

Random walk

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Definition (Random walk)

Let $\{\xi_n\}_{n \geq 1}$ be i.i.d. real-valued random variables.

Define

$$S_n := \sum_{k=1}^n \xi_k, \quad S_0 := 0.$$

Note

S_n is adapted to the natural filtration $\mathcal{F}_n := \sigma(\xi_1, \dots, \xi_n)$.

Symmetric random walk

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Definition (Symmetric random walk)

Let $\{X_k\}_{k \geq 1}$ be i.i.d. random variables such that, for each k ,

$$\mathbb{P}(X_k = 1) = \mathbb{P}(X_k = -1) = \frac{1}{2}.$$

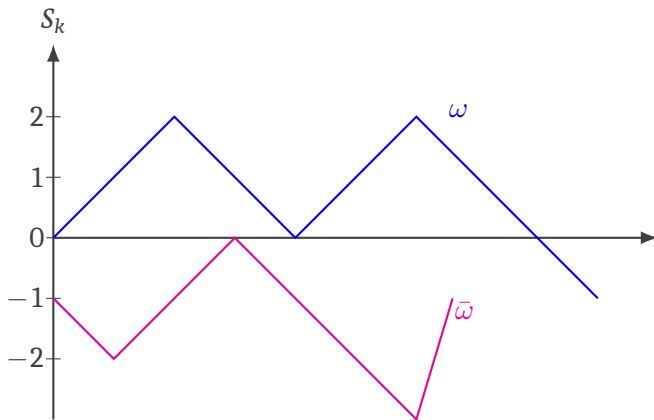
Define

$$S_n := \sum_{k=1}^n X_k, \quad n \geq 1.$$

One scenario (coin-toss view)

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Identify $H \leftrightarrow +1$ and $T \leftrightarrow -1$.

Symmetric random walk: sample paths



Properties of the symmetric random walk

Properties:

1. **Independent increments.** Fix indices $0 = k_0 < k_1 < k_2 < \dots < k_n$ and define

$$\Delta_{k_i} := S_{k_i} - S_{k_{i-1}} = \sum_{j=1}^{k_i} X_j - \sum_{j=1}^{k_{i-1}} X_j = \sum_{j=k_{i-1}+1}^{k_i} X_j.$$

Hence $\Delta_{k_1}, \Delta_{k_2}, \dots, \Delta_{k_n}$ are independent random variables.

2. $\mathbb{E}[X_j] = 0 \quad \forall j.$
3. $\mathbb{E}[S_n] = 0.$
4. $\text{Var}(X_j) = 1.$
5. $\text{Var}(S_n) = n$ (grows linearly).

More properties

Additional properties:

6. $\mathbb{E}[\Delta_{k_i}] = 0.$
7. $\text{Var}(\Delta_{k_i}) = 1.$

Symmetric random walk is a martingale

Statement

The symmetric random walk $(S_k)_{k \geq 0}$ is a martingale with respect to its natural filtration $(\mathcal{F}_k)$, i.e.

$$\mathbb{E}[S_\ell \mid \mathcal{F}_k] = S_k, \quad \ell > k.$$

Proof sketch:

1. S_k is $\mathcal{F}_k$ -measurable.
2. (S_k) is adapted to $(\mathcal{F}_k)$.
3. $\mathbb{E}[|S_k|] < \infty$ for all k .

Now,

$$\mathbb{E}[S_\ell \mid \mathcal{F}_k] = \mathbb{E}[S_\ell - S_k \mid \mathcal{F}_k] + \mathbb{E}[S_k \mid \mathcal{F}_k] = \mathbb{E}[S_\ell - S_k] + S_k = S_k,$$

since $S_\ell - S_k = \sum_{j=k+1}^{\ell} X_j$ is independent of $\mathcal{F}_k$ and has mean 0.

6/22 Therefore the symmetric random walk has no drift: on average it does not move up or

Quadratic variation of the symmetric random walk

Quadratic variation is a measure of how strong the randomness is per unit time.

It quantifies the intensity of randomness in the path (not the randomness itself), i.e., a measure of randomness present in the path.

The quadratic variation up to time k is defined by

$$[S, S]_k := \sum_{j=1}^k (S_j - S_{j-1})^2 = \sum_{j=1}^k \left(\sum_{i=1}^j X_i - \sum_{i=1}^{j-1} X_i \right)^2 = \sum_{j=1}^k X_j^2 = k.$$

Here the computation is pathwise.

Scaled random walk

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let $(S_n)_{n \geq 0}$ be a symmetric random walk.

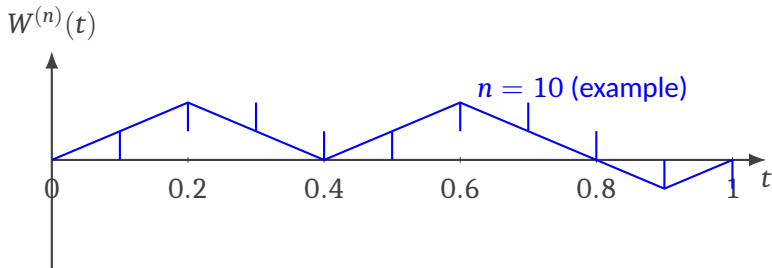
Definition (Scaled random walk)

For each $n \in \mathbb{N}$, define the process

$$W^{(n)}(t) := \frac{1}{\sqrt{n}} S_{\lfloor nt \rfloor}, \quad t \in [0, 1].$$

The idea is to speed up time, shrink space, and make the variance finite. The $1/\sqrt{n}$ scaling is taken from the CLT normalization and helps the random-walk increments converge to Gaussian increments.

Scaled random walk: sample path



Scaled random walk: basic properties

Properties:

1. **Independent increments.** For $t > s$,

$$W^{(n)}(t) - W^{(n)}(s) = \frac{1}{\sqrt{n}}(S_{\lfloor nt \rfloor} - S_{\lfloor ns \rfloor}),$$

and the increments inherit independence from (S_k) .

2. **Mean.**

$$\mathbb{E}[W^{(n)}(t)] = \mathbb{E}\left[\frac{1}{\sqrt{n}}S_{\lfloor nt \rfloor}\right] = \frac{1}{\sqrt{n}}\sum_{j=1}^{\lfloor nt \rfloor}\mathbb{E}[X_j] = 0.$$

3. **Variance.**

$$\text{Var}(W^{(n)}(t)) = \frac{1}{n}\text{Var}(S_{\lfloor nt \rfloor}) = \frac{1}{n}\sum_{j=1}^{\lfloor nt \rfloor}\text{Var}(X_j) = \frac{\lfloor nt \rfloor}{n} \approx t.$$

Scaled random walk: increments

Let $t > s$.

4. Mean of increments

$$\mathbb{E}[W^{(n)}(t) - W^{(n)}(s)] = \sum_{i=1}^{\lfloor nt \rfloor} \mathbb{E}\left[\frac{X_i}{\sqrt{n}}\right] - \sum_{i=1}^{\lfloor ns \rfloor} \mathbb{E}\left[\frac{X_i}{\sqrt{n}}\right] = 0.$$

5. Variance of increments

$$\begin{aligned} \text{Var}(W^{(n)}(t) - W^{(n)}(s)) &= \text{Var}\left(\frac{1}{\sqrt{n}}S_{\lfloor nt \rfloor} - \frac{1}{\sqrt{n}}S_{\lfloor ns \rfloor}\right) = \frac{1}{n} \text{Var}(S_{\lfloor nt \rfloor} - S_{\lfloor ns \rfloor}) \\ &= \frac{1}{n} \text{Var}\left(\sum_{i=\lfloor ns \rfloor+1}^{\lfloor nt \rfloor} X_i\right) = \frac{1}{n} \sum_{i=\lfloor ns \rfloor+1}^{\lfloor nt \rfloor} \text{Var}(X_i) \\ &= \frac{\lfloor nt \rfloor - \lfloor ns \rfloor}{n} \approx t - s. \end{aligned}$$

Filtration for the scaled random walk

The filtration associated with the scaled random walk is

$$\mathcal{F}_t^{(n)} := \sigma(X_1, X_2, \dots, X_{\lfloor nt \rfloor}).$$

Scaled random walk is also a martingale

Statement

The scaled random walk $(W^{(n)}(t))_{t \in [0,1]}$ is a martingale with respect to $(\mathcal{F}_t^{(n)})$:

$$\mathbb{E}[W^{(n)}(t) \mid \mathcal{F}_s^{(n)}] = W^{(n)}(s), \quad 0 \leq s < t \leq 1.$$

Proof sketch:

1. $W^{(n)}(t)$ is $\mathcal{F}_t^{(n)}$ -measurable.
2. $\mathbb{E}[|W^{(n)}(t)|] < \infty$.

Scaled random walk is also a martingale (cont.)

Proof sketch (cont.):

3. Using $W^{(n)}(t) = (W^{(n)}(t) - W^{(n)}(s)) + W^{(n)}(s)$,

$$\mathbb{E}[W^{(n)}(t) \mid \mathcal{F}_s^{(n)}] = \mathbb{E}[W^{(n)}(t) - W^{(n)}(s) \mid \mathcal{F}_s^{(n)}] + W^{(n)}(s) = 0 + W^{(n)}(s),$$

since $W^{(n)}(t) - W^{(n)}(s)$ depends only on $X_{[ns]+1}, \dots, X_{[nt]}$ and is independent of $\mathcal{F}_s^{(n)}$ with mean 0.

Therefore, it is a martingale.

Quadratic variation of the scaled random walk

Fix n and define, for $t \in [0, 1]$,

$$[W^{(n)}, W^{(n)}](t) := \sum_{j=1}^{\lfloor nt \rfloor} \left(W^{(n)}\left(\frac{j}{n}\right) - W^{(n)}\left(\frac{j-1}{n}\right) \right)^2.$$

Using $W^{(n)}(j/n) = \frac{1}{\sqrt{n}}S_j$, we get

$$[W^{(n)}, W^{(n)}](t) = \sum_{j=1}^{\lfloor nt \rfloor} \left(\frac{1}{\sqrt{n}}S_j - \frac{1}{\sqrt{n}}S_{j-1} \right)^2 = \sum_{j=1}^{\lfloor nt \rfloor} \frac{1}{n}(S_j - S_{j-1})^2 = \sum_{j=1}^{\lfloor nt \rfloor} \frac{1}{n}X_j^2 = \frac{\lfloor nt \rfloor}{n} \approx t.$$

As $n \rightarrow \infty$,

$$[W^{(n)}, W^{(n)}](t) \rightarrow t \quad \text{almost surely.}$$



Functional CLT / Donsker's theorem / invariance principle

The classical CLT asserts that

$$W^{(n)}(1) \xrightarrow{d} W(1),$$

where $W(1) \sim \mathcal{N}(0, 1)$.

Donsker's theorem extends this convergence to the whole process

$$W^{(n)} := \left(W^{(n)}(t) \right)_{t \in [0,1]}:$$

$$W^{(n)}(t) \xrightarrow{d} W(t),$$

where $(W(t))_{t \in [0,1]}$ is a standard Brownian motion (Wiener process).

Brownian motion

Definition (Brownian motion / Wiener process)

A process $\{W_t : t \geq 0\}$ on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ is called a **Brownian motion** if:

- (i) $\mathbb{P}(W_0 = 0) = 1$.
- (ii) **Independent increments:** if $0 = t_0 \leq t_1 \leq \dots \leq t_k$, then for any Borel sets $H_1, \dots, H_k$,

$$\mathbb{P}\left(W_{t_i} - W_{t_{i-1}} \in H_i \text{ for } i = 1, \dots, k\right) = \prod_{i=1}^k \mathbb{P}(W_{t_i} - W_{t_{i-1}} \in H_i).$$

- (iii) **Gaussian increments:** for $0 \leq s < t$, $W_t - W_s \sim \mathcal{N}(0, t - s)$.
- (iv) **Continuous paths:** for almost every ω , the map $t \mapsto W(t, \omega)$ is continuous.

Brownian motion: notes

Gaussian increment distribution: for $0 \leq s < t$ and a Borel set $H \subset \mathbb{R}$,

$$\mathbb{P}(W_t - W_s \in H) = \frac{1}{\sqrt{2\pi(t-s)}} \int_H \exp\left(-\frac{x^2}{2(t-s)}\right) dx.$$

Note: if $0 < t_1 < \dots < t_k$, then the joint density of $(W_{t_1}, W_{t_2} - W_{t_1}, \dots, W_{t_k} - W_{t_{k-1}})$ is the product of the corresponding normal densities.

Filtration associated with Brownian motion

Note:

1. Brownian motion is continuous.
2. Brownian motion is nowhere differentiable.

Filtration:

1. For $0 \leq s \leq t$, $\mathcal{F}_s \subseteq \mathcal{F}_t$.
2. $W(t)$ must be adapted to the filtration.

Brownian motion is a martingale

Let $\mathcal{F}_t := \sigma(W_s : s \leq t)$. Then for any $s < t$,

$$\mathbb{E}[W_t \mid \mathcal{F}_s] = W_s.$$

Proof sketch:

$$\mathbb{E}[W_t \mid \mathcal{F}_s] = \mathbb{E}[W_t - W_s + W_s \mid \mathcal{F}_s] = \mathbb{E}[W_t - W_s \mid \mathcal{F}_s] + \mathbb{E}[W_s \mid \mathcal{F}_s] = \mathbb{E}[W_t - W_s] + W_s = W_s,$$

since $W_t - W_s$ is independent of $\mathcal{F}_s$ and has mean 0.

Stationary increments

Statement

The increments of Brownian motion are stationary; for $0 \leq s < t$,

$$W_t - W_s \stackrel{d}{=} W_{t-s} - W_0.$$

Proof sketch: since $W_0 = 0$ and $W_t - W_s \sim \mathcal{N}(0, t - s)$, we have

$$W_{t-s} - W_0 = W_{t-s} \sim \mathcal{N}(0, t - s),$$

hence $W_t - W_s \stackrel{d}{=} W_{t-s} - W_0$.