

Brownian motion continued

1.

Def: Wiener process/Brownian motion is a stochastic process

$$\bar{W} = \{W(t) : t \geq 0\} \text{ such that}$$

i) $W(0) = 0$ almost surely (i.e. $P(W(0)=0) = 1$)

ii) for any $n \in \mathbb{N}$ and times $0 < t_1 < t_2 < \dots < t_n$, and $x_1, x_2, \dots, x_n \in \mathbb{R}$ the joint probability density of $W(t_1), W(t_2), \dots, W(t_n)$ is

$$f_{W(t_1), W(t_2), \dots, W(t_n)}(x_1, x_2, \dots, x_n) = p(t_1, x_1, 0) \cdot p(t_2 - t_1, x_2, x_1) \\ \times p(t_3 - t_2, x_3, x_2) \cdots p(t_n - t_{n-1}, x_n, x_{n-1}) //$$

where $p(t, y, x) := \frac{1}{\sqrt{2\pi t}} e^{-\frac{(y-x)^2}{2t}}$, $t > 0$, $x, y \in \mathbb{R}$.
 "transition probabilities"

Claim: \bar{W} is a Gaussian process.

(2)

Lemma: Auto correlation function of \bar{W}

$$R_{\bar{W}}(t, s) = \min(t, s), \text{ for } t, s \geq 0.$$

Proof: Assume that $t > s$

$$\begin{aligned} R_{\bar{W}}(t, s) &= \mathbb{E}[W(t) \cdot W(s)] = \mathbb{E}\left[\mathbb{E}\left[W(t) W(s) \mid W(s)\right]\right] \\ &= \mathbb{E}\left[W(s) \underbrace{\mathbb{E}[W(t) \mid W(s)]}_{\substack{\text{law of total expectation} \\ \text{see first video} \rightarrow (\text{xxx}) = W(s)}}\right] \\ &= \mathbb{E}[(W(s))^2] = s \quad \text{used that } W(s) \in \mathcal{N}(0, s) \end{aligned}$$

In case $t \leq s$: $R_{\bar{W}}(t, s) = \dots = t$.

$$\Rightarrow R_{\bar{W}}(t, s) = \min(t, s)$$

■

Hence the covariance matrix of $(W(t_1), W(t_2), \dots, W(t_n))^T$, with $t_1 < t_2 < \dots < t_n$. 3.

is given by

$$\Lambda = \begin{pmatrix} R_W(t_1, t_1) & R_W(t_1, t_2) & R_W(t_1, t_3) & \dots \\ R_W(t_2, t_1) & R_W(t_2, t_2) & \dots & \dots \\ \vdots & \ddots & \ddots & \ddots \\ \vdots & & \ddots & \ddots \end{pmatrix}$$

$$= \begin{pmatrix} t_1 & t_1 & t_1 & \dots & \dots \\ t_1 & t_2 & t_2 & t_2 & \dots \\ t_1 & t_2 & t_3 & t_3 & \dots \\ t_1 & t_2 & t_3 & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ & & & & t_n \end{pmatrix}$$

Corollary: $\mathbb{E}[(W(t) - W(s))^2]^{(\text{***})} = |t-s| \quad t, s \geq 0$

Proof: Exercise, choose first $t > s$, expand the square. //

Lemma: Let $t > s \geq 0$, then the increment $W(t) - W(s)$ (4.)
satisfies

$$W(t) - W(s) \in \mathcal{N}(0, t-s) \quad \blacksquare$$

Proof: Since \bar{W} is a Gaussian process, we know that
 $W(t) - W(s)$ is Gaussian (Cramér-Wold device).

Mean is zero, variance is given (**), i.e. $t-s$. \blacksquare

Thm: Let $0 = t_0 < t_1 < t_2 < \dots < t_n$, then the increments

$$W(t_1) - W(t_0), W(t_2) - W(t_1), \dots, W(t_n) - W(t_{n-1})$$

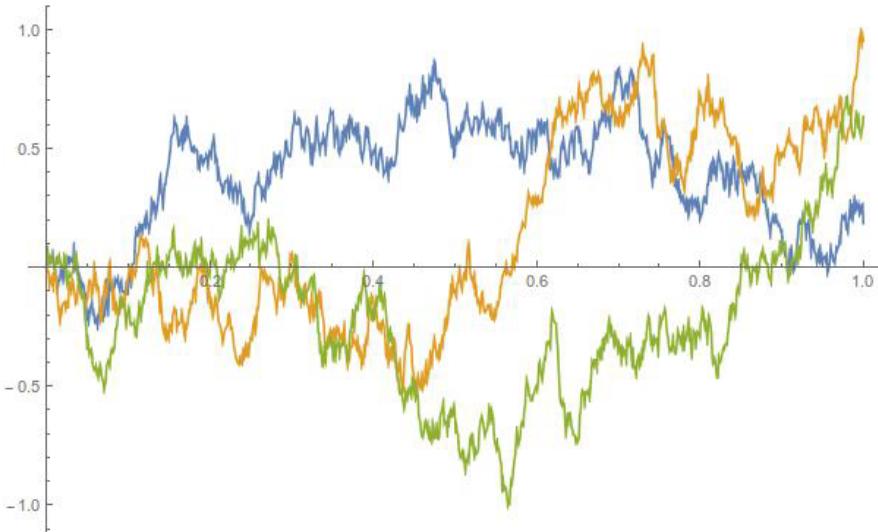
are independent Gaussian random variables with mean zero
and variance $(t_{i+1} - t_i)$. //

Proof: It suffices to show that they are uncorrelated r.v. $0 \leq i, k \leq n-1$

$$\begin{aligned} & \text{Cov}(W(t_{k+1}) - W(t_k), W(t_{i+1}) - W(t_i)) \quad \underline{k > i} \\ &= \mathbb{E} [(W(t_{k+1}) - W(t_k)) \cdot (W(t_{i+1}) - W(t_i))] \\ &= \mathbb{E}[W(t_{k+1}) \cdot W(t_{i+1})] - \mathbb{E}[W(t_{k+1}) \cdot W(t_i)] - \mathbb{E}[W(t_i) \cdot W(t_{i+1})] \\ &\quad + \mathbb{E}[W(t_i) \cdot W(t_j)] \\ &= \underbrace{\min(t_{k+1}, t_{i+1})}_{t_{i+1}} - \underbrace{\min(t_{k+1}, t_i)}_{t_i} - \underbrace{\min(t_i, t_{i+1})}_{t_{i+1}} + \underbrace{\min(t_k, t_i)}_{t_i} = 0 \quad \blacksquare \end{aligned}$$

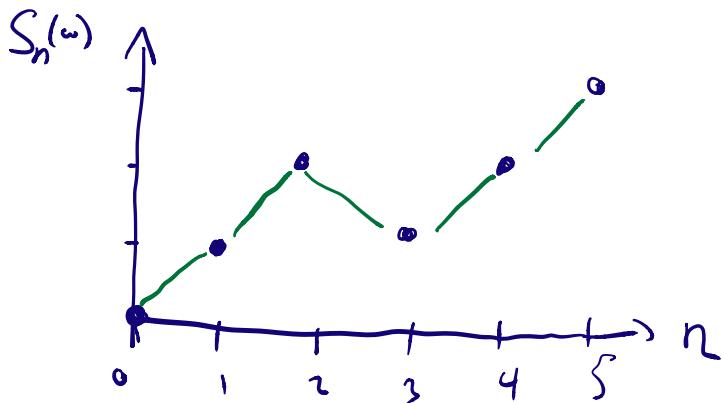
5.

Remarks about sample paths



- The sample paths $\{W(t_\theta) : \theta \geq 0\}$ are almost surely continuous vs Ω fixed.
- The sample paths are almost surely nowhere differentiable.

Donsker's invariance principle: Recall symmetric simple random walk: (X_i) iid
 $P(X_i = 1) = P(X_i = -1) = \frac{1}{2}$. $S_n := \sum_{i=1}^n X_i$, $S_0 = 0$.



$$\frac{S_n}{\sqrt{n}} \xrightarrow[n \rightarrow \infty]{d} \mathcal{N}(0, 1)$$

CLT.

6.

Two rescaling with n : Space: replace step size one by $\frac{1}{\sqrt{n}}$.

Time: replace unit time steps by $\frac{1}{n}$.

Let $(X_i^{(n)})_{i=1, \dots, n}, n \geq 0$, all i.i.d. with $P(X_i^{(n)} = \frac{1}{\sqrt{n}}) = P(X_i^{(n)} = -\frac{1}{\sqrt{n}}) = \frac{1}{2}$

Observe: $\text{Var}(X_i^{(n)}) = \frac{1}{2}(\frac{1}{\sqrt{n}})^2 + \frac{1}{2}(-\frac{1}{\sqrt{n}})^2 = \frac{1}{n}$.

For $t \geq 0$ define $\bar{W}^{(n)}(t) := \sum_{i=1}^{\lfloor tn \rfloor} X_i^{(n)}$

$\lfloor tn \rfloor$: integer part of tn .

In particular, $\bar{W}^{(n)}(1) = \sum_{i=1}^n X_i^{(n)} \xrightarrow[n \rightarrow \infty]{d} W(1) \in \mathcal{N}(0, 1)$ CLT in R distinguise.

but also $\bar{W}^{(n)}(t) \xrightarrow[n \rightarrow \infty]{d} W(t) \in \mathcal{N}(0, t)$

In fact: For any $k \in \mathbb{N}$, $t_1 < t_2 < \dots < t_k$, we have

$$\begin{aligned} & (\bar{W}^{(n)}(t_1), \bar{W}^{(n)}(t_2), \dots, \bar{W}^{(n)}(t_k)) \\ & \xrightarrow[n \rightarrow \infty]{d} (W(t_1), W(t_2), \dots, W(t_k)) \end{aligned}$$

where \bar{W} is a Wiener process. /

7.

Why do we scale space and time in this manner?

Recall from (***) that

$$\mathbb{E} \left[(W(t_{k+1}) - W(t_k))^2 \right] = \underbrace{t_{k+1} - t_k}_{\frac{1}{n}}$$

\approx typical size of the increments is
of order $\frac{1}{\sqrt{n}}$.

"diffusive scaling: distance squared growth like the time!"

(8)

Thm: A stochastic process $\{W(t) : t \geq 0\}$

is a Wiener process if and only if

- 1.) $W(0) = 0$ a.s.
- 2.) The sample paths $t \mapsto W(t)$ are almost surely continuous
- 3.) $\{W(t) : t \geq 0\}$ has independent increments.
- 4.) $W(t) - W(s)$, $t > s$, is Gaussian with mean zero
and variance $t-s$. //

Exercises: W a Brownian motion:

1.) Find $P(W(2) > W(1)) = P(W(2) - W(1) > 0) = \frac{1}{2}$

2.) Find $P(W(2) > 2W(1))$ since $W(2) - W(1) \in N(0, 1)$
and symmetry of $N(0, 1)$.

3.) Find $P(W(2) > 0 \mid W(1) = 1)$

$$= \int_0^\infty P(1, y, 1) dy = \frac{1}{\sqrt{2\pi}} \int_0^\infty e^{-\frac{(y-1)^2}{2}} dy$$

change of variable

4.) Find $P(W(2) > 0 \mid W(1) > 1)$

$$= \frac{1}{\sqrt{2\pi}} \int_1^\infty e^{-\frac{y^2}{2}} dy = 1 - \Phi(-1)$$

cdf of $N(0, 1)$.