Brownian Motion

Emma Zhang

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Erratic movements of particles in fluids, now used to model many random processes

• first observed by Robert Brown when studying pollen in water: random sporadic movements

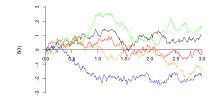
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Erratic movements of particles in fluids, now used to model many random processes

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- $\bullet\,$ mathematically formalized by Norbert Wiener \rightarrow Wiener Process

Applications of Brownian Motion



Time (t)

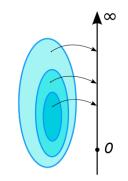
Important in biology(movements of liquids, evolution), chemistry(kinetic theory, stability), physics(heat diffusion, conduction,etc), finance (modeling stock prices), etc

Measure Theory

Definition

Let a measurable space be (X, A, μ)

- X : set
- A: special collection of subsets of X
- μ : a measure, maps the sample space onto [0, ∞], giving it a generalized length/volume



Probability Space

Definition

In probability theory, a probability space is a measure space used to define random processes. It looks like (Ω, A, \mathbb{P}) , and consists of three elements:

() Ω : the **sample space** of all possible outcomes.

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- **(**) Ω : the **sample space** of all possible outcomes.
- **2** A: a **sigma-algebra**, a collection of subsets of Ω . Each set is called an event.
- P: probability measure that maps events onto their probability values from 0 to 1, with 0 being impossible* and 1 being certain. Because all events are "cut out" of Ω,
 P(Ω) = 1.

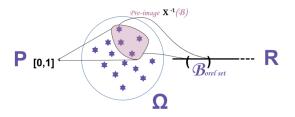
Random Variables

Definition

A random variable on the probability space (Ω, A, \mathbb{P}) is an σ -measurable function from the set of all possible outcomes to the set of real numbers: $X : \Omega \to \mathbb{R}$.

A random variable is a function:

 $X: \Omega \rightarrow R$



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Probability Preliminaries

Expectation

$$\mathbb{E}(X) = \int_{\Omega} X d\mathbb{P}$$
 (0.1)

The bounds Ω being the set of all functions in Ω from $(-\infty, \infty)$.

Variance

$$Var(X) = E((X - E(X))^2),$$
 (0.2)

denoted as σ^2 .

Covariance

$$Cov(X,Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])]. \tag{0.3}$$

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Definition

A **normal distribution** or **Gaussian distribution** is a continuous probability for a real valued random variable, typically shown a bell curve. The probability density function is as follows:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}.$$
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Definition

A stochastic process X_t is a collection of random variables indexed by time.

Definition

A stochastic process $(B_t)_{t\geq 0}$ is a Standard Brownian Motion if it satisfies the following properties:

• $B_0 = 0$ (with probability 1). Brownian Motion starts at 0 when t = 0.

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- Stationary Increments of Normal Distribution: Each interval of B_(s+t) − B_s, given that s < t, is normally distributed with expectation 0 and variance s shown by ~ N(0, t), and independent of starting time s.</p>

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Let's Construct Brownian Motion!

• BM is constructed from random walks

Definition

A **random walk** is a stochastic process formed by successive summation of independent, identically distributed random variables (i.i.d.s).

ex: drunkard's walk, a fair die



Theorem

Standard Brownian motion exists, and satisfies the above conditions.

We can divide the real line $[0, \infty)$ into tiny intervals of length δ . Each sub-interval is a time slot of length δ . $[0, \delta), [\delta, 2\delta), [2\delta, 3\delta) \dots [(k - 1\delta), k\delta)$ for $k < \infty$. We toss a fair coin. Random variables X_i :

$$X_{i} = \begin{cases} +\sqrt{\delta}, \text{ with probability 1/2,} \\ -\sqrt{\delta}, \text{ with probability 1/2,} \end{cases}$$
(0.5)

where X_i s are independent (i.i.d's).

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where X_i s are independent (i.i.d's).

$$E(X_i) = 0$$
 due to being symmetrical (0.6)
 $Var(X_i) = \delta$ (0.7)

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$B_0 = 0$

Define W(t) where W(0) = 0. Then,

$$W(t) = W(n\delta) = \sum_{i=1}^{n} X_i. \qquad (0.8)$$

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Define W(t) where W(0) = 0. Then,

$$W(t) = W(n\delta) = \sum_{i=1}^{n} X_i.$$
(0.8)

Since W(t) is the sum of *n* i.i.d. variables,

$$E(W(t)) = \sum_{i=1}^{n} E(X_i)$$
 (0.9)

$$Var(W(t)) = \sum_{i=1}^{n} Var(X_i)$$
(0.11)

 $= n\delta$

$$= nVar(X_1) \tag{0.12}$$

 $\langle \Box \rangle \langle B \rangle \langle E \rangle \langle E \rangle \langle B \rangle \langle B$

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Independent Increments

For $0 \le t_1 < t_2 < t_3 \dots < t_n$, $W(t_2) - W(t_1), W(t_3) - W(t_2), \dots W(t_n) - W(t_{n-1})$ (0.15) are independent.

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Independent Increments

For $0 \le t_1 < t_2 < t_3 \ldots < t_n$, $W(t_2) - W(t_1), W(t_3) - W(t_2), \ldots W(t_n) - W(t_{n-1})$ (0.15) are independent. For $t \in (0, \infty)$, as $n \to \infty$, $\delta \to 0$. By the Central Limit Theorem:

$$W(t) \sim \mathcal{N}(0, t). \tag{0.16}$$

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Stationary Increments

W(t) must only depend on the length of the interval: $W(t_2) - W(t_1)$ must be equal to $W(t_2 + s) - W(t_1 + s)$.

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Stationary Increments

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$$W(t_1) = \sum_{i=1}^{n_1} X_i, \qquad (0.17)$$

$$W(t_2) = \sum_{i=1}^{n_2} X_i.$$
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Then, to find the interval in between,

$$W(t_1) - W(t_2) = \sum_{i=1+n_1}^{n_2} X_i.$$
 (0.19)

$$E(W(t_1) - W(t_2)) = E(\sum_{1+n_1}^{n_2} X_i)$$
(0.20)
= 0 (0.21)

$$Var(W(t_1) - W(t_2)) = Var(\sum_{1+n_1}^{n_2} X_i)$$
 (0.22)

$$= (n_2 - n_1) Var(X_1)$$
 (0.23)

$$= (n_2 - n_1)\delta \qquad (0.24)$$

$$= t_2 - t_1$$
 (0.25)

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$$= t_2 - t_1$$
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Hence, $W(t_2) - W(t_1)$ converges to $\mathcal{N}(0, t_2 - t_1)$, normally distributed with expectation 0 and variance *t*.

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Continuity

 $\mathbb{P}(\omega \in \Omega : B_{\omega}(t) \text{ is a continuous function of t}) = 1$

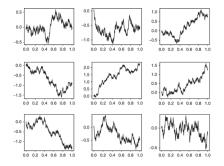


Figure: Sample paths of Brownian motion on [0, 1]

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Brownian motion is both a Markov process and a Martingale.

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Brownian motion is both a Markov process and a Martingale.

Definition

A Markov process $(X_t)_{t\geq 0}$ can be mathematically represented if

$$P((X_{t+s} \le y) | X_u, 0 \le u \le s) = P((X_{t+s} \le y) | X_s)$$
 (0.26)

for all s, t > 0 and real y.

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for all s, t > 0 and real y.

This means the probability of state X time t after s only depends on the state at X_s , not anything in between.

Martingale Properties

Definition

A stochastic process $(Y_t)_{t\geq 0}$ is a martingale if:

- $E(Y_t|Y_r, 0 \le r \le s) = Y_s$ for all $0 \le s \le t$.
- $e (|Y_t|) < \infty.$

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• $E(|Y_t|) < \infty$.

future expectation of an event is equal to it's current value:

$$E(Y_0) = E(E(Y_t|Y_{0+s})) = E(Y_s).$$

See paper for BM and random walks proof $+\ensuremath{\,\text{optional stopping}}$ theorem

BM in Quantative Genetics

Mean value of a trait \overline{z} , population with size N_e , mutations (random variables) mean 0 and variance σ_m^2 . The population evolves purely based on this mutation and genetic drift (random chance). The limit of these random walks, the mean value of the trait, is thus a Brownian motion path as time *t* increases.

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$$\mathbb{E}[\overline{z}_t]=\overline{z}_0.$$

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$$\mathbb{E}[\overline{z}_t] = \overline{z}_0.$$

$$\sigma_B^2(t) = \frac{h^2 \sigma_W^2 t}{N_e}$$

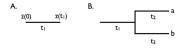
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Phylogenetic Trees



Phylogenetic Trees

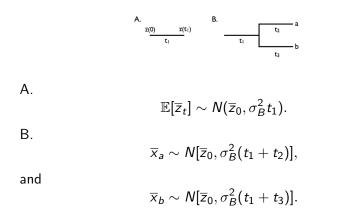


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 $\mathbb{E}[\overline{z}_t] \sim N(\overline{z}_0, \sigma_B^2 t_1).$

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Phylogenetic Trees



$$x_{a} = \Delta x_{1} + \Delta x_{2}$$
$$\overline{x}_{b} = \Delta \overline{x}_{1} + \Delta \overline{x}_{3}$$
$$Cov(\overline{x}_{b}, \overline{x}_{b}) = Var(\Delta \overline{x}_{1}) = \sigma_{B}^{2} t_{1}.$$
 (0.27)

$$\begin{bmatrix} \sigma^2(t_1+t_2) & \sigma^2 t_1 \\ \sigma^2 t_1 & \sigma^2(t_1+t_3) \end{bmatrix} = \sigma^2 \begin{bmatrix} t_1+t_2 & t_1 \\ t_1 & t_1+t_3 \end{bmatrix} = \sigma^2 \mathbf{C}$$

Figure: Variance-Covariance Matrix

More in my paper!

Thank you for listening!

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