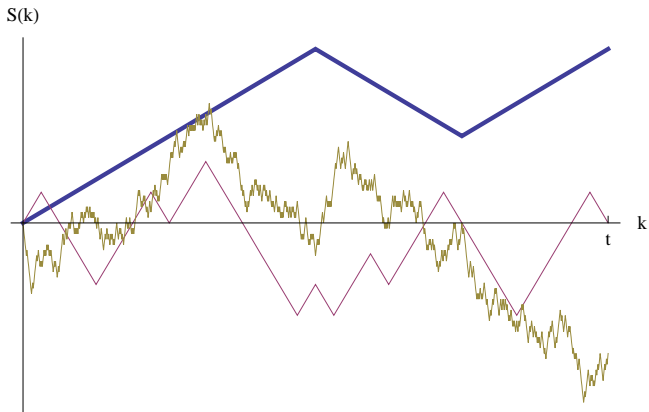
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Find $E[S(t)]$ and $\text{Var}(S(t))$.

Illustration



Brownian Motion/Wiener Process

The continuous limit of this random walk is denoted $W(t)$ and is called a **Wiener process**.

Brownian Motion/Wiener Process

The continuous limit of this random walk is denoted $W(t)$ and is called a **Wiener process**.

- 1 $W(t)$ is a continuous function of t ,
- 2 $W(0) = 0$ with probability one,
- 3 Spatial homogeneity: if $W_0(t)$ represents a Wiener process for which the initial state is 0 and if $W_x(t)$ represents a Wiener process for which the initial state is x , then $W_x(t) = x + W_0(t)$.
- 4 Markov property: for $0 < s < t$ the conditional distribution of $W(t)$ depends on the value of $W(s) + W(t - s)$.
- 5 For each t , $W(t)$ is normally distributed with mean zero and variance t ,
- 6 The changes in W in non-overlapping intervals of t are independent random variables with means of zero and variances equal to the lengths of the time intervals.

More Properties

Suppose $0 \leq t_1 < t_2$ and define $\Delta W_{[t_1, t_2]} = W(t_2) - W(t_1)$.

$$\begin{aligned}\text{Var}(\Delta W_{[t_1, t_2]}) &= \text{E}[(W(t_2) - W(t_1))^2] - \text{E}[W(t_2) - W(t_1)]^2 \\ &= \text{E}[(W(t_2))^2] + \text{E}[(W(t_1))^2] - 2\text{E}[W(t_1)W(t_2)] \\ &= t_2 + t_1 - 2\text{E}[W(t_1)(W(t_2) - W(t_1) + W(t_1))] \\ &= t_2 + t_1 - 2\text{E}[W(t_1)(W(t_2) - W(t_1))] \\ &\quad - 2\text{E}[(W(t_1))^2] \\ &= t_2 + t_1 - 2t_1 \\ &= t_2 - t_1.\end{aligned}$$

We have seen that for $0 \leq t_1 < t_2$,

$$\text{Var}(\Delta W) = \text{E}[(\Delta W)^2] = \Delta t.$$

This is also true in the limit as Δt becomes small, thus we write

$$(dW(t))^2 = dt.$$

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Theorem

The derivative dW/dt does not exist for any t .

Recall the limit definition of the derivative from calculus,

$$\frac{df}{dt} = \lim_{h \rightarrow 0} \frac{f(s+h) - f(s)}{h}.$$

Suppose $f(t)$ is a Wiener process $W(t)$. Since

$$\mathbb{E} \left[(W(s+h) - W(s))^2 \right] = \mathbb{E} \left[|W(s+h) - W(s)|^2 \right] = h$$

then on average $|W(s+h) - W(s)| \approx \sqrt{h}$, and therefore

$$\lim_{h \rightarrow 0} \frac{W(s+h) - W(s)}{h} \text{ does not exist.}$$

Integral of a Wiener Process

The **stochastic integral** of $f(x)$ on the interval $[0, t]$ is defined to be

$$\begin{aligned} Z(t) - Z(0) &= \int_0^t f(\tau) dW(\tau) \\ &= \lim_{n \rightarrow \infty} \sum_{k=1}^n f(t_{k-1}) (W(t_k) - W(t_{k-1})) \end{aligned}$$

where $t_k = kt/n$.

Note: The function f is evaluated at the left-hand endpoint of each subinterval.

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where $t_k = kt/n$.

Note: The function f is evaluated at the left-hand endpoint of each subinterval.

The stochastic integral is equivalent to its **differential form**

$$dZ = f(t) dW(t)$$

ODE: Exponential Growth

If $P(0) = P_0$ and the rate of change of P is proportional to P , then

$$\frac{dP}{dt} = \mu P,$$

and $P(t) = P_0 e^{\mu t}$.

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If we let $Z = \ln P$ then the ODE becomes

$$dZ = \mu dt.$$

Stochastic Differential Equation (SDE)

Perturb dZ by adding a Wiener process with mean zero and standard deviation $\sigma\sqrt{dt}$.

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This is a **generalized Wiener process**. The constant μ is called the **drift** and the constant σ is called the **volatility**. The solution to the SDE is

$$Z(t) = Z(0) + \mu t + \int_0^t \sigma dW(\tau).$$

Expectation and Variance

$$\begin{aligned} E[Z(t) - Z(0)] &= \mu t \\ \text{Var}(Z(t) - Z(0)) &= \sigma^2 t \end{aligned}$$

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In terms of numerical approximation,

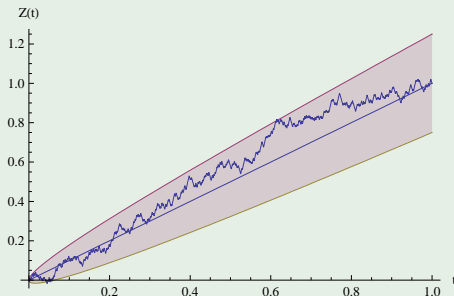
$$\int_0^t dW(\tau) \approx \sum_{j=1}^n X_j$$

where X_j is a normal random variable with mean 0 and variance t/n .

Example

Example

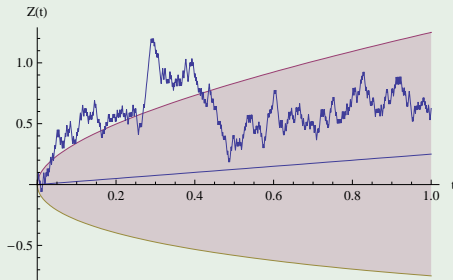
Suppose the drift parameter is $\mu = 1$ and the volatility is $\sigma = 1/4$, then the expected value of the Wiener process is t and the standard deviation is $\sqrt{t}/4$.



Example

Example

Suppose the drift parameter is $\mu = 1/4$ and the volatility is $\sigma = 1$, then the expected value of the Wiener process is $t/4$ and the standard deviation is \sqrt{t} .



Simple Generalization

If the drift and volatility are functions of t then

$$dZ = \mu(t) dt + \sigma(t) dW(t).$$

and

$$Z(t) = Z(0) + \int_0^t \mu(\tau) d\tau + \int_0^t \sigma(\tau) dW(\tau).$$

A stochastic process of the form

$$dS = a(S, t) dt + b(S, t) dW(t)$$

is called an **Itô process**.

We will shortly be called upon to develop new stochastic processes which are functions of S . Suppose $Z = \ln S$, then $dZ = dS/S$ (by the chain rule), but are the following two stochastic processes equivalent?

$$dS = \mu S dt + \sigma S dW(t)$$

$$dZ = \mu dt + \sigma dW(t)$$

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- $\mu S \rightarrow 0$ and $\sigma S \rightarrow 0$ as $S \rightarrow 0^+$.

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- First equation makes a suitable mathematical model for a stock price $S \geq 0$, in second equation Z could go negative.

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- Second equation can be integrated, first cannot.

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- $\mu S \rightarrow 0$ and $\sigma S \rightarrow 0$ as $S \rightarrow 0^+$.
- First equation makes a suitable mathematical model for a stock price $S \geq 0$, in second equation Z could go negative.
- Second equation can be integrated, first cannot.
- The two equations are not equivalent because the chain rule does not apply to functions of stochastic quantities.

Lemma (Itô's Lemma)

Suppose that the random variable X is described by the Itô process

$$dX = a(X, t) dt + b(X, t) dW(t)$$

where $dW(t)$ is a normal random variable. Suppose the random variable $Y = F(X, t)$. Then Y is described by the following Itô process.

$$dY = \left(a(X, t)F_X + F_t + \frac{1}{2}(b(X, t))^2 F_{XX} \right) dt + b(X, t)F_X dW(t)$$

Multivariable Form of Taylor's Theorem (1 of 3)

If $f(x)$ is an $(n + 1)$ -times differentiable function on an open interval containing x_0 then the function may be written as

$$f(x) = f(x_0) + f'(x_0)(x - x_0) + \frac{f''(x_0)}{2!}(x - x_0)^2 \quad (1) \\ + \cdots + \frac{f^{(n)}(x_0)}{n!}(x - x_0)^n + \frac{f^{(n+1)}(\theta)}{(n + 1)!}(x - x_0)^{n+1}$$

The last term above is usually called the Taylor remainder formula and is denoted by R_{n+1} . The quantity θ lies between x and x_0 . The other terms form a polynomial in x of degree at most n and can be used as an approximation for $f(x)$ in a neighborhood of x_0 .

Multivariable Form of Taylor's Theorem (2 of 3)

Suppose the function $F(y, z)$ has partial derivatives up to order three on an open disk containing the point with coordinates (y_0, z_0) . Define the function $f(x) = F(y_0 + xh, z_0 + xk)$ where h and k are chosen small enough that $(y_0 + h, z_0 + k)$ lie within the disk surrounding (y_0, z_0) . Since f is a function of a single variable then we can use the single-variable form of Taylor's formula in Eq. (1) with $x_0 = 0$ and $x = 1$ to write

$$f(1) = f(0) + f'(0) + \frac{1}{2}f''(0) + R_3. \quad (2)$$

Using the multivariable chain rule for derivatives we have, upon differentiating $f(x)$ and setting $x = 0$,

$$f'(0) = hF_y(y_0, z_0) + kF_z(y_0, z_0) \quad (3)$$

$$f''(0) = h^2F_{yy}(y_0, z_0) + 2hkF_{yz}(y_0, z_0) + k^2F_{zz}(y_0, z_0). \quad (4)$$

Multivariable Form of Taylor's Theorem (3 of 3)

We have made use of the fact that $F_{yz} = F_{zy}$ for this function under the smoothness assumptions. The remainder term R_3 contains only third order partial derivatives of F evaluated somewhere on the line connecting the points (y_0, z_0) and $(y_0 + h, z_0 + k)$. Thus if we substitute Eqs. (3) and (4) into (2) we obtain

$$\begin{aligned}\Delta F &= f(1) - f(0) && (5) \\ &= F(y_0 + h, z_0 + k) - F(y_0, z_0) \\ &= R_3 + hF_y(y_0, z_0) + kF_z(y_0, z_0) \\ &\quad + \frac{1}{2} \left(h^2 F_{yy}(y_0, z_0) + 2hkF_{yz}(y_0, z_0) + k^2 F_{zz}(y_0, z_0) \right).\end{aligned}$$

This last equation can be used to derive Itô's Lemma.

Let X be a random variable described by an Itô process of the form

$$dX = a(X, t) dt + b(X, t) dW(t) \quad (6)$$

where $dW(t)$ is a normal random variable and a and b are functions of X and t . Let $Y = F(X, t)$ be another random variable defined as a function of X and t . Given the Itô process which describes X we will now determine the Itô process which describes Y .

Using a Taylor series expansion for Y detailed in (5) we find

$$\begin{aligned}\Delta Y &= F_X \Delta X + F_t \Delta t + \frac{1}{2} F_{XX} (\Delta X)^2 + F_{Xt} \Delta X \Delta t \\ &\quad + \frac{1}{2} F_{tt} (\Delta t)^2 + R_3 \\ &= F_X (a \Delta t + b dW(t)) + F_t \Delta t + \frac{1}{2} F_{XX} (a \Delta t + b dW(t))^2 \\ &\quad + F_{Xt} (a \Delta t + b dW(t)) \Delta t + \frac{1}{2} F_{tt} (\Delta t)^2 + R_3.\end{aligned}$$

Upon simplifying, the expression ΔX has been replaced by the discrete version of the Itô process. Thus as Δt becomes small

$$\Delta Y \approx F_X(a dt + b dW(t)) + F_t dt + \frac{1}{2!} F_{XX} b^2 (dW(t))^2.$$

Using the relationship $(dW(t))^2 = dt$

$$\Delta Y \approx F_X(a dt + b dW(t)) + F_t dt + \frac{1}{2!} F_{XX} b^2 dt. \quad (7)$$

Example

If $Z = \ln S$ and

$$dS = \mu S dt + \sigma S dW(t),$$

find the stochastic process followed by Z .

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If $Z = \ln S$ then

$$\begin{aligned} dZ &= \left(\mu S \left[\frac{1}{S} \right] + 0 + \frac{1}{2} \sigma^2 S^2 \left[-\frac{1}{S^2} \right] \right) dt + \sigma S \left(\frac{1}{S} \right) dW(t) \\ &= \left(\mu - \frac{\sigma^2}{2} \right) dt + \sigma dW(t) \end{aligned}$$

Example

If $S = e^Z$ and

$$dZ = \mu dt + \sigma dW(t),$$

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Example

If $S = e^Z$ and

$$dZ = \mu dt + \sigma dW(t),$$

find the stochastic process followed by S .

If $S = e^Z$ then

$$\begin{aligned} dS &= \left(\mu [e^Z] + 0 + \frac{1}{2} \sigma^2 [e^Z] \right) dt + \sigma (e^Z) dW(t) \\ &= \left(\mu + \frac{\sigma^2}{2} \right) S dt + \sigma S dW(t) \end{aligned}$$

Stock Example (1 of 2)

- Suppose we collect stock prices for $n + 1$ days:
 $\{S(0), S(1), \dots, S(n)\}$.

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Stock Example (1 of 2)

- Suppose we collect stock prices for $n + 1$ days: $\{S(0), S(1), \dots, S(n)\}$.
- Under the lognormal assumption $Z(i) = \ln S(i + 1)/S(i)$ is a normal random variable.
- If the mean (drift) and variance (volatility squared) of Z are μ and σ^2 respectively, then

$$dZ = \mu dt + \sigma dW(t).$$

Stock Example (2 of 2)

Hence

$$Z(t) = Z(0) + \mu t + \int_0^t \sigma dW(\tau)$$

and

$$S(t) = S(0)e^{\mu t + \int_0^t \sigma dW(\tau)}.$$

Stock Example (2 of 2)

Hence

$$Z(t) = Z(0) + \mu t + \int_0^t \sigma dW(\tau)$$

and

$$S(t) = S(0)e^{\mu t + \int_0^t \sigma dW(\tau)}.$$

The mean and variance of $S(t)$ are

$$\begin{aligned} E[S(t)] &= S(0)e^{(\mu + \sigma^2/2)t} \\ \text{Var}(S(t)) &= (S(0))^2 e^{(2\mu + \sigma^2)t} (e^{\sigma^2 t} - 1). \end{aligned}$$