Notes on Probability

Contents

1 Modes of Convergence

1.1 Uniform Integrablity (u.i.)

Definition 1.1 (Uniformly Integrable)**.** $\mathcal{K}$ - a family of real-value RVs

$\mathcal{K}$ is uniformly intergrable if

$$k(b) = \sup_{X\in\mathcal{K}} \mathbb{E}(|X|\mathbf{1}_{\{|X|>b\}}) \\ \to 0 \quad \text{as } b\to\infty$$

Proposition 1.2. *Let $\psi : [0,\infty) \to [0,\infty)$ be a non-negative increasing convex function such that $\lim\limits_{r\to\infty} \frac{\psi(r)}{r} = \infty$. Then*

$$\sup_n \mathbb{E}(\psi(|X_n|)|) < \infty \implies X \textit{ is u.i.}$$

Remark. The converse is also true: if $\{X_n\}$ is a u.i. family, then there exists a non-negative increasing convex function satisfying these properties.

Possible choices of ψ: $r \longrightarrow r^2$, $r \longrightarrow \big[(1+r)\log(1+r) - r\big]$, ...

Proof. Let $M = \sup_n \mathbb{E}(\psi(|X_n|))$. Notice that $\lim\limits_{r\to\infty} \frac{\psi(r)}{r} = \infty$ means: For all $n > 0$, there exists $r_n > 0$ such that for all $r > r_n$,

$$\psi(r) > nM \cdot r.$$

Then for a fixed n, we choose $r > r_n$:

$$M \geq \mathbb{E}(\psi(|X_n|)) \geq \mathbb{E}(\psi(|X_n|)\mathbf{1}_{\{|X_n|>r\}}) \\ \geq nM\mathbb{E}|X_n|\mathbf{1}_{\{|X_n|>r\}}$$

$\implies \mathbb{E}|X_n|\mathbf{1}_{\{|X_n|>r\}} \leq \frac{1}{n}$. We are done. □

Theorem 1.3.
$\{X_k\}_{k\in\mathcal{K}}$ *is u.i.* $\iff$ *for all $\epsilon > 0$, $\exists\delta$, such that for all A with $\mathbb{P}A < \delta$: $\sup_{k\in\mathcal{K}} \mathbb{E}X_k\mathbf{1}_A < \epsilon$.*

Exercises

Exercise 1.1.1. Let X be integrable and define $X_n = X$ for all n. Show that $\{X_n\}$ is u.i.

Proof. Compute $k(b)$:

$$k(b) = \sup_n \mathbb{E}\Big(|X_n|\mathbf{1}_{\{|X_n|>b\}}\Big) = \mathbb{E}\Big(|X|\mathbf{1}_{\{|X|>b\}}\Big).$$

Notice that $|X|\mathbf{1}_{\{|X|>b\}} \leq |X|$. By the dominated convergence theorem:

$$\lim_{b\to\infty} \mathbb{E}\Big(|X|\mathbf{1}_{\{|X|>b\}}\Big) = \mathbb{E}\Big(\lim_{b\to\infty}|X|\mathbf{1}_{\{|X|>b\}}\Big) = 0.$$

The last equality is baesd on the integrability of X. Then by the definition, $\{X_n\}$ is u.i. □

Exercise 1.1.2. u.i. $\implies$ $\sup_n \mathbb{E}X_n^+ < \infty$

Proof. Notice that

$$\mathbb{E}X_n^+ \leq \mathbb{E}|X_n| \leq \mathbb{E}|X_n|\mathbf{1}_{\{|X|>b\}} + b.$$

By u.i., for all $\epsilon > 0$, $\exists b_0$ s.t. $\forall b > b_0$,

$$\sup_n |X_n|\mathbf{1}_{\{|X_n|>b\}} < \epsilon.$$

$\implies \sup_n \mathbb{E}X_n^+ \leq b_0 + 1 + \epsilon < \infty$ (Take $b = b_0 + 1$). □

Exercise 1.1.3. Let $\{X_n\}$ be a sequence of RVs such that $\mathbb{E}(\sup_n |X_n|) < \infty$.

(a) Show that $\{X_n\}$ is u.i.

(b) Give an example of a sequence $\{Y_n\}$ such that $\sup_n \mathbb{E}|Y_n| < \infty$ but $\{Y_n\}$ is not u.i.

Proof. (a) Notice two facts:

$$|X_n| \leq \sup_n |X_n|$$
$$\{|X_n| > b\} \subset \{\sup_n |X_n| > b\}$$

For all n, we have:

$$|X_n|\mathbf{1}_{\{|X_n|>b\}} \leq \sup_n |X_n| \cdot \mathbf{1}_{\{\sup_n |X_n|>b\}}$$
$$\mathbb{E}\Big(|X_n|\mathbf{1}_{\{|X_n|>b\}}\Big) \leq \mathbb{E}\Big(\sup_n |X_n| \cdot \mathbf{1}_{\{\sup_n |X_n|>b\}}\Big)$$

Compute $k(b)$:

$$\begin{aligned}\sup_n \mathbb{E}\Big(|X_n|\mathbf{1}_{\{|X_n|>b\}}\Big) &\leq \mathbb{E}\Big(\sup_n |X_n| \cdot \mathbf{1}_{\{\sup_n |X_n|>b\}}\Big) \\ &\longrightarrow 0,\end{aligned}$$

since $\sup_n |X_n|$ is integrable.

(b) Define $Y_n(\omega) = \begin{cases} n & 0 < \omega \leq \frac{1}{n} \\ 0 & \text{o.w.} \end{cases}$

Then $\sup \mathbb{E}Y_n = 1$; however, $\sup_n \mathbb{E}Y_n\mathbf{1}_{\{Y_n>b\}} = 1$ for all $n > b$. Thus, $\{Y_n\}$ is not u.i. □

Exercise 1.1.4. Let $\{X_n\}$ and $\{Y_n\}$ be two u.i. sequences. Then

(a) $\{X_n + Y_n\}$ is u.i.

(b) $\{X_n \vee Y_n\}$ is u.i.

Proof. Part (b) is trivial.
For (a), consider the following inequality:

$$|X+Y|\mathbf{1}_{\{|X+Y|\geq 2b\}} \leq 2|X|\mathbf{1}_{|X|\geq b} + 2|Y|\mathbf{1}_{|Y|\geq b}.$$

Or we have another option: Theorem 1.3. By the u.i. of X and Y, we have:
For all $\epsilon > 0$ there exsits $\delta > 0$ such that if $\mathbb{P}A < \delta$ then $\sup_n \mathbb{E}|X_n|\mathbf{1}_A < \epsilon$ and $\sup_n \mathbb{E}|Y_n|\mathbf{1}_A < \epsilon$.
$\implies \mathbb{E}|X_n + Y_n|\mathbf{1}_A \leq \mathbb{E}|X_n|\mathbf{1}_A + \mathbb{E}|Y_n|\mathbf{1}_A < 2\epsilon$.
Then use Theorem 1.3 again. □

Exercise 1.1.5. Let $\{X_i\}$ be a sequence of i.i.d integrable RVs with mean μ. Show that the sample mean is u.i. and $\bar{X}_n = S_n/n \xrightarrow{L^1} \mu$ as $n \to \infty$.

Proof. Recall the SLLN: $\{X_i\}$ are i.i.d. RVs and $\mathbb{E}|X| = \mu < \infty \implies \bar{X}_n \xrightarrow{a.s.} \mu$.
$\implies \bar{X}_n \xrightarrow{\mathbb{P}} \mu$.
Because $X_n \xrightarrow{L^1} X \iff X_n \xrightarrow{\mathbb{P}} X + \{X_n\}$ is u.i. (Theorem 1.8), it suffices to prove $\{\bar{X}_n\}$ is a u.i. sequence.
Use the following result ( ): if $X_n \xrightarrow{w} X$,

$$\{X_n\} \text{ is u.i.} \iff X_n, X \text{ are integrable} + \mathbb{E}X_n \to \mathbb{E}X.$$

$\implies \{X_n\}$ is a u.i. sequence. □

Exercise 1.1.6. Any u.i. sequence is tight.

Proof. Tool: the definition of the tightness. Let $\{X_n\}$ be a u.i. sequence.

$$\begin{aligned}\sup_n \mathbb{P}(|X_n| > M) &= \sup_n \mathbb{E}\mathbf{1}_{\{|X_n|>M\}} \\ (M > 1) \quad &< \sup_n \mathbb{E}\{|X_n|\mathbf{1}_{\{|X_n|>M\}}\} \\ (\text{u.i.}) \quad &\to 0 \quad \text{as } M \to \infty\end{aligned}$$

$\implies$ $\forall \epsilon > 0,\ \exists M_\epsilon$ such that

$$\sup_n \mathbb{P}(|X_n| > M_\epsilon) < \epsilon$$

$\implies$ $\{X_n\}$ is tight. □

Exercise 1.1.7. Let B be a Brownian motion. Show that B_t, $B_t^2 - t$, and $e^{\lambda B_t - \frac{\lambda^2}{2}t}$ are not uniformly integrable.

Proof. Notice that $\mathbb{E}|X_t|\mathbf{1}_{\{|X_t|>b\}}$ can be calculated explicitly. □

1.2 Convergence: Almost Sure, in Probability, and in L^p

Definition 1.4. Let (X_n) be a sequence RVs.

- $X_n \xrightarrow{a.s.} X$ if
$$\mathbb{P}\{\omega : X_n(\omega) \to X(\omega)\} = 1.$$
- $X_n \xrightarrow{\mathbb{P}} X$ if for every $\epsilon > 0$,
$$\mathbb{P}(|X_n - X| > \epsilon) \to 0.$$
- $X_n \xrightarrow{L^p} X$ if
$$\mathbb{E}|X_n - X|^p \to 0.$$

Theorem 1.5 (Continuous mapping theorem)**.** *Let (X_n) be a sequence RVs and $f : \mathbb{R} \to \mathbb{R}$ be continuous.*

- $X_n \xrightarrow{a.s.} X$
  $\implies$ $f \circ X_n \xrightarrow{a.s.} f \circ X$.
- $X_n \xrightarrow{\mathbb{P}} X$
  $\implies$ $f \circ X_n \xrightarrow{\mathbb{P}} f \circ X$.

Almost sure convergence

Theorem 1.6 (Borel-Canteli lemma)**.** *Let $A_1, A_2, \dots$ be a sequence of events.*

a)
$$\sum_{n=1}^{\infty} \mathbb{P}A_n < \infty \implies \mathbb{P}(\limsup_n A_n) = 0.$$

b) If $\{A_i\}$ are independent, then
$$\sum_{n=1}^{\infty} \mathbb{P}A_n = \infty \implies \mathbb{P}(\limsup_n A_n) = 1.$$

Remark.

- Prove that $X_n \xrightarrow{a.s.} X$:
  Define $A_k = \{\omega : |X_k(\omega) - X(\omega)| \geq a_k\}$. Choose $\{a_k\} \downarrow 0$ such that
$$\sum_{n=1}^{\infty} \mathbb{P}A_n < \infty.$$
  Or we check for every $\epsilon > 0$,
$$\sum_{n=1}^{\infty} \mathbb{P}(|X_n - X| > \epsilon) < \infty.$$
- Prove that $X_n \not\xrightarrow{a.s.} X$:
  Define $A_k = \{\omega : |X_k(\omega) - X(\omega)| > \epsilon\}$. If the independence of the sequence of RVs $\{X_n\}$ is given, it suffices to check if
$$\sum_{n=1}^{\infty} \mathbb{P}A_n = \infty.$$

Example 1.7. **Note**: There exists a sequence of events such that $\sum \mathbb{P}A_n = \infty$ and $\mathbb{P}(\limsup_n A_n) = 0$. For example, take $A_n = (0, a_n)$ with $a_n \downarrow 0$ and $a_n \geq \frac{1}{n}$.

Convergence in probability

Proposition 1.8 (Relations to a.s. convergence)**.**

- $X_n \xrightarrow{a.s.} X \implies X_n \xrightarrow{\mathbb{P}} X$
- $X_n \xrightarrow{\mathbb{P}} X \iff$ *Each subsequence* $\{X_{n_k}\}$ *contains a further subsequence* $X_{n_{k_i}} \xrightarrow{a.s.} X$.

Proposition 1.9 (Relations to convergence in L^p)**.**

- $X_n \xrightarrow{L^p} X \implies X_n \xrightarrow{\mathbb{P}} X$

Convergence in L^p

Proposition 1.10. *$\forall p > q \geq 1$, if $X_n \to X$ in L^p, then $X_n \to X$ in L^q.*

Remark. Lyapunov's inequality: $\|X\|_p \geq \|X\|_q$ for $p \geq q \geq 1$.

Theorem 1.11. *If $X_n \xrightarrow{\mathbb{P}} X$, the following are equivalent:*

a) $\{X_n\}_{n\in\mathbb{N}}$ is uniform integrable.

b) $\mathbb{E}|X_n| < \infty$ for all n, $\mathbb{E}|X| < \infty$, and $X_n \xrightarrow{L^1} X$.

c) $\mathbb{E}|X_n| < \infty$ for all n, and $\mathbb{E}|X_n| \to \mathbb{E}|X| < \infty$.

Theorem 1.12.
$$X_n \xrightarrow{L^1} X \iff \{X_n\} \text{ is u.i. and } X_n \xrightarrow{\mathbb{P}} X.$$

Exercises

Exercise 1.2.1. Let (X_n) be a sequence of independent RVs such that $\mathbb{P}(X_n < \infty) = 1,\ \forall n$.
(a) Show that
$$\sup_n X_n < \infty \iff \sum_n \mathbb{P}(X_n > A) < \infty \text{ for some } A.$$
(b) With no assumption of indep., give an example s.t. $\sup_n X_n < \infty$ while $\sum_n \mathbb{P}(X_n > A) = \infty$.

Proof.

(a) $\Longleftarrow$: By B-C (a), $\mathbb{P}(X_n > A \text{ i.o.}) = 0$. It implies

$$\mathbb{P}(X_n \leq A \text{ i.o.}) = \mathbb{P}(\sup_n X_n \leq A) = 1.$$

$\Longrightarrow$: Assume $\sum_n \mathbb{P}(X_n > A) = \infty$ for all A. Notice that $\{X_n > A\}$ is indep. of $\{X_m > A\}$ because X_n is indep. of X_m when $n \neq m$. Then by B-C (b),

$$\mathbb{P}(X_n > A \text{ i.o.}) = 1$$

for all A. It implies $\sup_n X_n = \infty$. Contradiction.

(b) $(\Omega, \mathcal{F}, \mathbb{P}) = ([0,1], \mathcal{B}, \text{Leb})$. Let $X_n(\omega) = \begin{cases} n & 1 - \frac{1}{n} < \omega \leq 1 \\ 0 & \text{o.w.} \end{cases}$. Then

$$\sum_n \mathbb{P}(X_n > A) = \infty.$$

However, $\limsup_n X_n = \begin{cases} \infty & \omega = 1 \\ 0 & \omega \in [0,1) \end{cases}$. So

$$\mathbb{P}(\limsup_n X_n < \infty) = 1.$$

□

Exercise 1.2.2. $X_n \overset{iid}{\sim} F$ with $F(x) < 1$ for all x. Set $M_n = \max\{X_1, \ldots, X_n\}$. Prove that $M_n \uparrow \infty$.

Proof. Let $N_j = \bigcap_{j=1}^{\infty} \{M_n \leq j\}$.

$$\mathbb{P}(N_j) = \lim_{n\to\infty} \mathbb{P}\{M_n \leq j\} = \lim_{n\to\infty} F^n(j) = 0.$$

Let $N = \bigcup_j N_j$. It is a measurable set and $\mathbb{P}(N) \leq \sum_j \mathbb{P}(N_j) = 0$. Thus, if we take

$$\begin{aligned}
& \omega \in N^c = \bigcap_j N_j^c \\
\Longrightarrow\ & \omega \notin N_j,\ \forall j \\
\Longrightarrow\ & \omega \notin \bigcap_n \{M_n \leq j\},\ \forall j \\
\Longrightarrow\ & \omega \notin \lim_n \{M_n \leq j\},\ \forall j \\
\Longrightarrow\ & \forall j,\ \exists n_0(\omega, j),\ \text{such that } \forall n > n_0(\omega, j),\ M_n(\omega) > j
\end{aligned}$$

It is equivalent to say $\lim_n M_n = +\infty$. □

Exercise 1.2.3. (a) Show that for the non-negative RV X,

$$\sum_{i=1}^{\infty} \mathbb{P}(X \geq i) \leq \mathbb{E}X < 1 + \sum_{i=1}^{\infty} \mathbb{P}(X \geq i).$$

(b) Show that if the integer-valued RV $X \geq 0$,

$$\mathbb{E}X = \sum_{i=1}^{\infty} \mathbb{P}(X \geq i).$$

(c) Let $X_0, X_1, \ldots$ be i.i.d. continuous RVs and $N = \inf\{n \geq 1 : X_n > X_0\}$. Show that $\mathbb{E}N = \infty$.

Proof. (a) Define $A_i = \{i-1 \le X < i\}$. Then

$$X = \sum_{i=1}^{\infty} X\mathbf{1}_{A_i}, \text{ and}$$
$$(i-1)\mathbf{1}_{A_i} \le X\mathbf{1}_{A_i} \le i\mathbf{1}_{A_i}, \ \forall i.$$

$\implies$ $\sum_i (i-1)\mathbf{1}_{A_i} \le X \le \sum_i i\mathbf{1}_{A_i}$.
$\implies$ $\sum_i (i-1)\mathbb{P}(i-1 \le X < i) \le \mathbb{E}X \le \sum_i i\mathbb{P}(i-1 \le X < i)$.
$\implies$ $\sum_{i=1}^{\infty} \mathbb{P}(X \ge i) \le \mathbb{E}X < 1 + \sum_{i=1}^{\infty} \mathbb{P}(X \ge i)$.

(b) Because $X = \sum_{i=1}^{\infty} X\mathbf{1}_{A_i}$,
$\implies$ $\mathbb{E}X = \sum_{i=1}^{\infty} \mathbb{E}(X\mathbf{1}_{A_i}) = \sum_{i=1}^{\infty}(i-1)\mathbb{P}(X = i-1) = \sum_{i=1}^{\infty} \mathbb{P}(X \ge i)$

(c) Notice that $\mathbb{E}N = \sum_{n=0}^{\infty} \mathbb{P}(N > n)$. Now, we want to find $\mathbb{P}(N > n)$.
For $n = 1$, by symmetry,

$$\mathbb{P}(N > 1) = \mathbb{P}(X_1 \le X_0) = \mathbb{P}(X_0 \le X_1)$$

So $\mathbb{P}(N > 1) = 1/2$. (Note: $\mathbb{P}(X_1 = X_0) = 0$ by continuity.)
For $n > 1$,

$$\begin{aligned}\mathbb{P}(N > n) &= \mathbb{P}(X_1 \le X_0, \dots, X_n \le X_0) \\ &= \mathbb{P}(X_1 < X_2 < \cdots < X_n < X_0) + \cdots + \mathbb{P}(X_n < X_{n-1} < \cdots < X_1 < X_0) \\ &= n!\mathbb{P}(X_1 < X_2 < \cdots < X_n < X_0)\end{aligned}$$

And notice that $\mathbb{P}(X_1 < X_2 < \cdots < X_n < X_0) = \frac{1}{(n+1)!}$, by symmetry. Thus, we have $\mathbb{P}(N > n) = \frac{1}{n+1}$; and $\mathbb{E}N = \sum_{n=0}^{\infty} \frac{1}{n+1} = \infty$.

□

Exercise 1.2.4. $X_n \xrightarrow{\mathbb{P}} 0$ if and only if $\mathbb{E}\big(|X_n|/(1+|X_n|)\big) \to 0$.

Proof. $\implies$: By continuous mapping theorem,

$$|X_n|/(1+|X_n|) \xrightarrow{\mathbb{P}} 0.$$

Notice that $\mathbb{E}\Big(\sup_n \frac{|X_n|}{1+|X_n|}\Big) \le 1$. So $\{\frac{|X_n|}{1+|X_n|}\}_{n\in\mathbb{N}}$ is u.i.
Then use the following theorem: u.i. + $\xrightarrow{\mathbb{P}}$ $\implies$ $\xrightarrow{L^1}$.
$\impliedby$: Notice that $\xrightarrow{L^1} \implies \xrightarrow{\mathbb{P}}$. Then by continuous mapping theorem,

$$|X_n|/(1+|X_n|) \xrightarrow{\mathbb{P}} 0.$$

□

-Applications of Borel-Canteli lemma-

Exercise 1.2.5. Let $Y_n = \begin{cases} 1 & \text{w.p. } \frac{1}{n} \\ 0 & \text{w.p. } 1-\frac{1}{n} \end{cases}$ and $Z_n = \begin{cases} n^2 & \text{w.p. } \frac{1}{n^2} \\ 0 & \text{w.p. } 1-\frac{1}{n^2} \end{cases}$ be two independent RVs sequences. Assume Y and Z are independent. Define $X_n = Y_nZ_n$. Show $X_n \xrightarrow{a.s.} 0$.

Proof. First, compute the distribution of X.

$$X_n = \begin{cases} n^2 & \text{w.p. } 1/n^3 \\ 0 & \text{o.w.} \end{cases}$$

For any $\epsilon > 0$, let $A_n = \{|X_n| > \epsilon\}$. Then notice that

$$\sum_n \mathbb{P}A_n = \sum_n \frac{1}{n^3} < \infty.$$

By Borel-Canteli (a),

$$\mathbb{P}(A_n \text{ i.o.}) = 0, \ \forall \epsilon > 0.$$

$\implies \quad X_n \xrightarrow{a.s.} 0.$ □

Exercise 1.2.6. Let $H_n = \begin{cases} 1 & \text{w.p. } \frac{1}{n} \\ 0 & \text{w.p. } 1 - \frac{1}{n} \end{cases}$ be an independent RVs sequence. Define $X_n = (-1)^n n H_n$. Show that $X_n \xrightarrow{\mathbb{P}} 0$, but $\limsup_{n\to\infty} X_n = \infty$ a.s. and $\liminf_{n\to\infty} X_n = -\infty$ a.s.

Proof. First, directly check the definition of $\xrightarrow{\mathbb{P}}$.

For every $\epsilon > 0$,

$$\mathbb{P}(|X_n| > \epsilon) = \mathbb{P}(nH_n > \epsilon) \le \mathbb{P}(nH_n = n) = \frac{1}{n} \to 0.$$

$\implies \quad X_n \xrightarrow{\mathbb{P}} 0.$

Then, let $A_n = \{X_n > \frac{n}{2}\}$.

$$\sum_{n=1}^{\infty} \mathbb{P}A_n = \sum_{n=1}^{\infty} \mathbb{P}(X_n = n) = \sum_{n=2,4,\ldots} \frac{1}{n} = \infty$$

By Borel-Canteli (b),

$$\mathbb{P}(A_n \text{ i.o,}) = \mathbb{P}(X_n > \frac{n}{2} \text{ i.o.}) = \mathbb{P}(\limsup_{n\to\infty} X_n = \infty) = 1.$$

Similarly, take $B_n = \{X_n < -\frac{n}{2}\}$.

$$\sum \mathbb{P}B_n = \sum_{n=1,3,\ldots} \frac{1}{n}.$$

By Borel-Canteli (b) again,

$$\mathbb{P}(B_n \text{ i.o.}) = \mathbb{P}(\liminf_{n\to\infty} = -\infty) = 1.$$

□

Exercise 1.2.7. Let $Y_n = \begin{cases} 1 & \text{w.p. } \frac{1}{n} \\ 0 & \text{w.p. } 1 - \frac{1}{n} \end{cases}$ be an independent RVs sequence and X be another RV independent of $\{Y_n\}$. Define $Z_n = X + Y_n$. Does $\{Z_n\}$ converge weakly? in probability? a.s.?

Proof.

- **in probability.** Yes, its limit is X.

  For all $\epsilon > 0$,

$$\begin{aligned} \mathbb{P}(|Z_n - X| > \epsilon) &= \mathbb{P}(|Y_n| > \epsilon) \\ &\le \mathbb{P}(|Y_n| = 1) = 1/n \to 0 \end{aligned}$$

- **in distribution** Yes, its limit is X.

  Implied by convergence in probability.

- **a.s.** No, it doesn't converge almost surely.
  Assume (Z_n) converge almost surely. Then the limit must be X.
  For $\epsilon \in (0,1)$, let $A_n = \{|Z_n - X| > \epsilon\} = \{|Y_n| > \epsilon\}$. Because
  $$\sum_n \mathbb{P}A_n = \sum_n \mathbb{P}(Y_n = 1) = \sum_n \frac{1}{n} = \infty$$
  and $\{A_n\}$ are independent (by independence of (Y_n)), by Borel-Canteli (b),
  $$\mathbb{P}(A_n \text{ i.o.}) = 1.$$
  Thus, Z_n doesn't converge to X. Contradiction.

$\square$

-m.s. convergence-

Exercise 1.2.8. $X_n \xrightarrow{L^2} X$ as $n \to \infty$ implies that $\mathbb{E}X_n \to \mathbb{E}X$ and $\mathbb{E}X_n^2 \to \mathbb{E}X^2$.

Proof. By Minkowski inequality,

$$\begin{aligned}\|X_n\|_2 = \|X + (X_n - X)\|_2 \le \|X\|_2 + \|X - X_n\|_2,\\ \|X\|_2 = \|X_n + (X - X_n)\|_2 \le \|X_n\|_2 + \|X - X_n\|_2.\end{aligned}$$

Therefore, we have
$$\Big|\|X_n\|_2 - \|X\|_2\Big| \le \|X - X_n\|_2 \to 0.$$

$\implies \mathbb{E}X_n^2 \to \mathbb{E}X^2.$ $\square$

Exercise 1.2.9 (Loeve's criterion)**.** $\{X_n\}$ converges in L^2 if and only if $\mathbb{E}X_nX_m \to C$ as $m,n \to \infty$ for some constant C.

Proof. $\Longleftarrow$: Take $m = n$. We are done.
$\Longrightarrow$: By Cauchy criterion for L^2-convergence,

$$\|X_n - X_m\|_2 \to 0, \text{ as } m,n \to \infty.$$

Thus, we have

$$\begin{aligned}\|X_m - X_n\|_2^2 &= \mathbb{E}X_m^2 + \mathbb{E}X_n^2 - 2\mathbb{E}X_mX_n\\ \lim_{m,n\to\infty} \|X_m - X_n\|_2^2 &= \lim_{m,n\to\infty} \left(\mathbb{E}X_m^2 + \mathbb{E}X_n^2 - 2\mathbb{E}X_mX_n\right)\\ 0 &= \mathbb{E}X^2 + \mathbb{E}X^2 - 2\lim_{m,n\to\infty} \mathbb{E}X_mX_n\end{aligned}$$

It implies that $\mathbb{E}X_nX_m \to \mathbb{E}X^2$. $\square$

1.3 Weak Convergence

Definition 1.13. Let (X_n) be a sequence RVs. The following definitons of $X_n \xrightarrow{w} X$ are equivalent:

- $\mathbb{P} \circ X_n^{-1} \xrightarrow{w} \mathbb{P} \circ X^{-1}$.
- $F_n \to F$ for all continous points of F.

The following theorem can be used to check the weak convergence conveniently.

Theorem 1.14.

- ***Lévy's continuity theorem***
  Let $\{F_n\}$ be a sequence of CDFs, and $\{\phi_n\}$ be the corresponding CFs.

(i) If $F_n \xrightarrow{w} F$, then $\phi_n(t) \to \phi(t)$ for all t; and conversely,

(ii) suppose that $\lim \phi_n$ exists for all t, and ϕ is continuous at 0. Then $F_n \xrightarrow{w} F$ and $\{F_n\}$ are tight.

- ***Cramer-Wald device***

  $\{X_n\}$ are $\mathbb{R}^k$-value RVs.

$$X_n \xrightarrow{w} X \iff a^T X_n \xrightarrow{w} a^T X \quad \forall a \in \mathbb{R}^k$$

Theorem 1.15 (Scheffé's Theorem: Convergence of PDF $\implies$ Weak convergence)**.** *Assume there is a sequence of PDFs $f_n \to f_\infty$ almost surely. Define the corresponding Borel measures*

$$\mu_n(B) = \int_B f_n(x) \, \mathrm{d}x.$$

Then we have

$$\sup_{B \in \mathcal{B}(\mathbb{R})} |\mu_n(B) - \mu_\infty(B)| \to 0.$$

Remark.

- A more general result holds for L^p space ($p \geq 1$): if we have $\lim_n \|f_n\|_p = \|f\|_p$ and $f_n \xrightarrow{a.s.} f$, then

$$\lim_n \|f - f_n\|_p = 0.$$

- If we take $B = (-\infty, x]$, we can get the weak convergence.

Proof. For all $B \in \mathcal{B}(\mathbb{R})$,

$$|\int_B f_n \, \mathrm{d}x - \int_B f_\infty \, \mathrm{d}x| \leq \int_B |f_n - f_\infty| \, \mathrm{d}x.$$

Therefore,

$$\begin{aligned} \sup_B |\int_B f_n \, \mathrm{d}x - \int_B f_\infty \, \mathrm{d}x| &\leq \int_{\mathbb{R}} |f_n - f_\infty| \, \mathrm{d}x \\ &\longrightarrow 0. \end{aligned}$$

For "$\longrightarrow 0$" part, we first notice the fact where $\int (f_\infty - f) \, \mathrm{d}x = 1 - 1 = 0$, which implies that

$$\int_{\mathbb{R}} |f_n - f_\infty| \, \mathrm{d}x = 2 \int_{\mathbb{R}} (f_\infty - f_n)^+ \, \mathrm{d}x;$$

then, we use the dominated convergence theorem: because $(f_\infty - f_n)^+ < f_\infty$,

$$\lim \int (f_\infty - f_n)^+ \, \mathrm{d}x = \int \lim (f_\infty - f_n)^+ \, \mathrm{d}x.$$

□

Example 1.16 (Counterexample: Weak convergence doesn't imply the convergence of PDF)**.** Consider

$$f_n(x) = (1 - \cos 2\pi n x) \mathbf{1}_{\{0 \leq x \leq 1\}}.$$

Then for $0 < x \leq 1$,

$$\begin{aligned} F_n(x) &= \int_0^x (1 - \cos 2\pi n x) \, \mathrm{d}x \\ &= x - \frac{\sin 2\pi n x}{2\pi n} \\ &\to x \end{aligned}$$

It means the limit of weak convergence is the uniform distribution on $[0, 1]$. However, (f_n) doesn't converge to $f(x) = \mathbf{1}_{\{0 \leq x \leq 1\}}$.

Proposition 1.17 (Connection between $\xrightarrow{\mathbb{P}}$ and $\xrightarrow{w}$)**.**

- $X_n \xrightarrow{\mathbb{P}} X \implies X_n \xrightarrow{w} X$.
- $X_n \xrightarrow{\mathbb{P}} c \iff X_n \xrightarrow{w} c$.

Theorem 1.18 (Skorohod's representation theorem)**.** *If RVs $\{X_n\}$ and X have DFs $\{F_n\}$ and F such that $X_n \xrightarrow{w} X$, then there exists a probability space $(\Omega', \mathcal{F}', \mathbb{P}')$ and real-value RVs $\{Y_n\}$ and Y such that they have DFs $\{F_n\}$ and $\{F\}$, and $Y_n \xrightarrow{a.s.} Y$.*

Remark. $X_n \overset{D}{=} Y_n$; however, in general, the distribution of (X_n, X_m) doesn't equal to that of (Y_n, Y_m)!

The proof of CMT is an application of Skorohod's representation theorem.

Theorem 1.19 (Continuous mapping theorem)**.** *Let (X_n) be a sequence RVs and $f : \mathbb{R} \to \mathbb{R}$ be continuous.*

- $X_n \xrightarrow{w} X$
  $\implies \quad f \circ X_n \xrightarrow{w} X.$

Proof. By Skorohod's representation theorem, $Y_n \xrightarrow{a.s.} Y$ in $(\Omega', \mathcal{F}', \mathbb{P}')$. Using CMT of a.s. convergence,

$$f \circ Y_n \xrightarrow{a.s.} f \circ Y.$$

Note that the weak convergence is implied by a.s. convergence. Thus,

$$f \circ X_n \overset{D}{=} f \circ Y_n \xrightarrow{w} f \circ Y \overset{D}{=} f \circ X.$$

□

Theorem 1.20 (Portmanteau)**.** *Omitted.*

In the rest of part, we will focus on the tightness and vague convergence.

Question. *Does evey sequence of DFs converge?*

Theorem 1.21 (Helly's selection Theorem)**.** *Any seq. of DFs contains a convergent subseq.*

Remark. This theorem gives a partial answer for the precceding question.

Question. *If a sequence of DFs $F_n \to F$, is F a DF? When is the limit of a sequence of DFs a DF?*

Example 1.22. Let $X_n = n$ almost surely. Then $F_n(x) = \begin{cases} 0 & x < n \\ 1 & x \geq n \end{cases}$.

$\implies \quad F_n(x) = \mathbf{1}_{[n,\infty)} \to 0$ as $n \to \infty$ for all $x \in \mathbb{R}$; however, 0 is not a DF.

When $\{F_n\}$ is tight, the limit must be a DF.

Definition 1.23. $\{F_n\}$ is tight, if for all $\epsilon > 0$, there exists $M = M_\epsilon > 0$ s.t.

$$F_n([-M_\epsilon, M_\epsilon]) > 1 - \epsilon, \forall n.$$

Remark. It is equivalent to require

$$\sup_n \mathbb{P}(|X_n| > M_\epsilon) \leq \epsilon.$$

The following theorems can be used to check tightness.

Theorem 1.24 (Prohorov)**.** *Every subsequential limit the DF of a prob. measure $\iff$ $\{F_n\}$ is tight.*

Theorem 1.25. *Let (X_n) be RVs with DFs $\{F_n\}$. If there is $\varphi \geq 0$ s.t. $\varphi \uparrow \infty$ as $|x| \uparrow \infty$ and*

$$C = \sup_n \mathbb{E}\varphi(X_n) < \infty$$

$\implies$ *$\{F_n\}$ is tight.*

Remark. The most commonly choice of φ is $\varphi(x) = |x|^r$ for $r > 0$.

Exercises

Exercise 1.3.1. (a) Let X_n and X be positive integer-values RVs. Prove

$$X_n \xrightarrow{w} X \iff \mathbb{P}(X_n = k) \to \mathbb{P}(X = k),\ \forall k \in \mathbb{N}.$$

(b) Let (X_n) be a sequence of RV with $\mathbb{P}(X_n = 1 - 1/n) = 1/2$ and with $\mathbb{P}(X_n = 1 + 1/n) = 1/2$. Show that $X_n \xrightarrow{w} 1$ but the pmf of X_n doesn't converge to that of 1.

Proof. (a) $\Longleftarrow$: The CDF of X_n is

$$F_n(t) = \sum_{k=1}^{\lfloor t \rfloor} \mathbb{P}(X_n = k).$$

Because $\mathbb{P}(X_n = k) \to \mathbb{P}(X = k)$ as $n \to \infty$, we have

$$F_n(t) \to F(t).$$

$\Longrightarrow$: Notice that

$$\begin{aligned}
\mathbb{P}(X_n = k) &= \mathbb{P}(X_n \le k) - \mathbb{P}(X_n \le k-1) \\
\lim_{n\to\infty} \mathbb{P}(X_n = k) &= \lim_{n\to\infty} \Big(\mathbb{P}(X_n \le k) - \mathbb{P}(X_n \le k-1)\Big) \\
\lim_{n\to\infty} \mathbb{P}(X_n = k) &= \mathbb{P}(X = k)
\end{aligned}$$

(b) Compute the CDF of X_n:

$$\begin{aligned}
F_n(t) = \mathbb{P}(X_n \le t) &= \begin{cases} 1 & t \ge 1 + \frac{1}{n} \\ \frac{1}{2} & 1 + \frac{1}{n} > t \ge 1 - \frac{1}{n} \\ 0 & t < 1 - \frac{1}{n} \end{cases} \\
&= \frac{1}{2}\mathbf{1}_{\{t \ge 1 + \frac{1}{n}\}} + \frac{1}{2}\mathbf{1}_{\{t \ge 1 - \frac{1}{n}\}}
\end{aligned}$$

$\Longrightarrow$ $\lim_{n\to\infty} F_n(t) = \frac{1}{2}\mathbf{1}_{\{t>1\}} + \frac{1}{2}\mathbf{1}_{\{t\ge1\}} = \mathbf{1}_{\{t>1\}} + \frac{1}{2}\mathbf{1}_{\{t=1\}}$
And we notice that the distribution function of X is

$$F(t) = \mathbb{P}(X \le t) = \mathbf{1}_{\{t \ge 1\}}.$$

Therefore, $X_n \xrightarrow{w} X$; because $t = 1$ is the unique discontinuous point of F.

Now we compute the pmf of X_n:

$$p_n(x) = \mathbb{P}(X_n = x) = \begin{cases} \frac{1}{2} & x = 1 \pm \frac{1}{n} \\ 0 & \text{o.w.} \end{cases}$$

$\Longrightarrow$ $\lim_{n\to\infty} p_n(x) = 0$.

However, $p(x) = \mathbb{P}(X = x) = \begin{cases} 1 & x = 1 \\ 0 & \text{o.w.} \end{cases}$. Thus, the pmf of X_n doesn't converge to that of X.

□

Exercise 1.3.2 (Discrete RVs with a continuous weak limit)**.** Suppose F_n puts mass $\frac{1}{n}$ at points $\{\frac{1}{n}, \frac{2}{n}, \dots, \frac{n}{n}\}$. If $F(x) = x$ on $[0, 1]$, then show that $F_n \to F$.

Proof. Compute F_n:

$$F_n(t) = \sum_{k=1}^{n} \frac{1}{n} \mathbf{1}_{\{t \geq \frac{k}{n}\}}.$$

If $t \geq 1$ or $t \leq 0$, there is nothing to prove. Assume $0 < t < 1$.
Notice that for every $\epsilon > 0$, letting $N_0 > \frac{1}{\epsilon}$, $\forall n > N_0$, $\exists k = k(n)$ s.t. $\frac{k}{n} \leq t \leq \frac{k+1}{n}$,

$$|F_n(t) - t| \leq \frac{1}{n} < \epsilon.$$

$\implies F_n(t) \to t.$ $\square$

-Applications of Skorohod's representation theorem-

Exercise 1.3.3. Let $X_n \xrightarrow{w} X$, $a_n \to a$, and $b_n \to b$. Show that $a_n X_n + b_n \xrightarrow{w} aX + b$.

Proof. By Skorohod's, there exists $\{Y_n\}$ and Y such that $Y_n \xrightarrow{a.s.} Y$. So $a_n Y_n + b_n \xrightarrow{a.s.} aY + b$.
$\implies a_n Y_n + b_n \xrightarrow{w} aY + b$
$\implies a_n X_n + b_n \xrightarrow{w} aX + b$, by noticing that $a_n X_n + b_n \overset{D}{=} a_n Y_n + b_n$, and $aX + b \overset{D}{=} aY + b$. $\square$

Exercise 1.3.4 (Fatou's lemma)**.** Let $g \geq 0$ be continuous, and $X_n \xrightarrow{w} X$. Show that

$$\liminf_n \mathbb{E}g(X_n) \geq \mathbb{E}g(X).$$

Proof. By Skorohod's, $\exists Y_n \xrightarrow{a.s.} Y$ with $Y_n \overset{D}{=} X_n$ and with $Y \overset{D}{=} X$. By Fatou's lemma,

$$\liminf \mathbb{E}g(Y_n) \geq \mathbb{E}g(Y).$$

Because $Y_n \overset{D}{=} X_n$ and $Y \overset{D}{=} X \implies \mathbb{E}g(Y_n) = \mathbb{E}g(X_n),\ \mathbb{E}g(Y) = \mathbb{E}g(X)$. Thus,

$$\liminf \mathbb{E}g(X_n) \geq \mathbb{E}g(X).$$

$\square$

-Slutsky's theorem-

Exercise 1.3.5. Let $X_n \xrightarrow{w} X$. Show the following results:

(a) $|Y_n - X_n| \xrightarrow{w} 0$, then $Y_n \xrightarrow{w} X$.

(b) $Y_n \xrightarrow{w} c$, then $(X_n, Y_n) \xrightarrow{w} (X, c)$.

(c) $Y_n \xrightarrow{w} c$, then $X_n + Y_n \xrightarrow{w} X + c$, $X_n Y_n \xrightarrow{w} cX$, and $X_n / Y_n \xrightarrow{a.s.} X/c$.

1.4 Examples

Example 1.26 (Counterexample: $X_n \xrightarrow{a.s.} X$ but not $X_n \xrightarrow{L^p} X$)**.**
Let $\{X_n\}$ be a sequence of independent RVs such that $\mathbb{P}(X_n = n^3) = \frac{1}{n^2}$ and $\mathbb{P}(X_n = 0) = 1 - \frac{1}{n^2}$.
It converges to 0 almost surely by Borel-Canteli (a); however, it doesn't converge in L^1 because we have $\mathbb{E}|X_n| = n$.

Example 1.27.
Let N_t be a Poisson process with $\mathbb{E}N_t = \lambda t$. Define $X_t = N_t / t$.

- We consider its limit when $t \to \infty$.

  It is easy to see $\mathbb{E}|X_t - 0| = \lambda \not\to 0$; moreover, $X_t \to \lambda$ almost surely. See here for another proof.

  First, for $n \in \mathbb{N}$, we re-write $N_n = \sum_{i=1}^n (N_i - N_{i-1})$. By SLLN,

$$N_n/n \xrightarrow[\text{a.s.}]{L^2} \mathbb{E}(N_1 = N_0) = \lambda.$$

  Then, for $t \in \mathbb{R}_+$, we re-write $N_t = N_{\lfloor t \rfloor} + (N_t - N_{\lfloor t \rfloor})$; so

$$N_t/t = N_{\lfloor t \rfloor}/\lfloor t \rfloor \cdot \frac{\lfloor t \rfloor}{t} + (N_t - N_{\lfloor t \rfloor})/t.$$

  It suffices to prove $\limsup_t (N_t - N_{\lfloor t \rfloor})/t = 0$. We can use the tail probabilities of Poisson RV

$$\mathbb{P}(X \geq x) \leq e^{-\lambda}(e\lambda)^x / x^x.$$

  Then $\sum_{n=1}^\infty \mathbb{P}(N_{t_n} - N_{\lfloor t_n \rfloor} \geq t\epsilon)$ converges. Finally, use Borel-Cantelli (a).

- And we are also interested in the limit when $t \to 0$. Its L^1 limit is same.

  However, it almost sure limit is 0.

Example 1.28 (Counterexample: $X_n \xrightarrow{L^p} X$ but not $X_n \xrightarrow{a.s.} X$)**.**
Let $\{X_n\}$ be a sequence of independent RVs such that $\mathbb{P}(X_n = 1) = \frac{1}{n}$ and $\mathbb{P}(X_n = 0) = 1 - \frac{1}{n}$. Then $X_n \xrightarrow{L^1} 0$ but X_n doesn't converge to 0 almost surely.
See Exercise 1.2.6.

Example 1.29 (Counterexample: $X_n \xrightarrow{\mathbb{P}} X$ but not $X_n \xrightarrow{L^p} X$)**.**
Let $\{X_n\}$ be a sequence of independent RVs such that $\mathbb{P}(X_n = n^3) = \frac{1}{n^2}$ and $\mathbb{P}(X_n = 0) = 1 - \frac{1}{n^2}$. Then $X_n \xrightarrow{\mathbb{P}} 0$ but X_n doesn't converge to 0 in L^p for $p \geq 1$.
Because for every $\epsilon > 0$, $\mathbb{P}(|X_n| > \epsilon) = \mathbb{P}(X_n = n^3) = \frac{1}{n^2} \to 0$. However,

$$\mathbb{E}X^p = \frac{1}{n^2} n^{3p} = n^{3p-2} \to \infty.$$

Example 1.30 (Two Counterexamples: $X_n \xrightarrow{\mathbb{P}} X$ but not $X_n \xrightarrow{a.s.} X$)**.**

- $\Omega = (0, 1]$; $\mathcal{H} =$ the Borel σ-algebra on Ω; $\mathbb{P} =$ the Lebesgue measure.

  Define the following sequence of RVs

$$\begin{aligned}
&X_1 = \mathbf{1}_{(0,1]};\\
&X_2 = \mathbf{1}_{(0,\frac{1}{2}]},\ X_3 = \mathbf{1}_{(\frac{1}{2},1]};\\
&X_4 = \mathbf{1}_{(0,\frac{1}{3}]},\ X_5 = \mathbf{1}_{(\frac{1}{3},\frac{2}{3}]},\ X_6 = \mathbf{1}_{(\frac{2}{3},1]};\\
&\cdots
\end{aligned}$$

  It converges in probability, because $\mathbb{P}\{X_n > \epsilon\}$ form the sequence $(1, \frac{1}{2}, \frac{1}{2}, \frac{1}{3}, \frac{1}{3}, \frac{1}{3}, \dots)$.

  But it doesn't converge a.s. because $\liminf X_n(\omega) = 0$ and $\limsup X_n(\omega) = 1$ for every $\omega \in \Omega$.

- Let (X_n) be a sequence of independent RVs with $\mathbb{P}(X_n = 1) = p_n$ and $\mathbb{P}(X_n = 0) = 1 - p_n$, and $\sum p_n = \infty$. Then $X_n \xrightarrow{\mathbb{P}} 0$ but X_n doesn't converge to 0 almost surely.

  It is because $\mathbb{P}(|X_n - 0| > \epsilon) = p_n \to 0$, so $X_n \xrightarrow{\mathbb{P}} 0$; however, letting $A_n = \{|X_n| > \epsilon\}$, we have

$$\sum_{n=1}^\infty \mathbb{P}A_n = \sum_{n=1}^\infty p_n = \infty.$$

  By Borel-Canteli (b), $X_n \not\to 0$ almost surely.

Example 1.31 (Counterexample: $X_n \xrightarrow{\mathbb{P}} X$ but not $X_n \xrightarrow{L^p} X$)**.**

Let $\Omega = (0,1]$; $\mathcal{H} =$ the Borel σ-algebra on Ω; $\mathbb{P} =$ the Lebesgue measure.

Define $X_n = 2^n \mathbf{1}_{(0,\frac{1}{n})}$. Then $X_n \xrightarrow{\mathbb{P}} 0$ but X_n doesn't converge to 0 in L^p for all $p \geq 1$.

$\mathbb{P}(|X_n - 0| > \epsilon) = \frac{1}{n} \to 0$, so $X_n \xrightarrow{\mathbb{P}} 0$; however,

$$\mathbb{E}|X_n - 0| = \mathbb{E}X_n = 2^n \cdot \frac{1}{n} \to \infty.$$

Thus, it doesn't converge to 0 in L^1.

Example 1.32 (Two Counterexamples: $X_n \xrightarrow{w} X$ but not $X_n \xrightarrow{\mathbb{P}} X$)**.**

- Let $X \sim \text{Bin}(1, \frac{1}{2})$, and $\{X_n\}$ be a sequence of RVs given by $X_n = X$ for all n. Then $X_n \xrightarrow{w} 1-X$; however, X_n doesn't converge to $1 - X$ in probability.

  And the weak limit is unique (in distribution) because $X \overset{D}{=} 1 - X$.

- Let $N \sim N(0,1)$ and $X_n = (-1)^n N$.

  It is easy to see $X_n \xrightarrow{w} N$, for $X_n \sim N(0,1)$, $\forall n$.

  Howerver, X_n doesn't converge to N, because when n is odd, $\mathbb{P}(|X_n - N| > \epsilon) = \mathbb{P}(|N| > \frac{\epsilon}{2}) > 0$.

1.5 The Moment Problem

Theorem 1.33. *If $X_n \xrightarrow{w} X$, then $\forall \beta > 0$, the following are equivalent:*

(a) $\mathbb{E}|X_n|^\beta < \infty$ for all n, $\mathbb{E}|X| < \infty$, and $\mathbb{E}|X_n|^\beta \to \mathbb{E}|X|^\beta$.

(b) $\{|X_n|^\beta\}$ is u.i.

Question. *Let X be a RV with DF F, and its all finite-order moments $m_k = \mathbb{E}X^k$. Is F the only DF with this moment sequence?*

Example 1.34 (Heyde)**.** Assume $X \sim N(0,1)$, $Y = e^X$. Consider the following PDFs:

$$f_Y(x) = \frac{1}{x\sqrt{2\pi}} e^{-\frac{1}{2}(\log x)^2} \mathbf{1}_{\{x>0\}}$$
$$f_a(x) = f_Y(x)(1 + a \sin(2\pi \log x)) \quad |a| \leq 1$$

In fact, f_a is a density function with finite moments of all oreders, none of which depend on the value of a. Thus, we construct a family of RVs that admit the same moment sequence.

Theorem 1.35. *The moment problem has a unique solution, if one of the following conditions is satisfied:*

a)

$$\limsup_k \frac{(m_{2k})^{1/2k}}{2k} = r < \infty$$

b) Carleman's.

$$\sum_{k=1}^{\infty} \frac{1}{(m_{2k})^{1/2k}} < \infty$$

2 Law of Large Numbers and Central Limit Theorem

2.1 Strong Law of Large Numbers and Weak Law of Large Numbers

Theorem 2.1 (SLLN)**.**

- (X_n) - *i.i.d. RVs.* $\mathbb{E}X_i = \mu$. $\mathbb{E}X_i^2 < \infty$. *Then*

$$\frac{1}{n}\sum_{i=1}^{n} X_i \xrightarrow[L^2]{a.s.} \mu.$$

- X_i *are uncorrelated RVs.* $\mathbb{E}X_i = \mu$ *and* $\mathrm{Var}X_i \leq C < \infty$. *Then*

$$S_n/n \xrightarrow[L^2]{a.s.} \mu.$$

- (X_n) - *i.i.d. RVs. Then* $\frac{1}{n}\sum_{i=1}^{n} X_i \xrightarrow{a.s.} \mu$ *for some* μ *if and only if* $\mathbb{E}|X_i| < \infty$.

Remark. SLLN holds $\iff$ $\mathbb{P}(\lim_{n\to\infty} S_n/n = \mu) = 1$. Therefore, to show SLLN doesn't hold, we have two methods:

(i) When X_i are iid, show $\mathbb{E}|X_i| = \infty$.

(ii) Use B-C lemma (b) to show $\mathbb{P}(|S_n/n - \mu| > 0 \text{ i.o.}) = 1$. Then $\mathbb{P}(\lim_{n\to\infty} S_n/n = \mu) < 1$.

Theorem 2.2 (WLLN)**.** $\{X_n\}$ *are independent RVs. Define* $S_n = \sum_{j=1}^{n} X_j$, *and*

$$a_n = \sum_{j=1}^{n} \mathbb{E}(X_j 1_{\{|X_j|\leq n\}}).$$

Then

$$\frac{S_n - a_n}{n} \xrightarrow{\mathbb{P}} 0$$

if and only if the following conditions hold:

a) $\sum_{j=1}^{n} \mathbb{P}(|X_j| > n) \to 0$ *as* $n \to \infty$.

b) $\frac{1}{n^2}\sum_{j=1}^{n} \mathbb{E}(X_j^2 \mathbf{1}_{\{|X_n|\leq n\}}) \to 0$ *as* $n \to \infty$.

Remark. No assumptions of moments of X_j's are made. Note that now we have two methods to show WLLN holds:

(i) Check these conditons.

(ii) Show $\mathbb{P}(|S_n/n - \mu| > \epsilon) \to 0$ for all $\epsilon > 0$. (i.e. check the def. of conv. in prob.)

The following corollary is an example of how to check the conditions of WLLN.

Corollary 2.3 (Feller's WLLN)**.** *Let* $\{X_n\}$ *be i.i.d. with* $\lim\limits_{n\to\infty} x\mathbb{P}(|X| > x) = 0$. *Then*

$$S_n/n - \mathbb{E}(X\mathbf{1}_{\{|X|\leq n\}}) \xrightarrow{\mathbb{P}} 0,$$

as $n \to \infty$.

Proof. Check (a) + (b).

To check (a), we notice

$$\begin{aligned}\sum_{j=1}^{n} \mathbb{P}(|X_j| \geq n) &= n\mathbb{P}(|X| > n) \quad \text{(by iid)}\\ &\longrightarrow 0 \quad \text{(it is given)}\end{aligned}$$

To check (b), we have

$$
\begin{aligned}
\frac{1}{n^2}\sum_{j=1}^{n}\mathbb{E}(X_j^2\mathbf{1}_{\{|X_j|\le n\}}) &= \frac{1}{n}\mathbb{E}(X^2\mathbf{1}_{|X|\le n}) \quad \text{(by iid)}\\
&= \frac{1}{n}\int_{|X|\le n} X^2 \ \mathrm{d}\mathbb{P}\\
&= \frac{1}{n}\int_{|X|\le n} (\int_0^{|X|} 2y \ \mathrm{d}y) \ \mathrm{d}\mathbb{P}\\
&= \frac{1}{n}\int_{|x|\le n} (\int_0^{|x|} 2y \ \mathrm{d}y) \ \mathrm{d}\mathbb{P}\circ X^{-1}\\
&= \frac{1}{n}\int_0^{n} (\int_y^{n} 2y \ \mathrm{d}\mathbb{P}\circ X^{-1}) \ \mathrm{d}y \quad \text{(Fubini)}\\
&= \frac{1}{n}\int_0^{n} 2y\Big(\mathbb{P}(|X|>y)-\mathbb{P}(|X|>n)\Big) \ \mathrm{d}y\\
&= \frac{2}{n}\int_0^{n} y\mathbb{P}(|X|>y) \ \mathrm{d}y - n\mathbb{P}(|X|>n)
\end{aligned}
$$

Let $\tau(y) = y\mathbb{P}(|X|>y)$. We just showed

$$
\frac{1}{n^2}\sum_{j=1}^{n}\mathbb{E}(X_j^2\mathbf{1}_{\{|X_j|\le n\}}) = \frac{1}{n}\int_0^n \tau(y) \ \mathrm{d}y - \tau(n).
$$

Note that $\tau(n)\to 0$ is given. So it remains to show that

$$
\frac{1}{n}\int_0^n \tau(y) \ \mathrm{d}y \to 0.
$$

Let $M = \sup_{y\ge 0}\tau(y)$, and $\epsilon_k = \sup\{\tau(y) : y > k\}$.
For $0<k<n$,

$$
\begin{aligned}
\frac{1}{n}\int_0^n \tau(y) \ \mathrm{d}y &= \frac{1}{n}\int_0^k \tau(y) \ \mathrm{d}y + \frac{1}{n}\int_k^n \tau(y) \ \mathrm{d}y\\
&\le \frac{1}{n}\int_0^k M \ \mathrm{d}y + \frac{1}{n}\int_k^n \epsilon_k \ \mathrm{d}y\\
&= \frac{1}{n}kM + \frac{1}{n}(n-k)\epsilon_k.
\end{aligned}
$$

$\implies$ $\limsup \frac{1}{n}\int_0^n \tau(y) \le \epsilon_k$. Then, we let $k\to\infty$. ☐

Corollary 2.4 (Khinchin's WLLN)**.** *Let $\{X_n\}$ be i.i.d. RVs such that $\mathbb{E}|X| = \mu < \infty$. Then*

$$
S_n/n \xrightarrow{\mathbb{P}} \mu.
$$

Proof. It suffices to check the condition of Feller's WLLN. We notice that

$$
\begin{aligned}
x\mathbb{P}(|X|>x) &= x\cdot\mathbb{E}\mathbf{1}_{\{|X|>x\}}\\
&\le \mathbb{E}|X|\mathbf{1}_{\{|X|>x\}}\\
&\longrightarrow 0
\end{aligned}
$$

because X is integrable. Thus, $S_n/n \xrightarrow{\mathbb{P}} \mu$. ☐

Exercises

Exercise 2.1.1. Let $\{X_n\}$ be a sequence i.i.d RVs with $\mathbb{E}X_n = 0$ and $\mathbb{E}X_n^2 < \infty$. Let (c_n) be a bounded sequence of real numbers and define $Z_n = \frac{1}{n}\sum_{i=1}^n c_i X_i$. Show that $Z_n \xrightarrow{\mathbb{P}} 0$ as $n \to \infty$.

Proof. Directly use SLLN. $\square$

Exercise 2.1.2 (WLLN for a Triangular Array)**.** Let $\{X_{n,k},\ 1 \le k \le n,\ n \ge 1\}$ be a family of RVs and $S_n = X_{n,1} + \cdots + X_{n,n}$. Let $\mathbb{E}S_n = a_n$ and $\sigma_n^2 = \mathrm{Var}S_n$. If $\sigma_n^2/b_n^2 \to 0$ for some sequence $\{b_n\}$, then

$$\frac{S_n - a_n}{b_n} \xrightarrow{\mathbb{P}} 0.$$

Proof. Check the definition of $\xrightarrow{\mathbb{P}}$.

For all $\epsilon > 0$:

$$\begin{aligned}
\mathbb{P}(|\frac{S_n - a_n}{b_n}| > \epsilon) &= \mathbb{P}(|S_n - a_n| > \epsilon |b_n|) \\
&\le \frac{\mathrm{Var}S_n}{\epsilon^2 b_n^2} \quad \text{(Chebyshev)} \\
&\longrightarrow 0 \quad (\frac{\sigma^2}{b_n^2} \to 0)
\end{aligned}$$

$\square$

Exercise 2.1.3 (Monte Carlo Integration)**.** Let f be a measurable function on $[0,1]$ with $\int_0^1 |f(x)|\ \mathrm{d}x < \infty$, and $\{U_n\}_{n\in\mathbb{N}}$ be i.i.d. RVs uniform on $[0,1]$. (a) Prove

$$I_n = \frac{f(U_1) + \cdots + f(U_n)}{n} \xrightarrow{\mathbb{P}} I = \int_0^1 f(x)\ \mathrm{d}x.$$

(b) Estimate $\mathbb{P}(|I - I_n| > a/n^{1/2})$, $a > 0$.

Proof. (a) Check the conditions of Khinchin's WLLN.

First, $f(U_1), \ldots, f(U_n)$ are iid. And second, $\mathbb{E}f(U) = \int_0^1 f(u)\ \mathrm{d}u \le \int_0^1 |f(u)|\ \mathrm{d}u < \infty$.

By Khinchin's WLLN, $\frac{f(U_1)+\cdots+f(U_n)}{n} \xrightarrow{\mathbb{P}} \mathbb{E}f(U) = \int_0^1 f(u)\ \mathrm{d}u$.

(b) Note $\mathbb{E}I_n = I$.

$$\begin{aligned}
\mathbb{P}(|I - I_n| > \frac{a}{n^{1/2}}) &\le \frac{\mathrm{Var}I_n}{a^2/n} \\
&= \frac{\frac{1}{n^2} \cdot n\mathrm{Var}f(U)}{a^2/n} \\
&= \frac{1}{a^2}\mathrm{Var}f(U)
\end{aligned}$$

$\square$

Exercise 2.1.4. Prove the following WLLN using the method of CFs:

Let (X_n) be i.i.d. with mean $\mu < \infty$, and $S_n = \sum_{i=1}^n X_i$. Then $S_n/n \xrightarrow{\mathbb{P}} \mu$ as $n \to \infty$.

Exercise 2.1.5 (WLLN fails)**.** Let (Y_n) be i.i.d Cauchy RVs. Show that $\bar{Y}_n = \sum_{i=1}^n Y_i/n$ also has the Cauchy density. Check the condition of Feller's WLLN, and explain why the WLLN does not hold.

Exercise 2.1.6. Let X_i be iid RVs such that $\mathbb{E}|X_i| = \infty$. Show that

$$\mathbb{P}(|X_n| > n \text{ i.o.}) = 1$$

and

$$\mathbb{P}(\lim_{n\to\infty} \bar{X} \in (-\infty, +\infty)) = 0.$$

Exercise 2.1.7. Let (X_n) be a sequence of independent RVs such that $\mathbb{E}X_n = 0$ and $\mathbb{E}X_n^2 = Cn^\alpha$ for some $C > 0$, $\alpha \geq 0$, and $n = 1, 2, \ldots$. Describe the set of values of α for which the WLLN holds.

-Examples: SLLN doesn't hold-

Exercise 2.1.8. Let $1 - F(x) = \frac{e}{2x \log x} \mathbf{1}_{\{x \geq e\}}$. And $X_n \overset{iid}{\sim} F$. Show that WLLN holds but SLLN fails.

Proof. To show SLLN doesn't hold, it suffices to show $\mathbb{E}|X_i| = \infty$ (Just compute its integral). Then use the result of Exercise 2.1.6.

And to prove WLLN holds, we use Feller's WLLN: we only need to check

$$x\mathbb{P}(|X| > x) = x \cdot 2(1 - F(x)) \to 0;$$

therefore, $S_n/n \xrightarrow{\mathbb{P}} 0$. □

Exercise 2.1.9. Let X_i be a sequence of indep. RVs. $\mathbb{P}(X_n = n) = \mathbb{P}(X_n = -n) = \frac{1}{2}[n \log(n+2)]^{-1}$ and $\mathbb{P}(X_n = 0) = 1 - [n \log(n+2)]^{-1}$.

(a) Show that $\{X_n\}$ is tight.

(b) Show that SLLN doesn't hold.

(c) Show that WLLN holds.

Proof. Omitted. See Exercise 2.1.11. □

-Trancation technique-

Exercise 2.1.10. Let $X_n, X \in L^p$ be two RVs with $X_n \xrightarrow{a.s.} X$ and with $\|X_n\|_p \to \|X\|_p$. Show that

$$X_n \xrightarrow{L^p} X.$$

Proof. **Trancation techenique.** Define

$$X_n^* = \begin{cases} X_n & |X_n| \leq |X|, \\ |X| \cdot \mathrm{sgn} X_n & |X_n| > |X|. \end{cases}$$

Notice that

$$\|X_n - X\|_p \leq \|X_n - X_n^*\|_p + \|X - X_n^*\|_p.$$

To show $X_n \xrightarrow{L^p} X$, it suffices to prove that

$$\|X_n - X_n^*\|_p \to 0 \quad \text{and} \quad \|X - X_n^*\|_p \to 0$$

as $n \to \infty$.

- We have $|X - X_n^*| \leq |X| + |X_n^*| \leq 2|X|$. Thus, $|X - X_n^*|$ is dominated by an integrable RV $2|X|$. By the dominated convergence theorem

  $$\lim \mathbb{E}|X - X_n^*|^p = \mathbb{E} \lim |X - X_n^*|^p = 0;$$

  that is $\|X - X_n^*\|_p \to 0$.

- Moreover, we can get $\lim \mathbb{E}|X_n^*|^p = \mathbb{E} \lim |X_n^*|^p = \mathbb{E}|X|^p$, by using the dominated convergence theorem and noticing that $X_n^* \to X$.

- We have $|X_n - X_n^*| = |X_n| - |X_n^*|$, by noticing the definition of X_n^* and using $X_n = |X_n| \cdot \mathrm{sgn} X_n$. So we can get

  $$|X_n - X_n^*|^p \leq |X_n|^p - |X_n^*|^p$$

  by the convexity of $x \mapsto x^p$. Then

  $$\mathbb{E}|X_n - X_n^*|^p \leq \mathbb{E}|X_n|^p - \mathbb{E}|X_n^*|^p \to \mathbb{E}|X|^p - \mathbb{E}|X|^p = 0;$$

  that is $\|X_n^* - X_n\| \to 0$.

$\square$

-Tightness and SLLN-

Exercise 2.1.11. (a) If $\{X_n\}$ is a tight sequence of independent RVs with its r-th moments ($r > 1$) uniformly bounded, then $\{X_n\}$ satisfies the SLLN.

(b) Let $\{X_n\}$ be a sequence of independent RVs such that

$$X_n = \begin{cases} n & w.p.\ \frac{1}{2}[n\log(n+2)]^{-1} \\ 0 & w.p.\ 1-[n\log(n+2)]^{-1} \\ -n & w.p.\ \frac{1}{2}[n\log(n+2)]^{-1} \end{cases}.$$

Show that $\{X_n\}$ is tight.

(d) Show that the first moments of $\{X_n\}$ are uniformly bounded.

(c) Show that SLLN doesn't hold for $\{X_n\}$.

2.2 Central Limit Theorem (CLT)

Theorem 2.5 (iid sequence)**.** *Let X_i be iid RVs with $\mathbb{E}X_i = \mu$ and $\mathrm{Var}X_i = \sigma^2 \in (0,\infty)$. Then*

$$n^{1/2}(\bar{X}-\mu)/\sigma \xrightarrow{w} Z$$

where $Z \sim N(0,1)$.

Theorem 2.6 (Lindeberg-Feller)**.** *For each n, let $X_{n,m}$, $1 \le n \le m$, be independent RVs with $\mathbb{E}X_{n.m} = 0$. Suppose*

(i) $\sum_{m=1}^n \mathbb{E}X_{n,m}^2 \to \sigma^2 > 0$; and

(ii) For all $\epsilon > 0$,

$$\lim_{n\to\infty} \sum_{m=1}^{n} \mathbb{E}(X_{n,m}^2 \mathbf{1}_{\{|X_{n,m}|>\epsilon\}}) = 0.$$

Then $S_n = X_{n,1} + \cdots + X_{n,n} \xrightarrow{w} \sigma Z$.

Remark. Lindeberg-Feller conditons are not necessary. For example, let $X_k \sim N(0, 2^{k-2})$ for $k \ge 2$ and let $X_1 \sim N(0,1)$.

Exercises

Exercise 2.2.1. Let $\{X_n\}$ be a sequence i.i.d RVs with $\mathbb{E}X_n = 0$ and $\mathbb{E}X_n^2 < \infty$. Let $S_n = \sum_{i=1}^n X_i$. Show that S_n^2, appropriately normalized, converges in distribution as $n \to \infty$.

Proof. First, use CLT to show $S_n/n \xrightarrow{w} N(0, \sigma^2/n)$. Then use CMT to get its limit, chi-square distribution. $\square$

2.3 Delta's Method

Theorem 2.7. *Let g be a smooth function which has non-zero derivative at μ. If $X_n \xrightarrow{w} N(\mu, \sigma_n^2)$ with $\sigma_n^2 \to 0$, then*

$$g(X_n) \xrightarrow{w} N(g(\mu), [g'(\mu)]^2\sigma_n^2).$$

3 Discrete-Time Martingales

3.1 Conditional Expectation

Definition 3.1. Let X be a RV on $(\Omega, \mathcal{F}, \mathbb{P})$ s.t. $\mathbb{E}|X| < \infty$, $\mathcal{F}_1 \subset \mathcal{F}$ be a sub-σ-algebra of $\mathcal{F}$.
Then $Y = \mathbb{E}(X|\mathcal{F}_1)$ (the conditional expectation of X given $\mathcal{F}_1$) is a RV s.t.

- $Y \in \mathcal{F}_1$ and $\mathbb{E}|Y| < \infty$
- $\forall A \in \mathcal{F}_1,\ \int_A X \, \mathrm{d}\mathbb{P} = \int_A Y \, \mathrm{d}\mathbb{P}$ (i.e. $\mathbb{E}(X 1_A) = \mathbb{E}(Y 1_A)$).

Remark. In L^2 space, the conditional expectation can be considered as the orthogonal projection in m.s. sense; that is

$$\|X - \mathbb{E}(X|\mathcal{F}_1)\| = \min_{Z \in \mathcal{F}_1} \|X - Z\|.$$

Proposition 3.2.

- ***Linearity.*** $\mathbb{E}(\alpha X + \beta Y|\mathcal{F}_1) = \alpha\mathbb{E}(X|\mathcal{F}_1) + \beta\mathbb{E}(Y|\mathcal{F}_1)$
- *X is independent of $\mathcal{F}_1 \implies \mathbb{E}(X|\mathcal{F}_1) = \mathbb{E}X$.*
- *$X \in \mathcal{F}_1 \implies \mathbb{E}(XY|\mathcal{F}_1) = X\mathbb{E}(Y|\mathcal{F}_1)$.*
- *$\mathbb{E}(\mathbb{E}(X|\mathcal{F}_1)) = \mathbb{E}(X)$.*
- *σ-algebra $\mathcal{F}_2 \subset \mathcal{F}_1 \subset \mathcal{F} \implies \mathbb{E}(\mathbb{E}(X|\mathcal{F}_1)|\mathcal{F}_2) = \mathbb{E}(X|\mathcal{F}_2)$.*
- ***Monotone Convergence Theorem.*** *If $X_n \geq 0$ and $X_n \uparrow X$ almost surely, then*
$$\mathbb{E}(X_n|\mathcal{F}_1) \uparrow \mathbb{E}(X|\mathcal{F}_1), \ a.s.$$
- ***Dominated Convergence Theorem.*** *If $X_n \xrightarrow{a.s.} X$ and $|X_n| \leq Y$ with $\mathbb{E}Y < \infty$, then*
$$\mathbb{E}(X_n|\mathcal{F}_1) \xrightarrow{a.s.} \mathbb{E}(X|\mathcal{F}_1).$$
- ***Jensen's Inequality.*** *Let g be convex. Then*
$$\mathbb{E}(g(X)|\mathcal{F}_1) \geq g(\mathbb{E}(X|\mathcal{F}_1)).$$

Exercises

Exercise 3.1.1. Let X be an integrable *RV* on $(\Omega, \mathcal{F}, \mathbb{P})$, and $H \in \mathcal{F}$.

(a) Let $\mathcal{F}_1 = \{\emptyset, \Omega\}$. Find all RVs which are measurable w.r.t. $\mathcal{F}_1$, and find $\mathbb{E}(X|\mathcal{F}_1)$.

(b) Let $\mathcal{F}_H = \{\emptyset, H, H^c, \Omega\}$. Find $\mathbb{E}(X|\mathcal{F}_H)$.

Proof. (a) **First**, we prove all constant maps are measurable w.r.t $\mathcal{F}_1$.

For all $c \in \mathbb{R}$, we define $c : \Omega \to \mathbb{R}$ by $\omega \mapsto c$ (constant maps). Then

$$\{c \leq x\} = \begin{cases} \Omega & x \geq c; \\ \emptyset & x < c. \end{cases}$$

$\implies c \in \mathcal{F}_1$.

Then, we prove if $f \in \mathcal{F}_1$, then f is a constant map.

Assume f is not a constant map; that is $\exists \omega_1, \omega_2$ s.t. $f(\omega_1) \neq f(\omega_2)$.

Let $c_1 = f(\omega_1)$ and $c_2 = f(\omega_2)$. WLOG, $c_1 < c_2$. Consider the following set

$$A = \{f < c_2\}.$$

Notice that $\omega_1 \in A$ and $\omega_2 \notin A$, which implies $A \notin \mathcal{F}_1$; that is, f is not measurable. Contradiction.

Finally, to compute $\mathbb{E}(X|\mathcal{F}_1)$, it suffices to notice that $\mathbb{E}(X|\mathcal{F}_1) \in \mathcal{F}_1$. So it is a constant map.

Let $c = \mathbb{E}(X|\mathcal{F}_1)$. Take expectation on both sides. We get $\mathbb{E}(X|\mathcal{F}_1) = \mathbb{E}(X)$.

(b) Define $\mathbb{E}(X \mid H) = \frac{1}{\mathbb{P}(H)} \int_H X \, d\mathbb{P}$. We will show $\mathbb{E}(X \mid \mathcal{F}_H) = \mathbb{E}(X \mid H)$.

Directly check the definiton: For all $A \in \mathcal{F}_H$,

$$\mathbb{E}\Big(\mathbb{E}(X \mid H) \cdot \mathbf{1}_A\Big) = \mathbb{E}(X\mathbf{1}_A).$$

Therefore, $\mathbb{E}(X \mid \mathcal{F}_H) = \mathbb{E}(X \mid H)$.

□

Exercise 3.1.2. Let X_1, X_2 and Y be RVs with zero means and finite variances. Let $\mathbb{E}X_1X_2 = 0$. Find the best mean square linear approximation of Y in terms of X_1 and X_2.

Remark. In this exercise, we will see that $\text{span}\{X_1, X_2\}$ is different from $L^2(\Omega, \mathcal{F}_1, \mathbb{P})$ where $\mathcal{F}_1$ is the sigma algebra generated by X_1 and X_2.

Proof. Let $\hat{Y} = \alpha_1 X_1 + \alpha_2 X_2$. We want to minimize:

$$\begin{aligned}\mathbb{E}(Y - \hat{Y})^2 &= \mathbb{E}Y^2 - 2\mathbb{E}Y\hat{Y} + \mathbb{E}\hat{Y}^2 \\ &= \mathbb{E}Y^2 - 2\alpha_1\mathbb{E}X_1Y - 2\alpha_2\mathbb{E}X_2Y + \alpha_1^2\mathbb{E}X_1^2 + \alpha_2^2\mathbb{E}X_2^2\end{aligned}$$

Let $\frac{\partial}{\partial \alpha_i}\mathbb{E}(Y - \hat{Y})^2 = 0$ for $i = 1, 2$. We get:

$$\begin{cases} \alpha_1^* = \frac{\mathbb{E}X_1Y}{\mathbb{E}X_1^2} \\ \alpha_2^* = \frac{\mathbb{E}X_2Y}{\mathbb{E}X_2^2} \end{cases}$$

Because $J = \begin{pmatrix} 2\mathbb{E}X_1^2 & 0 \\ 0 & 2\mathbb{E}X_2^2 \end{pmatrix}$ is positive definite, the loss is a convex function of α_1, α_2. Therefore, it is minimized by (α_1^*, α_2^*). □

-Monotone class theorem-

Definition 3.3.

- The collection $\mathcal{C}$ is called a p-system (or π-system) if

$$A, B \in \mathcal{C} \implies A \cap B \in \mathcal{C}.$$

- The collection $\mathcal{D}$ is called a d-system (or λ-system) if
  (a) $\Omega \in \mathcal{D}$.
  (b) $A, B \in \mathcal{D}$ and $B \subset A \implies A \setminus B \in \mathcal{D}$.
  (c) $(A_n) \subset \mathcal{D}$ and $A_n \uparrow A \implies A \in \mathcal{D}$.
- The collection $\mathcal{M}$ is called a monotone class if
  (a) $1 \in \mathcal{M}$.
  (b) $f, g \in \mathcal{M}_b$ and $a, b \in \mathbb{R} \implies af + bg \in \mathcal{M}$.
  (c) $(f_n) \subset \mathcal{M}$ and $f_n \uparrow f \implies f \in \mathcal{M}$.

Theorem.

- *If $\mathcal{P}$ is a π-system contained in a λ-system $\mathcal{L}$, then $\sigma(\mathcal{P}) \subset \mathcal{L}$.*
- *Let $\mathcal{E}$ be a σ-algebra generated by the π-system $\mathcal{P}$ and $\mathcal{M}$ is a monotone clasee. If $\mathbf{1}_A \in \mathcal{M}$ for all $A \in \mathcal{P}$, then $\mathcal{M}$ contains all positive $\mathcal{E}$-measurable functions and all bounded $\mathcal{E}$-measurable functions.*

Exercise 3.1.3. Let X_i be a sequence of indep. RVs and $M_0 = 1$, $M_n = \prod_{i=1}^n X_i$. Let $\mathcal{D}_n = \sigma\{M_1, \ldots, M_n\}$ and $\mathcal{F}_n = \sigma\{X_1, \ldots, X_n\}$. Show that in general $\mathcal{D}_n \subset \mathcal{F}_n$.

Exercise 3.1.4. Let Y be a RV with $\mathbb{E}|Y| < \infty$. Let X_1 and X_2 be RVs such that X_2 is indep. of Y and indep. of X_1. Prove that

$$\mathbb{E}(Y|X_1, X_2) = \mathbb{E}(Y|X_1).$$

3.2 Basic Properties

Definition 3.4. X is L^1-bounded ($\mathbb{E}|X_n| < \infty\ \forall n$) and adapted to $\mathcal{F}$.
$(X, \mathcal{F})$ is called a martingale if

$$\mathbb{E}(X_{n+1}|\mathcal{F}_n) = X_n.$$

... a submartingale if

$$\mathbb{E}(X_{n+1}|\mathcal{F}_n) \geq X_n.$$

... a supermartingale if

$$\mathbb{E}(X_{n+1}|\mathcal{F}_n) \leq X_n.$$

Proposition 3.5. *$(X, \mathcal{F})$ is a martingale.*

- $\mathbb{E}X_n = \mathbb{E}X_m = \mathbb{E}X_0 \quad \forall m, n$
- $\mathbb{E}(X_n|\mathcal{F}_m) = X_m \quad \forall m \leq n$
- $\mathbb{E}((X_n - X_m)X_l) = 0 \quad \forall l \leq m \leq n$
- $\mathbb{E}((X_n - X_m)^2|\mathcal{F}_m) = \mathbb{E}(X_n^2|\mathcal{F}_m) - X_m^2 \quad \forall m \leq n$
- $\forall n\ \mathbb{E}X_n^2 \leq K \implies$ *X has a m.s. limit.*
- *φ is convex s.t. $\mathbb{E}|\varphi(X_n)| < \infty$. $\implies$ $(\varphi(X_n), \mathcal{F})$ is a submartingale.*

Proposition 3.6.

a) Let $(X, \mathcal{F})$ be a submartingale, and $(H, \mathcal{F})$ be a bounded predictable process with $H_n \geq 0$. Define

$$(H \cdot X)_n = \sum_{m=1}^{n} H_m(X_m - X_{m-1}).$$

Then $\big((H \cdot X), \mathcal{F}\big)$ is a submartingale.

b) Let $(X, \mathcal{F})$ be a submartingale, and φ be a non-decreasing convex function such that $\mathbb{E}|\varphi(X_n)| < \infty$ for all n. Then $\big(\varphi(X), \mathcal{F}\big)$ is a submartingale.

c) Let $(X, \mathcal{F})$ be a martingale, and φ be a convex function such that $\mathbb{E}|\varphi(X_n)| < \infty$ for all n. Then $\big(\varphi(X), \mathcal{F}\big)$ is a submartingale. In particular, X_n^2, $|X_n|$, X_n^+, $X_n \vee a$ all are submartingales.

Examples of Martingales

Example 3.7 (Sums of independent RVs with mean 0)**.** Let $\{X_i\}$ be indep. $\mathbb{E}X_i = 0\ \forall i$. $\mathbb{E}|X_i| < \infty$.
Let $S_0 = 0$, $S_n = X_1 + X_2 + \cdots + X_n$. $\mathcal{F} =$ the filtration generated by X.
$\implies$ $(S, \mathcal{F}) =$ martingale.

Example 3.8 (Products of nonneg. indep. RVs with mean 1)**.** Let $\{X_i\}$ be indep. $\mathbb{E}X_i \geq 0\ \forall i$. $\mathbb{E}X_i = 1$.
Let $M_0 = 1$, $M_n = X_1 X_2 \cdots X_n$. $\mathcal{F} =$ the filtration generated by X.
$\implies$ $(M, \mathcal{F}) =$ martingale.

Example 3.9. Let ξ be a RV with $\mathbb{E}|\xi| < \infty$, $\mathcal{F}$ be a filtration.
Let $M_n = \mathbb{E}(\xi|\mathcal{F}_n)$.
$\implies$ $(M, \mathcal{F}) =$ martingale.

Exercises

Exercise 3.2.1. Let X and Y be martingales w.r.t. $\mathcal{F}$. And T is a stopping time w.r.t. $\mathcal{F}$. And assume $X_T = Y_T$ on $\{T < \infty\}$. Define

$$Z_n = X_n \mathbf{1}_{\{n<T\}} + Y_n \mathbf{1}_{\{n\geq T\}}.$$

Show $(Z, \mathcal{F})$ is a martingale.

Proof. Notice that

$$\begin{aligned}
Z_n &= X_n \mathbf{1}_{\{n<T\}} + Y_n \mathbf{1}_{\{n\geq T\}} \\
(X,\ Y \text{ are mart.}) \quad &= \mathbb{E}(X_{n+1}|\mathcal{F}_n)\mathbf{1}_{\{n<T\}} + \mathbb{E}(Y_{n+1}|\mathcal{F}_n)\mathbf{1}_{\{n\geq T\}} \\
(T \text{ is st. time.}) \quad &= \mathbb{E}(\underset{\sim\sim\sim}{X_{n+1}\mathbf{1}_{\{n<T\}} + Y_{n+1}\mathbf{1}_{\{n\geq T\}}} \mid \mathcal{F}_n)
\end{aligned}$$

And because

$$\begin{aligned}
Z_{n+1} - \left(\underset{\sim\sim\sim}{X_{n+1}\mathbf{1}_{\{n<T\}} + Y_{n+1}\mathbf{1}_{\{n\geq T\}}}\right) &= X_{n+1}\mathbf{1}_{\{T=n+1\}} - Y_{n+1}\mathbf{1}_{\{T=n+1\}} \\
(\text{b/c } X_T = Y_T) \quad &= 0
\end{aligned}$$

$\implies \quad Z_n = \mathbb{E}(Z_{n+1} \mid \mathcal{F}_n).$ □

3.3 Doob's Decomposition

Definition 3.10.

- **Predictable Processes**. $X_0 \in \mathcal{F}_0,\ X_n \in \mathcal{F}_{n-1}$ for $n \geq 1$.
- **Increasing Processes**. predictable + $X_0 = 0,\ \mathbb{P}(X_n \leq X_{n+1}) = 1$.

Theorem 3.11. ***Doob's Decomposition***

- *Let $(X, \mathcal{F})$ be an adapted process with $\mathbb{E}|X_n| < \infty\ \forall n$.*
  $\implies$ *$(X, \mathcal{F})$ has a unique Doob's decomposition:*

  $$X_n = X_0 + M_n + A_n$$

  where $(M, \mathcal{F})$ = martingale; $(A, \mathcal{F})$ = predictable.
- *Let $(X, \mathcal{F})$ be a submartingale.*
  $\iff$ *$(A, \mathcal{F})$ = increasing.*

Proof. The constructions of M and A:

$$\begin{aligned}
A_0 = 0;\quad A_n &= A_{n-1} + \mathbb{E}(X_n - X_{n-1}|\mathcal{F}_{n-1}) \\
M_0 = 0;\quad M_n &= M_{n-1} + (X_n - \mathbb{E}(X_n|\mathcal{F}_{n-1}))
\end{aligned}$$

□

Exercises

Exercise 3.3.1. Let $(X, \mathcal{F})$ be a L^1-bounded submartingale. Its Doob's decomposition is given by

$$X = X_0 + M + A.$$

Prove (a) M and A are both convergent, and (b) their limits M_∞ and A_∞ are both integrable.

Proof. First, notice that $A_n = \sum_{i=1}^{n} \mathbb{E}(X_i - X_{i-1}|\mathcal{F}_{i-1}) \geq 0$. $\mathbb{E}|A_n| = \mathbb{E}A_n = \mathbb{E}X_n - \mathbb{E}X_0 < \infty$. Define $A_\infty(\omega) = \lim_{n\to\infty} A_n(\omega)$ (thus, $A_n \uparrow A_\infty$ almost surely).

By the monotone convergence theorem, A_∞ is $\mathcal{F}$-measurable and $\mathbb{E}A_\infty = \lim_{n\to\infty} \mathbb{E}A_n < \infty$.

Then, notice that $M_n = X_n - X_0 - A_n$. We have $M_\infty = X_\infty - X_0 - A_\infty$. So

$$\mathbb{E}|M_\infty| \leq \mathbb{E}|X_\infty| + \mathbb{E}|X_0| + \mathbb{E}|A_\infty| < \infty.$$

□

Exercise 3.3.2 (Another decomposition of submartingales)**.** Let $(X, \mathcal{F})$ be a L^1-bounded submartingale and $X_\infty = \lim_{n\to\infty} X_n$. Then

$$X = M + V$$

where M is a u.i. martingale and V is a submartingale with $\lim_{n\to\infty} V = 0$. Show this by the steps below:

a) Define $M_n = \mathbb{E}(X_\infty|\mathcal{F}_n)$. M is a u.i. martingale.

b) Define $V_n = X_n - M_n$. V is a submartingale with $\lim_{n\to\infty} V = 0$ almost surely.

c) The decomposition is unique.

Proof.

a) Know: $(X, \mathcal{F})$ is a L^1-bounded submartingale.

$\implies$ X_∞ is integrable. Theorem 3.12.

$\implies$ M is a u.i. martingale. Theorem 3.14.

b) $\mathbb{E}(V_{n+1}|\mathcal{F}_n) = \mathbb{E}(X_{n+1}|\mathcal{F}_n) - \mathbb{E}(\mathbb{E}(X_\infty|\mathcal{F}_{n+1})|\mathcal{F}_n) \geq X_n - M_n = V_n$.

$\implies$ submartingale.

Take $\lim_{n\to\infty}$ on both sides. We get $\lim V_n = \lim X_n - \lim M_n = X_\infty - \mathbb{E}(X_\infty|\mathcal{F}_\infty) = 0$.

c) Assume $X = M + V = \tilde{M} + \tilde{V}$. Letting $n \to \infty$, we get

$$M_\infty = \tilde{M}_\infty =: Z.$$

Because M and $\tilde{M}$ are u.i. martingale, they can be written as $M_n = \tilde{M}_n = \mathbb{E}(Z|\mathcal{F}_n)$. Then

$$V = X - M = X - \tilde{M} = \tilde{V}$$

holds almost surely.

□

-Riesz decomposition theorem for supermartingales-

Exercise 3.3.3 (Potentials)**.** Let X be a positive supermartingale. X is called a potential if $\lim_{n\to\infty} X_n = 0$ almost surely. Show that X is a potential if $\lim_{n\to\infty} \mathbb{E}X_n = 0$.

Remark. For submartingales and supermartingales, $X_n \xrightarrow{a.s.} 0$ is implied by $X_n \xrightarrow{L^1} 0$.

Proof. Know: X be a positive supermartingale.

$\implies$ X_∞ exists and is non-negative. $\implies$ $\mathbb{E}X_\infty = 0$, since $\lim_{n\to\infty} \mathbb{E}X_n = 0$.

$\implies$ $X_\infty = 0$ almost surely. □

Exercise 3.3.4 (Decomposition of supermartingales)**.** Let X be a supermartingale with $\sup \mathbb{E}X_n^- < \infty$. Show that there is a unique decomposition

$$X = M + V$$

where M is a u.i. martingale and V is a potential.

Proof. By Exercise 3.3.2,

$$-X = \tilde{M} + \tilde{V},$$

where $\tilde{M}$ is a u.i. martingale and $\tilde{V}$ is a submartingale with $\lim\limits_{n\to\infty} \tilde{V}_n = 0$.

Let $M = -\tilde{M}$ and $V = -\tilde{V}$. We are done. □

Exercise 3.3.5 (Riesz decomposition)**.** Every positive supermartingale X has the following decomposition

$$X = Y + Z$$

where Y is a positive martingale and Z is a potential. Show this by the steps below:

a) The limit $Y_m = \lim\limits_{n\to\infty} \mathbb{E}(X_{m+n}|\mathcal{F}_m)$ exists.

b) $Y = (Y_m)$ is a positve martingale.

c) $Z = X - Y$ is a positive supermartingale.

d) Z is a potential.

Remark. Recall that for any supermartingale X, we have a natural monotone sequence $\{\mathbb{E}X_n\}$.

Proof.

a) It suffices to prove for every m, $\{\mathbb{E}(X_{m+n}|\mathcal{F}_m)\}_{n>m}$ is a positive supermartingale.
X is positive $\implies$ $\{\mathbb{E}(X_{m+n}|\mathcal{F}_m)\}_{n\in\mathbb{N}}$ is positive.
Fix m. We only need to consider $m < n$:

$$\begin{aligned}\mathbb{E}(\mathbb{E}(X_{m+n+1}|\mathcal{F}_m)|\mathcal{F}_n) &= \mathbb{E}(X_{m+n+1}|\mathcal{F}_m) \\ (X \text{ is supermart.}) \quad &\le \mathbb{E}(X_{m+n}|\mathcal{F}_m)\end{aligned}$$

Thus, $\{\mathbb{E}(X_{m+n}|\mathcal{F}_m)\}_{n>m}$ is a positive supermartingale. Its a.s. limit is defined as Y_m.

b) $\{\mathbb{E}(X_{m+n}|\mathcal{F}_m)\}_{n\in\mathbb{N}}$ is positive $\implies$ Y is positive.
Notice that

$$\begin{aligned}\mathbb{E}(Y_{m+1}|\mathcal{F}_m) &= \mathbb{E}(\lim_{n\to\infty} \mathbb{E}(X_{m+n+1}|\mathcal{F}_{m+1})|\mathcal{F}_m) \\ (\text{Monotone conv. thm.}) \quad &= \lim_{n\to\infty} \mathbb{E}(X_{m+n+1}|\mathcal{F}_m) \\ &= \lim_{n\to\infty} \mathbb{E}(X_{m+n}|\mathcal{F}_m) \\ &= Y_m\end{aligned}$$

Therefore, Y is a positive martingale.

c) $\mathbb{E}(Z_{n+1}|\mathcal{F}_n) = \mathbb{E}(X_{n+1}|\mathcal{F}_n) - \mathbb{E}(Y_{n+1}|\mathcal{F}_n) \le X_n - Y_n = Z_n$.

d) Because

$$\lim_{n\to\infty} \mathbb{E}Z_n = \lim_{n\to\infty} \mathbb{E}X_n - \lim_{n\to\infty} \mathbb{E}Y_n = 0,$$

Z is a potential by Exercise 3.3.3.

□

Exercise 3.3.6. The martingale Y in the preceding decomposition is the maximal submartingale majorized by X.

Proof. Let W be a submartingale s.t. $W_n \le X_n$ for every n. We will prove $W_n \le Y_n$.

$$W_n \le \mathbb{E}(W_\infty|\mathcal{F}_n) \le \mathbb{E}(Y_\infty|\mathcal{F}_n) + \mathbb{E}(Z_\infty|\mathcal{F}_n) = Y_n.$$

□

-Krickeberg decomposition-

Exercise 3.3.7 (Krickeberg decomposition)**.** Let $(X, \mathcal{F})$ be a L^1-bounded martingale. Then

$$X = Y - Z$$

where Y and Z are positive and L^1-bounded martingales. Show this by the steps below:

a) $Y_n = \lim_m \mathbb{E}(X^+_{n+m}|\mathcal{F}_n)$ and $Z_n = \lim_m \mathbb{E}(X^-_{n+m}|\mathcal{F}_n)$ exist.

b) $Y = (Y_n)$ and $Z = (Z_n)$ are both positive and L^1-bounded martingales.

Proof. Omitted. See Exercise 3.3.5. It is similar. □

Exercise 3.3.8. A martingale is L^1-bounded $\iff$ it is the difference of two positive L^1-bounded martingales.

Proof.
$\Longrightarrow$: By Krickeberg decomposition.
$\Longleftarrow$: $\mathbb{E}|X_n| = \mathbb{E}|Y_n - Z_n| \leq \mathbb{E}|Y_n| + \mathbb{E}|Z_n| < \infty$. □

Exercise 3.3.9. In the Krickeberg decomposition of an L^1-bounded martingale X, the process Y is the minimal positive martingale majorizing X, and the process Z is the minimal positive martingale majorizing $-X$.

3.4 Martingale Convergence

a.s. convergence

Theorem 3.12. $(X, \mathcal{F})$ = *submartingale.* $\sup_n \mathbb{E}X^+_n < \infty$.

- $\exists X_\infty$ *s.t.* $X_n \xrightarrow{a.s.} X_\infty$
- $\mathbb{E}|X_\infty| < \infty$

Remark.

- For a submartingale, $\mathbb{E}X^+_n$ is increasing in n.
- Quick check:
  negative submartingales, positive supermartingales, martingales bounded by an integrable RV.
- Because $\mathbb{E}X^+_n \leq \mathbb{E}|X_n| = 2\mathbb{E}X^+_n - \mathbb{E}X_n \leq 2\mathbb{E}X^+_n - \mathbb{E}X_0$, X^+ is L^1-bounded is equivalent to that X is L^1-bounded.

Example 3.13 (a.s. convergence $\not\Rightarrow$ L^1-convergence)**. Double or Nothing.**
Let $X_0 = 1$. $\xi_1 = \mathbf{1}\{\text{wins on step } i\} - \mathbf{1}\{\text{lost at step } i\}$, and $S_n = \sum_{i=1}^n \xi_i$. Define

$$H_n = \begin{cases} 2^{n-1} & S_{n-1} = n-1 \\ 0 & \text{o.w.} \end{cases}$$

and define

$$X_n = 1 + \sum_{m=1}^{n} H_m(S_m - S_{m-1}).$$

As we can see, (X_n) converges to 0 almost surely, but $\mathbb{E}X_n = 1 \not\to 0$.

L^1 convergence and u.i. (sub)martingales

Theorem 3.14. *$(X, \mathcal{F})$ = submartingale. The following are equavilent:*

a) X = u.i.

b) X converges in L^1.

If $(X, \mathcal{F})$ = martingale, then they are also equavilent to

c) $\exists X_\infty$ integrable RV s.t. $X_n = \mathbb{E}(X_\infty | \mathcal{F}_n)$.

Remark. For submartingales, we always have $\xrightarrow{L^1} \implies \xrightarrow{a.s.}$, because $\xrightarrow{L^1}$ implies L^1 bounded.

Proof.

- $(a) \Rightarrow (b)$:

  u.i. $\implies$ $\sup_n \mathbb{E}X_n^+ < \infty$ $\implies$ $X_n \xrightarrow{a.s.} X$ $\implies$ $X_n \xrightarrow{\mathbb{P}} X$. And under $\xrightarrow{\mathbb{P}}$:

  $$\text{u.i.} \iff \xrightarrow{L^1}.$$

- $(a) \Leftarrow (b)$:

  $X_n \xrightarrow{L^1} X \implies X_n \xrightarrow{\mathbb{P}} X$. Use "u.i. $\iff \xrightarrow{L^1}$" again.

- $(b) \Rightarrow (c)$: Note that for now X is a martingale.

  Let $X = \lim\limits_{n\to\infty} X_n$. Use the continuity of conditional expectation in L^1 norm.

- $(c) \Rightarrow (a)$:

  Let $X_\mathcal{G} = \mathbb{E}(X|\mathcal{G})$ where $\mathcal{G}$ is a sub-σ-field of $\mathcal{F}$. Then

  $$\sup_{\mathcal{G}} \mathbb{E}(|X_\mathcal{G}| \mathbf{1}_{\{|X_\mathcal{G}| > b\}}) \to 0$$

  as $b \to \infty$. It is because $\{X_\mathcal{G}\}$ is L^1-bounded by $\mathbb{E}|X|$.

□

Exercises

Exercise 3.4.1 (Hunt's dominated convergence theorem)**.** Let (X_n) be dominated by Z, an integrable RV, and $X_\infty = \lim\limits_n X_n$ exists.

$\implies$ $\mathbb{E}(X_n|\mathcal{F}_n) \xrightarrow[L^1]{a.s.} \mathbb{E}(X_\infty|\mathcal{F}_\infty)$

Remark. No assumption of adptedness for (X_n).

Proof. Notice that

$$|\mathbb{E}(X_n|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_\infty)| \leq |\mathbb{E}(X_n|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_n)| + |\mathbb{E}(X_\infty|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_\infty)|.$$

Thus, it suffices to prove

(a) $|\mathbb{E}(X_\infty|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_\infty)| \xrightarrow[L^1]{a.s.} 0$

(b) $|\mathbb{E}(X_n|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_n)| \xrightarrow[L^1]{a.s.} 0$

(X_n) is dominated by Z, and $X_\infty = \lim_n X_n$ exists $\implies$ X_∞ is integrable (by the dominated convergence theorem). Then we define $Y_n = \mathbb{E}(X_\infty|\mathcal{F}_n)$. By Theorem 3.14, we immediately have

(a) $Y_n \xrightarrow[L^1]{a.s.} \mathbb{E}(X_\infty|\mathcal{F}_\infty)$; that is

$$|\mathbb{E}(X_\infty|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_\infty)| \xrightarrow[L^1]{a.s.} 0.$$

(b) To prove $|\mathbb{E}(X_n|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_n)| \xrightarrow[L^1]{a.s.} 0$, we firstly consider the L^1-convergence.

(i) Notice that

$$\mathbb{E}|\mathbb{E}(X_n|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_n)| \le \mathbb{E}|X_n - X_\infty|.$$

Obviously, $\mathbb{E}|X_n - X_\infty| \to 0$, by Theorem 1.12 (u.i. + a.s. conv.). Thus,

$$|\mathbb{E}(X_n|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_n)| \xrightarrow{L^1} 0.$$

(ii) Define $Z_m = \sup_{n\ge m} |X_n - X_\infty|$. Observe that

$$\begin{aligned}\limsup_{n\to\infty} |\mathbb{E}(X_n|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_n)| &\le \limsup_{n\to\infty} \mathbb{E}(|X_n - X_\infty|\ |\mathcal{F}_n)\\ &\le \limsup_{n\to\infty} \mathbb{E}(Z_m|\mathcal{F}_n)\\ &= \mathbb{E}(Z_m|\mathcal{F}_\infty)\end{aligned}$$

And since $|Z_m| \le \sup_{n\ge m}(|X_n| + |X_\infty|) \le 2|Z|$, by the dominated convergence theorem in the Proposition 3.2, we have

$$\lim \mathbb{E}(Z_m|\mathcal{F}_\infty) = \mathbb{E}(\lim Z_m|\mathcal{F}_\infty) = 0.$$

Therefore, $\limsup_{n\to\infty} |\mathbb{E}(X_n|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_n)| \xrightarrow{a.s.} 0$ as $n \to \infty$.

Combining (i) and (ii), we get $|\mathbb{E}(X_n|\mathcal{F}_n) - \mathbb{E}(X_\infty|\mathcal{F}_n)| \xrightarrow[L^1]{a.s.} 0$.

□

Exercise 3.4.2. Let X be a u.i. submartingale, $X_\infty = \lim_{n\to\infty} X_n$, and $M_n = \mathbb{E}(X_\infty|\mathcal{F}_n)$.
$\implies$ (a) M is a u.i. martingale, and (b) $X_n \le M_n$ for every $n \in \mathbb{N}$.

Proof. (a) Because X_∞ is integrable (Theorem 3.12), M is a u.i. martingale.

(b) By the definition of submartingales.

□

Exercise 3.4.3. Let $(X, \mathcal{F})$ be a martingale and $p > 1$. If $\sup_n \mathbb{E}|X_n|^p < \infty$, then

$$X_n \xrightarrow{L^p} X$$

where X is the a.s. limit of X_n.

Proof.

- First, we notice that

$$\sup_n \mathbb{E}|X_n|^p < \infty \implies (X_n) \text{ is u.i.}$$

  Thus, by Theorem 3.13, $X_n \xrightarrow{a.s.} X$ and $X_n \xrightarrow{L^1} X$.

- Because $|X_n - X|^p \le (2\sup_n |X_n|)^p$. If $\mathbb{E}(2\sup_n |X_n|)^p < \infty$, the dominated convergence theorem will imply

$$\mathbb{E}|X_n - X|^p \to 0.$$

  We prove it below.

- $|X_n|$ is a submartingale. Apply Doob's inequality for $|X_n|$:

$$\mathbb{E}(\sup_{0\le m\le n} |X_m|)^p \le (\frac{p}{1-p})^p \mathbb{E}|X_n|^p,$$

  and take $n \to \infty$.

□

3.5 Optinal Stopping Theorem

Definition 3.15.

- $T : \Omega \to \mathbb{N}$ is called a stopping time w.r.t. $\mathcal{F} = (\mathcal{F}_k)_{k\in\mathbb{N}}$ if
$$\{T \le k\} \in \mathcal{F}_k$$
for all $k \in \mathbb{N}$.
- Define $\mathcal{F}_T = \{A : A \cap \{T = n\} \in \mathcal{F}_n,\ \forall n\}$.

Remark. This definition is equivalent to $\{T = k\} \in \mathcal{F}_k$ for all k.

Example 3.16 (The first entrance/passage time)**.** Let B is a Borel set, and $T = \min\{n \in \mathbb{N} : X_n \in B\}$, where X is an adapted process. Then T is a stopping time because

$$\begin{aligned}\{T = n\} &= \{X_1 \notin B, \dots, X_{n-1} \notin B, X_n \in B\}\\ &= \{X_1 \notin B\} \cap \dots \cap \{X_{n-1} \notin B\} \cap \{X_n \in B\}\\ &\in \mathcal{F}_n.\end{aligned}$$

Or we can use $\{T \le n\} = \bigcup_{i=1}^n \{X_i \in B\}$.

Example 3.17 (A map that is not a stopping time)**.** Let B is a Borel set, and $L = \sup\{n \in \mathbb{N} : n \le 10,\ X_n \in B\}$, where X is an adapted process. Then L is not a stopping time in general.

For example, let X be a simple symmetric random walk, and $B = \{1\}$. By Wald's indentity, $\mathbb{E}X_L = 0$; however, $\mathbb{E}X_L = \mathbb{P}(X_L = 1) \ne 0$.

Proposition 3.18. *Let $(X_t)_{t\in\mathbb{N}}$ be a submartingale w.r.t. $\mathcal{F}$, and T be a stopping time w.r.t. $\mathcal{F}$. Then $(X_{t\wedge T})_{t\in\mathbb{N}}$ is also a submartingale w.r.t. $\mathcal{F}$.*

Theorem 3.19 (Optional stopping theorem for submartingales)**.**

(I) $0 \le S \le T \le K$ almost surely, then
$$\mathbb{E}X_T \ge \mathbb{E}X_S \ge \mathbb{E}X_0$$

(II) X is u.i. submartingale, then
$$\mathbb{E}X_\infty \ge \mathbb{E}X_T \ge \mathbb{E}X_S \ge \mathbb{E}X_0$$

(III) $X_{n\wedge T}$ is a u.i. martingale, then
$$\mathbb{E}X_T \ge \mathbb{E}X_S \ge \mathbb{E}X_0$$

Remark. For part (III), it is natural to ask when $X_{n\wedge T}$ is a u.i. submartingale. There are several sufficient conditions:

(i) X_n is u.i. $\implies$ $X_{n\wedge T}$ is u.i.

(ii) $\mathbb{E}|X_T| < \infty$ and $\mathbb{E}(|X_n|\mathbf{1}_{\{T>n\}}) \to 0$ as $n \to \infty$ $\implies$ $X_{n\wedge T}$ is u.i.

(iii) $\mathbb{E}(|X_{n+1} - X_n| \mid \mathcal{F}_n) \le C$ and $\mathbb{E}T < \infty$ $\implies$ $X_{n\wedge T}$ is u.i.

(iv) $X_{n\wedge T}$ is bounded by an integrable RV $\implies$ $X_{n\wedge T}$ is u.i.

Proof. We will only prove (iii).

(iii) Because $X_n = X_0 + (X_1 - X_0) + \dots + (X_n - X_{n-1})$, for $m \ge T$,

$$\begin{aligned}X_{n\wedge T} &= X_0 + (X_1 - X_0) + \dots + (X_{m\wedge T} - X_{m-1}) + (X_{(m+1)\wedge T} - X_{m\wedge T}) + \dots\\ &= X_0 + (X_1 - X_0) + \dots + (X_{m\wedge T} - X_{m-1})\end{aligned}$$
$$|X_{n\wedge T}| \le |X_0| + \sum_{m=0}^{\infty} |X_{m-1} - X_m|\mathbf{1}_{\{m<T\}}$$

Letting $Y = |X_0| + \sum_{m=0}^{\infty} |X_{m-1} - X_m| \mathbf{1}_{\{m<T\}}$, it suffices to prove $\mathbb{E}Y < \infty$. Notice that

$$\begin{aligned} \mathbb{E}|X_{m-1} - X_m| \mathbf{1}_{\{m<T\}} &= \mathbb{E}\Big(\mathbb{E}(|X_{m-1} - X_m| \cdot \mathbf{1}_{\{m<T\}} \mid \mathcal{F}_m)\Big) \\ &= \mathbb{E}\Big(\mathbf{1}_{\{m<T\}} \cdot \mathbb{E}(|X_{m-1} - X_m| \mid \mathcal{F}_m)\Big) \\ \text{(by the given cond.)} \quad &\le C\mathbb{P}(T > m) \end{aligned}$$

Thus, $\mathbb{E}Y \le \mathbb{E}|X_0| + C \sum_{m=1}^{\infty} \mathbb{P}(T > m) = \mathbb{E}|X_0| + C\mathbb{E}T < \infty$.

By (v) we know $X_{n \wedge T}$ is bounded by an integrable RV Y, so it is u.i.

□

Theorem 3.20 (Optinal stopping theorem for martingales)**.** *$(Y, \mathcal{F})$ = a martingale. T = a stopping time w.r.t $\mathcal{F}$ such that $T < \infty$ almost surely. If one of the following holds*

(I) *a)* $\mathbb{E}(|Y_T|) < \infty$
 b) $\mathbb{E}(Y_n 1_{T>n}) \to 0$

(II) *Y is u.i.*

(III) *a)* $\mathbb{E}T < \infty$
 b) *$\exists c$ s.t.* $\mathbb{E}(|Y_{n+1} - Y_n||\mathcal{F}_n) \le c \quad \forall n < T$

$\implies \quad \mathbb{E}Y_T = \mathbb{E}Y_0.$

Corollary 3.21 (Wald's identity)**.** *Let $S_n = \xi_1 + \dots \xi_n$ be a RW. For any stopping time T with $\mathbb{E}T < \infty$:*

$$\mathbb{E}S_T = \mathbb{E}\xi \cdot \mathbb{E}T.$$

Exercises

Exercise 3.5.1. Let $Q = \min\{n \ge 1 : X_{n-1} \in B\}$ and $R = \min\{n \ge 1 : X_{n+1} \in B\}$. Are Q and R stopping times?

Exercise 3.5.2. Let $f : \mathbb{N} \to \mathbb{N}$ be an increasing map such that $f(n) \ge n$ for all n, and T be a stopping time w.r.t $\mathcal{F}$. Then $f(T)$ is a stopping time w.r.t $\mathcal{F}$.

Proof. Because f is increasing,

$$\{f(T) \le k\} \in \mathcal{F}_k \iff \{T \le f^{-1}(k)\} \in \mathcal{F}_k.$$

And notice that $f^{-1}(k)$ is an integer that is not larger than k (by $f(n) \ge n$). So

$$\{T \le f^{-1}(k)\} \in \mathcal{F}_{f^{-1}(k)} \subset \mathcal{F}_k.$$

□

Exercise 3.5.3. Let τ be a stopping time w.r.t. $\mathcal{F}$. Then $\mathcal{F}_{k \wedge \tau} \uparrow \mathcal{F}_\tau$ as $k \to \infty$.

-Optional stopping theorem for continuous martingales-

Theorem. *Let $(X_t)_{t \ge 0}$ be a uniformly integrable martingale with right-continuous paths. Let S and T be two stopping times with $S < T$. Then X_S and X_T are in L^1 and*

$$X_S = \mathbb{E}(X_T|\mathcal{F}_S).$$

In particular, for every stopping time S, we have

$$X_S = \mathbb{E}(X_\infty|\mathcal{F}_S)$$

and

$$\mathbb{E}(X_S) = \mathbb{E}(X_\infty) = \mathbb{E}(X_0).$$

Exercise 3.5.4. Let B be a Brownian motion. Define

$$T_a = \inf\{t \geq 0 : B_t = a\}$$

and

$$U_a = \inf\{t \geq 0 : |B_t| = a\}.$$

(a) Show T_a and U_a are stopping times for all a.

(b) Find $\mathbb{P}(T_a < T_b)$ for $a < 0 < b$.

(c) Find $\mathbb{E}U_a$.

(d) Compute $\mathbb{E}(e^{-\lambda T_a})$ for $\lambda > 0$ (The Laplace transform of T_a).

(e) Compute $\mathbb{P}(T_a < \infty)$.

Remark. In this exercise, we should avoid using the distribution of T_a directly. Try to apply the optional stopping theorem.

Proof. (a) Note that $\{T_a < t\} = \bigcup_{s<t}\{B_s = a\}$. And $\{B_s = a\} \in \mathcal{F}_s$ and $\mathcal{F}_t = \bigcup_{s<t}\mathcal{F}_s$; thus, T_a is a stopping time.

Note that $\{U_a < t\} = \bigcup_{s<t}\{B_s = \pm a\}$. And $\{B_s = \pm a\} \in \mathcal{F}_s \subset \mathcal{F}_t$ for $s < t$; thus, U_a is a stopping time.

(b) **Tips 1:** In most cases, (stopped) martingale is bounded.

Let $T = T_a \wedge T_b$ and $M_t = B_{t\wedge T}$. Because T_a and T_b are stopping times, T is stopping time. Then M_t is a u.i. martingale (its boundedness is given by the definition of T). Apply the optional stopping theorem:

$$\mathbb{E}M_T = \mathbb{E}M_0 = 0$$

and notice that

$$\mathbb{E}M_T = a\mathbb{P}(T_a < T_b) + b\mathbb{P}(T_a > T_b).$$

Therefore, we have the following two equations:

$$\begin{cases} a\mathbb{P}(T_a < T_b) + b\mathbb{P}(T_a > T_b) & = 0 \\ \mathbb{P}(T_a < T_b) + \mathbb{P}(T_a > T_b) & = 1 \end{cases}$$

Solve it. We get $\mathbb{P}(T_a < T_b) = \frac{b}{b-a}$.

(c) **Tips 2:** Construct an appropriate martingale.

Let $M_t = B_t^2 - t$. Then $M_{t\wedge U_a}$ is uniform integrable.

It is because

$$M_{t\wedge U_a} \leq B^2_{t\wedge U_a} \leq a^2.$$

Apply the optional stopping theorem:

$$\mathbb{E}M_{U_a} = M_0 = 0$$

so we have

$$\mathbb{E}B^2_{t\wedge U_a} = \mathbb{E}(t \wedge U_a).$$

Notice that $(t \wedge U_a) \uparrow U_a$; thus, by the monotone convergence theorem,

$$\mathbb{E}(t \wedge U_a) \uparrow \mathbb{E}U_a.$$

And because $B^2_{t\wedge U_a} \leq a^2$ and $B_{U_a} = \pm a$; by the dominated convergence theorem,

$$\mathbb{E}B^2_{t\wedge U_a} \to \mathbb{E}B^2_{U_a} = a^2.$$

Therefore, taking $t \to \infty$ on both sides, we have

$$a^2 = \mathbb{E}U_a.$$

(d) **Tips 3:** Always check the uniform integrablity.

Consider the exponential martingale

$$N_t^\lambda = e^{\lambda B_t - \frac{\lambda^2}{2} t}.$$

- $\lambda > 0$.

  In this case, $N_{t\wedge T_a}^\lambda$ is a uniformly integrable martingale, because

  $$\exp(\lambda B_{t\wedge T_a} - \frac{\lambda}{2}(t \wedge T_a)) \le \exp(\lambda B_{t\wedge T_a}) \le e^{\lambda a}.$$

  Apply the optinal stopping theorem:

  $$e^{\lambda B_{T_a} - \frac{\lambda^2}{2} T_a} = 1;$$

  that is

  $$e^{-\lambda a} = e^{-\frac{\lambda^2}{2} T_a}.$$

  Then take $\lambda \mapsto \sqrt{2\lambda}$, we have $\mathbb{E}(e^{-\lambda T_a}) = e^{-a\sqrt{2\lambda}}$.
- $\lambda < 0$.

  Be careful! In this case, $N_{t\wedge T_a}^\lambda$ is not uniformly integrable.

(e) Letting $\lambda \to 0$, we have

$$\mathbb{P}(T_a < \infty) = \lim_{\lambda\to 0} e^{-\lambda T} = 1.$$

□

Exercise 3.5.5. Let M be a martingale with continuous path such that $M_0 = x \in \mathbb{R}_+$. We assume that $M_t \ge 0$ for every $t \ge 0$, and that $M_t \to 0$ when $t \to \infty$ almost surely. Show that for every $y > x$,

$$\mathbb{P}(\sup_{t\ge 0} M_t \ge y) = \frac{x}{y}.$$

Proof. Define $T = \inf\{t : M_t = y\}$. It is easy to see that $M_{t\wedge T}$ is bounded (so it is a u.i. martingale). So $\mathbb{E}M_T = \mathbb{E}M_0$. Notice that actually T is not almost surely finite. Therefore, we have

$$\mathbb{E}M_T \mathbf{1}_{\{T<\infty\}} + \mathbb{E}M_\infty \mathbf{1}_{\{T=\infty\}} = x.$$

It is known that M_∞ is 0. So

$$y\mathbb{P}(T < \infty) = x.$$

Finally, notice that $\{T < \infty\} \iff \{\sup_{t\ge 0} M_t \ge y\}$. □

Exercise 3.5.6. Recall that $T_a = \inf\{t > 0 : B_t = a\}$. Give the law of $\sup_{t\le T_0} B_t$ where B is a Brownian motion started from $x > 0$.

Proof. Notice that for $y > x$

$$\{\sup_{t\le T_0} B_t \le y\} \iff \{T_y \ge T_0\}.$$

Consider $B_{T_y\wedge T_0}$ for $y > 0$. It is a u.i. martingale. So we have

$$\mathbb{E}B_{T_y\wedge T_0} = \mathbb{E}B_0.$$

It implies that $y \cdot \mathbb{P}(T_y < T_0) + 0 \cdot \mathbb{P}(T_y \ge T_0) = x$. Therefore, we have

$$\mathbb{P}(\sup_{t\le T_0} B_t \le y) = \begin{cases} 1 - \frac{x}{y} & y > x; \\ 0 & y \le x. \end{cases}$$

□

Exercise 3.5.7. Let B be a Brownian motion started from 0, and let $\mu > 0$. Show that

$$\sup_{t\geq 0}(B_t - \frac{1}{2}\mu t)$$

is exponentially distributed with parameter μ.

Proof. Note that $N_t^\lambda = e^{\lambda B_t - \frac{\lambda^2}{2}t}$ forms a martingale with $\lim_{t\to\infty} N_t^\lambda = 0$ and with $N_0 = 1$. So by the preceding exercise, for all $\lambda \in \mathbb{R}$,

$$\mathbb{P}(\sup_{t\geq 0} N_t^\lambda \geq y) = \frac{1}{y}.$$

We want to find the distribution of $\sup_{t\geq 0}(B_t - \frac{1}{2}\mu t)$; that is

$$\begin{aligned}
\mathbb{P}(\sup_{t\geq 0}(B_t - \frac{1}{2}\mu t) \leq s) &= \mathbb{P}(\sup_{t\geq 0} e^{\mu(B_t - \frac{1}{2}\mu t)} \leq e^{\mu s}) \\
&= \mathbb{P}(\sup_{t\geq 0} N_t^\mu \leq e^{\mu s}) \\
&= 1 - e^{-\mu s}
\end{aligned}$$

Therefore, the distribution of $\sup_{t\geq 0}(B_t - \frac{1}{2}\mu t)$ is $\mathrm{Exp}(\mu)$. ◻

Exercise 3.5.8. Let B be a Brownian motion started from 0. Let $a > 0$ and

$$\sigma_a = \inf\{t \geq 0 : B_t \leq t - a\}.$$

(a) Show that σ_a is a stopping time and that $\sigma_a < \infty$ almost surely.

(b) Show that for every $\lambda \geq 0$,

$$\mathbb{E}e^{-\lambda\sigma_a} = e^{-a(\sqrt{1+2\lambda}-1)}.$$

Proof. (a) First, $\{\sigma_a \leq x\} = \bigcup_{t\leq x}\{B_t \leq t - a\}$; therefore, it is a stopping time.

Then notice that

$$\{\sigma_a < \infty\} \iff \{\inf_{t\geq 0}(B_t - t) \leq -a\}.$$

Finally, use $(B_t - t)/t \xrightarrow{a.s.} -1$.

(b) For $\mu \leq 0$, define $M_t = e^{\mu B_t - \frac{\mu^2}{2}t}$. Then $M_{t\wedge\sigma_a}$ is a u.i martingale.

Apply the optional stopping theorem:

$$\mathbb{E}e^{\mu B_{t\wedge\sigma_a} - \frac{\mu^2}{2}(t\wedge\sigma_a)} = 1.$$

It implies

$$\mathbb{E}e^{(\mu - \frac{\mu^2}{2})\sigma_a} = e^{a\mu}.$$

Letting $\lambda = -(\mu - \frac{\mu^2}{2})$ (obviously, we have $\lambda \leq 0$), we get the desired result.

◻

3.6 Inequalities

Definition 3.22.

- Let X be a sequence of RVs, $T_0 = 0$, and $[a, b]$ be an interval. For $k \in \mathbb{N}$, define

$$\begin{aligned} T_{2k-1} &= \min\{n > T_{2k-2} : X_n \le a\}; \\ T_{2k} &= \min\{n > T_{2k-1} : X_n \ge b\}. \end{aligned}$$

  Then $[T_{2k-1}, T_{2k}]$ is called an upcrossing of $[a, b]$.

- $U_n(a, b; X) =$ The number of upcrossing of $[a, b]$ by X up to time n.
- $U(a, b; X) = \lim_{n\to\infty} U_n(a, b; X)$.

Theorem 3.23 (The upcrossing inequality)**.** *Let $(X, \mathcal{F})$ be a submartingale.*

$$\mathbb{E}(U_n(a, b; X)) \le \frac{1}{b-a}\mathbb{E}\big((X_n - a)^+\big)$$

Theorem 3.24 (Doob's inequality)**.** *Let $(X, \mathcal{F})$ be a submartingale, and*

$$A = \{\max_{0\le m\le n} X_m \ge \lambda\}.$$

a) For $\lambda > 0$,

$$\lambda\mathbb{P}(\max_{1\le m\le n} X_m \ge \lambda) \le \mathbb{E}(X_n^+\mathbf{1}_A) \le \mathbb{E}X_n^+.$$

b) For $p > 1$,

$$\mathbb{E}(\max_{1\le m\le n} X_m^+)^p \le (\frac{p}{1-p})^p\mathbb{E}(X_n^+)^p.$$

Proof.

(a)
- Notice the following important relation:

$$\{\max_{1\le m\le n} X_m \ge \lambda\} = \{T \le n\}$$

  where $T = \min\{n \ge 1 : X_n \ge \lambda\}$. So we have

$$\begin{aligned} \lambda\mathbb{P}(\max X_m \ge \lambda) &= \lambda\mathbb{P}(\lambda \le n) \\ &= \lambda\mathbb{E}\mathbf{1}_{\{T\le n\}} \\ &\le \mathbb{E}(X_T^+\mathbf{1}_{\{T\le n\}}) \qquad (1) \end{aligned}$$

- Apply the optional stopping theorem for $(X_{n\wedge T}^+)$:

$$\mathbb{E}X_0^+ \le \mathbb{E}X_{n\wedge T}^+ \le \mathbb{E}X_n^+ \qquad (2)$$

  where $\mathbb{E}X_{n\wedge T}^+ = \mathbb{E}X_T^+\mathbf{1}_{\{T\le n\}} + \mathbb{E}X_n^+\mathbf{1}_{\{T>n\}}$.
- Finally, just put (1) and (2) together.

(b) Omitted.

$\square$

Corollary 3.25 (Doob-Kolmogorov inequality for martingales)**.** *Let $(X, \mathcal{F})$ be a martingale such that $\mathbb{E}X_n^2 < \infty$. Then*

$$\mathbb{P}(\max_{1\le m\le n} |X_m| \ge \lambda) \le \frac{\mathbb{E}X_n^2}{\lambda^2}.$$

Proof. Use the previous theorem for (X_n^2). $\square$

Theorem 3.26 (Hoeffding's inequality)**.** *Let $(Y, \mathcal{F})$ be a martingale. Suppose $\exists \{k_n\}_{n\geq 1}$ of real numbers s.t. $\mathbb{P}(|Y_n - Y_{n-1}| \leq k_n) = 1$ for all n. Then*

$$\mathbb{P}(|Y_n - Y_0| \geq x) \leq 2e^{-\frac{1}{2}x^2/\sum_{i=1}^n k_i^2}.$$

Proof.

- First, we show the following lemma:

  Let D be a RV s.t. $\mathbb{E}(D) = 0$ and $|D| \leq 1$ almost surely, then

  $$\mathbb{E}(e^{\psi D}) < e^{\frac{1}{2}\psi^2} \quad (*)$$

  holds for all $\psi > 0$.

- **Proof.**

  For $\psi > 0$, define

  $$g : d \mapsto e^{\psi d},$$

  which is a convex function. So for $|d| \leq 1$, we have

  $$e^{\psi d} \leq \frac{1}{2}(1-d)e^{-\psi} + \frac{1}{2}(1+d)e^{\psi}.$$

  Plug it in $\mathbb{E}e^{\psi D}$, we have

  $$\begin{aligned} \mathbb{E}e^{\psi D} &\leq \mathbb{E}\Big(\frac{1}{2}(1-D)e^{-\psi} + \frac{1}{2}(1+D)e^{\psi}\Big) \\ &= \frac{1}{2}e^{-\psi} + \frac{1}{2}e^{\psi} \\ \text{(Taylor series)} \quad &< \exp\big(\frac{1}{2}\psi^2\big) \end{aligned}$$

- Now we consider $\mathbb{P}(Y_n - Y_0 \geq x)$. Let $D_n = Y_n - Y_{n-1}$ be the martingale difference of Y. Then for all $\theta > 0$, we have

  $$\begin{aligned} \mathbb{P}(Y_n - Y_0 \geq x) &= \mathbb{P}\Big(e^{\theta(Y_n - Y_0)} \geq e^{\theta x}\Big) \\ \text{(Markov)} \quad &\leq \mathbb{E}\Big(e^{\theta(Y_n - Y_0)}\Big) \cdot e^{-\theta x} \\ &= e^{-\theta x}\mathbb{E}\Big(e^{\theta D_n} \cdot e^{\theta(Y_{n-1} - Y_0)}\Big) \\ &= e^{-\theta x}\mathbb{E}\Big(\mathbb{E}\big(e^{\theta D_n} \cdot e^{\theta(Y_{n-1} - Y_0)} \mid \mathcal{F}_{n-1}\big)\Big) \\ &= e^{-\theta x}\mathbb{E}\Big(e^{\theta(Y_{n-1} - Y_0)} \cdot \mathbb{E}\big(e^{\theta D_n} \mid \mathcal{F}_{n-1}\big)\Big) \end{aligned}$$

- Notice that $|\frac{D_n}{k_n}| < 1$ and $\mathbb{E}D_n = 0$. Applying $(*)$, we have

  $$\begin{aligned} \mathbb{E}\big(e^{\theta D_n} \mid \mathcal{F}_{n-1}\big) &= \mathbb{E}\big(e^{\theta k_n \frac{D_n}{k_n}} \mid \mathcal{F}_{n-1}\big) \\ &\leq e^{\frac{1}{2}\theta^2 k_n^2} \end{aligned}$$

  Therefore, by induction, we have

  $$\begin{aligned} \mathbb{P}(Y_n - Y_0 \geq x) &\leq e^{-\theta x} \cdot e^{\frac{1}{2}\theta^2 k_n^2} \cdot \mathbb{E}\Big(e^{\theta(Y_{n-1} - Y_0)}\Big) \\ &\leq \exp\big(-\theta x + \frac{1}{2}\theta^2 \sum k_i^2\big) \\ &\leq \exp\big(-\frac{1}{2}x/\sum k_i^2\big) \end{aligned}$$

- Finally, note that

  $$\begin{aligned} \mathbb{P}(|Y_n - Y_0| \geq x) &= \mathbb{P}(Y_n - Y_0 \geq x) + \mathbb{P}(Y_0 - Y_n \geq x) \\ &\leq 2\exp\big(-\frac{1}{2}x/\sum k_i^2\big) \end{aligned}$$

$\square$

Exercises

Exercise 3.6.1. Let X be a submartingale bounded in L^1. Let $a < b$ and

$$U(a, b; X) = \lim_{N \to \infty} U_N(a, b; X).$$

Show that

$$(b - a)\mathbb{E}U(a, b; X) \leq |a| + \sup_n \mathbb{E}|X_n|.$$

Proof. Use the upcrossing inequality and the monotone convergence theorem together. □

4 Examples of Discrete Stochastic Processes

4.1 Finite Martingales

Example 4.1. Let η be an integrable RV and $\mathcal{F}_1 \subset \mathcal{F}_2 \subset \cdots \subset \mathcal{F}_n$ be an increasng sequence of σ-fields.

a) Define $\xi_k = \mathbb{E}(\eta|\mathcal{F}_k)$. Then $(\xi, \mathcal{F})$ is a martingale.

b) Conversely, if $(\xi, \mathcal{F})$ is a finite martingale, there exists an integrable RV η such that

$$\xi_k = \mathbb{E}(\eta|\mathcal{F}_k).$$

c) However, for infinite martingales, (b) doesn't hold in general.

Example 4.2. Let $Y_1, \dots, Y_4$ be i.i.d. RVs with $\mathbb{E}|Y_i| < \infty$ for all i. Define

$$X_1 = \frac{1}{4}(Y_1 + Y_2 + Y_3 + Y_4),\ X_2 = \frac{1}{3}(Y_1 + Y_2 + Y_3),\ X_3 = \frac{1}{2}(Y_1 + Y_2),\ X_4 = Y_1.$$

Then X is a martingale.
To prove this, we notice the symmetry:

$$\begin{aligned}
\mathbb{E}(X_2|X_1) &= \frac{1}{3}\mathbb{E}(Y_1 + Y_2 + Y_3|Y_1 + Y_2 + Y_3 + Y_4) \\
&= \frac{1}{3}\mathbb{E}(Y_2 + Y_3 + Y_4|Y_1 + Y_2 + Y_3 + Y_4) \\
&= \frac{1}{3}\mathbb{E}(Y_3 + Y_4 + Y_1|Y_1 + Y_2 + Y_3 + Y_4) \\
&= \frac{1}{3}\mathbb{E}(Y_4 + Y_1 + Y_2|Y_1 + Y_2 + Y_3 + Y_4)
\end{aligned}$$

Thus, $4\mathbb{E}(X_2|X_1) = \mathbb{E}(Y_1 + Y_2 + Y_3 + Y_4|Y_1 + Y_2 + Y_3 + Y_4) = Y_1 + Y_2 + Y_3 + Y_4 = 4X_1$. Then it is easy to see that X is a martingale.

4.2 Markov Chains (MC)

Definition. The following definitions are equivalent:

- A process X is a <u>Markov chain</u> if it satisfies

$$\mathbb{P}(X_n = s \mid X_0 = x_0,\ X_1 = x_1,\ \dots,\ X_{n-1} = x_{n-1}) = \mathbb{P}(X_n = s \mid X_{n-1} = x_{n-1}).$$

- Let $\mathcal{F}$ be the natural filtration of X. X is a Markov chain if it satisfies

$$\mathbb{E}(f \circ X_{n+1}|\mathcal{F}_n) = (P_n f) \circ X_n$$

  for every non-negative bounded measurable function f and $n \in \mathbb{N}$, where

$$P_n(s, B) := \mathbb{P}(X_{n+1} \in B|X_n = s)$$

  is a Markov kernel on the state space of X.

Remark.

- Let $f = \mathbf{1}_{\{s\}}$, we have $\mathbb{P}(X_{n+1} = s|\mathcal{F}_n) = P_n(X_n, s) = \mathbb{P}(X_{n+1} = s|X_n)$. Recall that for any non-negative bounded measurable function g, we can find a sequence of simple functions $\{f_n\}_{n\in\mathbb{N}}$ such that $f_n \uparrow g$ almost surely as $n \to \infty$.

- Every discrete-time Markov chain has stronge Markov property; that is,

$$\mathbb{P}(X_{T+k} = x|\mathcal{F}_T) = \mathbb{P}(X_{T+k} = x|X_T),$$

  where T is a stopping time.

More properties of MCs will be given in Section 6. The following three examples will show the relation between MCs and martingales.

Example 4.3 (X is both a MC and a mart.)**.** Let X_i be i.i.d. RVs with $\mathbb{P}(X_i = -1) = \mathbb{P}(X_i = 1) = \frac{1}{2}$. Define $S_0 = 0$ and

$$S_n = S_0 + \sum_{i=1}^{n} X_i.$$

S_n is a simple symmetric random walk. It is both a Markov chain and a martingale.

Example 4.4 (X is a MC but is not a mart.)**.** Let $X_i \sim \text{Bin}(1, \frac{1}{2})$ be i.i.d.. Define $S_0 = 0$ and

$$S_n = S_0 + \sum_{i=1}^{n} X_i.$$

S_n is a Markov chain; however, it is not a martingale.

Example 4.5 (X is not a MC but is a mart.)**.** Let X_i be i.i.d. RVs with $\mathbb{P}(X_i = -1) = \mathbb{P}(X_i = 1) = \frac{1}{2}$; and $S_0 \sim \text{Bin}(1, \frac{1}{2})$, indep. of X. Define

$$S_n = S_{n-1} + X_n S_0.$$

It is a martingale; but it is not a Markov chain. Because the Markov property doesn't hold:

$$\begin{aligned}
&\mathbb{P}(S_2 = 1 \mid S_1 = 0,\ S_0 = 1) = 1/2;\\
&\mathbb{P}(S_2 = 1 \mid S_1 = 0,\ S_0 = 0) = 0;\\
&\mathbb{P}(S_2 = 1 \mid S_1 = 0) = 1/4.
\end{aligned}$$

The following example shows another difference between Markov chains and martingales. Let τ be a stopping time w.r.t. $\mathcal{F}$. If $(X_n)_{n\in\mathbb{N}}$ is a martingale, then $(X_{n\wedge\tau})_{n\in\mathbb{N}}$ is also a martingale. What will happen if X is a Markov chain?

Example 4.6 (Stopped Markov chains)**.** Let $X = (X_n)_{n\in\mathbb{N}}$ be a Markov chain with countable state space S and transition kernel P. Let $A \subset S$ and $\tau_A = \inf\{n \geq 1 : X_n \in A\}$.

- Define $Y_n = X_{n\wedge\tau_A}$. We consider two cases: If $n > \tau_A$, then

  $$Y_{\tau_A} = Y_{\tau_A+1} = \cdots = Y_{n-1} = Y_n;$$

  obviously, the value of Y_n totally depends on the value of Y_{n-1}. If $n \leq \tau$, then $Y_k = X_k$ for all $k \leq n$. And notice that X is a Markov chain.

  Therefore, Y is a Markov chain.

- Define $\tau = \inf\{n > \tau_A : X_n \in A\}$ as the second entrance time of A. Let $Y_n = X_{n\wedge\tau}$. Then Y is not a Markov chain. We still consider two cases: If $n \leq \tau$, it is same. However, if $n > \tau$, it is possible that $Y_n \neq Y_{n-1}$.

It is well-known that the sum of two martingales are also a martingale, and that the sum of two Lévy processes are also a Lévy process. However, the following example shows that the sum of two Markov chains may not be Markov chains.

Example 4.7 (Sums of two MCs may not be MC)**.**
See here. Let X be a RV such that $\mathbb{P}(X = 0) = \mathbb{P}(X = 1) = \frac{1}{2}$. Set $X_n = X$ for all n.
Let Y be anothor MC with state space $S = \{-1, 0, 1\}$ that is independent of X. Let $Y_0 = 0$ and its transition matrix be

$$P = \begin{pmatrix} \frac{1}{4} & \frac{3}{4} & 0 \\ \frac{1}{4} & \frac{1}{2} & \frac{1}{4} \\ 0 & \frac{3}{4} & \frac{1}{4} \end{pmatrix}.$$

Now set $Z_n = X_n + Y_n$. Notice that

$$\mathbb{P}(Z_2 = 0 | Z_1 = 1) = \frac{5}{12},$$
$$\mathbb{P}(Z_2 = 0 | Z_1 = 1, Z_0 = 1) = \frac{1}{4}.$$

Therefore, $X + Y$ is not a Markov chain.

The following proposition characterizes Markov chains in terms of martingales; and there is a more general result which holds for the continuous case. The proof of the following proposition is trivial by directly observing the martingale difference.

Proposition. *Let X be adapted to $\mathcal{F}$. Then X is a Markov chain with transition kernel P w.r.t. $\mathcal{F}$ if and only if*

$$M_n = f \circ X_n - \sum_{m=1}^{n-1} (Pf - f) \circ X_m, \quad n \in \mathbb{N},$$

is a martingale w.r.t $\mathcal{F}$ for every bounded $f \in \mathcal{E}_+$.

Exercises

Exercise 4.2.1. Consider a colony of cells that evolves as follows. Initially, there is one cell. During each discrete time step, each cell either dies or splits into two new cells, each possibility having probability one half. Suppose cells die or split independently. Let X_k denote the number of cells alive at time k; $X_0 = 1$. Determine which of the following properties are possessed by X:

(a) Markov; (b) martingale; (c) independent increments; (d) uniform integrability.

4.3 Branching Processes

Definition. Omitted.

Remark.

- In general, $(Z_n, \mathcal{F}_n)$ is not a martingale. Because

  $$\mathbb{E}Z_{n+1} = \mathbb{E}\Big(\mathbb{E}(Z_{n+1,1} + \cdots + Z_{n+1,z_n} | \mathcal{F}_n)\Big) = m \cdot \mathbb{E}Z_n = m^{n+1}$$

  relies on n. Define $M_n = Z_n/m^n$; then $(M_n, \mathcal{F}_n)$ is a martingale.

- And $(M_n, \mathcal{F}_n)$ gives an example of martingale which is not uniformly integrable (Example 4.7).

Example 4.8. Let Z_n denote the number of offsprings in the n-th generation of a branching process. Assume that $Z_0 = 1$ and that the offspring distribution has mean μ and variance $\sigma^2 > 0$. Define $M_n = Z_n/\mu^n$, $\mathcal{F} = \sigma\{Z_0, \ldots, Z_n\}$.

a) For $\mu \le 1$, $(M_n, \mathcal{F}_n)$ is a martingale but not a u.i. martingale.

b) For $\mu > 1$, $(M_n, \mathcal{F}_n)$ is a u.i. martingale; and hence $M_n \xrightarrow{a.s.} M_\infty$. Show that M_∞ is not a constant RV.

c) Suppose that $\mu > 1$ and $\mathbb{P}(Z_1 \ge 2) = 0$. Show that

$$\mathbb{E}(\sup_n Z_n) \le \eta/(\eta - 1),$$

where η is the largest root of the equation $x = G(x)$ and G is the probability generating function of Z_1.

5 General Stochastic Processes

5.1 Finite-Dimentional Distributions (fdd)

Definition 5.1. Let $X = (X_t, t \in T)$ be a stochastic process. The finite-dimentional distributions of X are the distributions of $(X_{t_1}, X_{t_2}, \ldots, X_{t_n})$ for all possible choices of $t_1, t_2, \ldots, t_n \in T$ and for all $n \geq 1$.

Definition 5.2. Let $X = (X_t, t \in T)$, $Y = (Y_t, t \in T)$ be two stochastic processes. If their fdds are same, they are called equivalent, or versions of one another.

Remark.

- Fdds can be considered as Borel probability measures on $\mathbb{R}^n$ for all $n \geq 1$. And they satisfy Kolmogorov consistency conditions.
- **Kolmogorov's existance theorem**

  Conversely, if there is a family of Borel probability measures satisfying Kolmogorov consistency conditions, we can find a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and a RV $X = (X_t)_{t\in T}$ defined on it such that its fdds are exactly the given Borel probability measures.

Definition 5.3. A stochastic process is called Gaussian if all fdds are (multivariate) normal.

Proposition 5.4. *Fdds of a Gaussian process are completely determined by its covariance functions.*

Exercises

Exercise 5.1.1. Let $U \sim U[0,1]$. And let f be a continuous function on $[0,1]$. Define $X_t = f(t)$, for all $t \in [0,1]$, and $Y_t = X_t + \mathbf{1}_{\{U=t\}}$.

(a) Prove X and Y have the same fdds. (b) Prove $\mathbb{P}\{Y_t \text{ is continuous on } T\} = 0$.

Proof. (a) We divide $\{Y_{t_1} \leq s_1, \ldots, Y_{t_n} \leq s_n\}$ into two disjoint parts:

$$\begin{aligned}
&\mathbb{P}(Y_{t_1} \leq s_1, \ldots, Y_{t_n} \leq s_n)\\
&= \mathbb{P}\Big(\big(\{Y_{t_1} \leq s_1, \ldots, Y_{t_n} \leq s_n\} \cap \{\forall i,\ U(\omega) \neq t_i\}\big) \bigcup \big(\{Y_{t_1} \leq s_1, \ldots, Y_{t_n} \leq s_n\} \cap \{\exists i,\ U(\omega) = t_i\}\Big)\\
&= \mathbb{P}\Big(\{X_{t_1} \leq s_1, \ldots, X_{t_n} \leq s_n\}\Big) + \mathbb{P}\big(\{Y_{t_1} \leq s_1, \ldots, Y_{t_n} \leq s_n\} \cap \{\exists i,\ U(\omega) = t_i\}\Big)
\end{aligned}$$

And notice

$$\begin{aligned}
\mathbb{P}\big(\{Y_{t_1} \leq s_1, \ldots, Y_{t_n} \leq s_n\} \cap \{\exists i,\ U(\omega) = t_i\}\Big) &\leq \mathbb{P}(\exists i,\ U(\omega) = t_i)\\
&= 0
\end{aligned}$$

$\implies$ $\mathbb{P}(Y_{t_1} \leq s_1, \ldots, Y_{t_n} \leq s_n) = \mathbb{P}(X_{t_1} \leq s_1, \ldots, X_{t_n} \leq s_n)$

(b) Fix $\omega = \omega^*$. Let $t_0 = U(\omega^*)$. Then $Y_{t_0} = f(t_0) + 1$, while $Y_{t_0-} = Y_{t_0+} = f(t_0)$.

$\implies$ For each path of Y, there exists a discontinuous point.

$\implies$ $\mathbb{P}\{Y_t \text{ is continuous on } T\} = 0$.

□

Exercise 5.1.2. Let $\Omega = [0,1]$, $\mathcal{F} = \mathcal{B}[0,1]$, and $\mathbb{P} = \text{Leb}[0,1]$. Define $X_t(\omega) = \mathbf{1}_{\{t=\omega\}}$ and $Y_t(\omega) = 0$.

(a) Prove X and Y are equivalent processes.

(b) Calculate $\mathbb{P}(\sup_{0\leq t\leq 1} X_t = 0)$ and $\mathbb{P}(\sup_{0\leq t\leq 1} Y_t = 0)$.

Proof. (a) To prove X and Y are equivalent, we need to calculate their fdds:

$$\begin{aligned}
\mathbb{P}(Y_{t_1} \leq s_1, \ldots, Y_{t_n} \leq s_n) &= \mathbb{P}(0 \leq s_1, \ldots, 0 \leq s_n)\\
\mathbb{P}(X_{t_1} \leq s_1, \ldots, X_{t_n} \leq s_n) &= \mathbb{P}(\mathbf{1}_{\{\omega=t_1\}} \leq s_1, \ldots, \mathbf{1}_{\{\omega=t_n\}} \leq s_n)\\
&= \mathbb{P}\Big(\{0 \leq s_1, \ldots, 0 \leq s_n\} \bigcup \{\omega : \exists i,\ 1 \leq s_i,\ \omega = t_i\}\Big)\\
&= \mathbb{P}(0 \leq s_1, \ldots, 0 \leq s_n)
\end{aligned}$$

$\implies$ X and Y are equivalent.

(b) It is easy to notice that

$$
\begin{aligned}
\mathbb{P}\big(\sup_{0\le t\le 1} Y_t = 0\big) &= 1\\
\mathbb{P}\big(\sup_{0\le t\le 1} X_t = 0\big) &= \mathbb{P}\big(\sup_{0\le t\le 1} \mathbf{1}_{\{\omega=t\}=0}\big)\\
&= \mathbb{P}(\emptyset) = 0
\end{aligned}
$$

$\square$

-Gaussian processes-

Exercise 5.1.3 (Brownian Bridge)**.** Let (B_t) be a BM, $X_t = B_t - tB_1$, $0 \le t \le 1$, and $Y_t = X_{1-t}$. Prove Y has the same fdds as X.

Proof. Notice that X and Y are both Gaussian. Calculate their covariance functions.

$$
\begin{aligned}
\mathrm{Cov}(X_t, X_s) &= \mathrm{Cov}(B_t - tB_1, B_s - sB_1)\\
&= \mathrm{Cov}(B_t, B_s) - st\\
&= \min(s,t) - st\\
\mathrm{Cov}(Y_t, Y_s) &= \mathrm{Cov}(B_{1-t} - (1-t)B_1, B_{1-s} - (1-s)B_1)\\
&= \mathrm{Cov}(B_{1-t}, B_{1-s}) - (1-t)(1-s)\\
&= \min(1-s, 1-t) - (1-t)(1-s)
\end{aligned}
$$

Obviously, they are same. $\square$

Exercise 5.1.4. Show the following statements:

(a) X is a Gaussian process $\iff$ every finite linear combination $Z = \sum_{i=1}^n a_i X_{t_i}$ is a Gaussian RV.

(b) Let $X_t = Z\cos(2\pi t + \theta)$ where Z and θ are independent, $\theta \sim U[0, 2\pi]$, and the density function of Z is $p_Z(z) = ze^{-z^2/2} \cdot \mathbf{1}_{\{z\ge 0\}}$.
X is a Gaussian process.

Proof. (a) Trivial.

(b) Notice that

$$
\begin{aligned}
\sum_{i=1}^n a_i X_i &= \sum_{i=1}^n a_i \cdot Z\cos(2\pi t_i + \theta)\\
&= \Big(\sum_{i=1}^n a_i \cos(2\pi t_i)\Big) Z\cos\theta - \Big(\sum_{i=1}^n a_i \sin(2\pi t_i)\Big) Z\sin\theta.
\end{aligned}
$$

It suffices to prove $\begin{pmatrix} Z\cos\theta \\ Z\sin\theta \end{pmatrix}$ is bi-normal.

In fact, $\begin{pmatrix} Z\cos\theta \\ Z\sin\theta \end{pmatrix} \sim N_2(0, \mathbf{1}_{2\times 2})$. We're done.

$\square$

-Stationarity-

Definition.

- X is called strictly stationary if for all $n \ge 1$, $t_1, \ldots, t_n \in T$ and $h > 0$:

$$
(X_{t_1}, \ldots, X_{t_n}) \overset{\mathcal{D}}{=} (X_{t_1+h}, \ldots, X_{t_n+h})
$$

- X is called weakly stationary if for all $t_1, t_2 \in T$ and $h > 0$:

$$\mathbb{E}X_{t_1} = \mathbb{E}X_{t_2} \quad \text{and} \quad \mathrm{Cov}(X_{t_1}, X_{t_2}) = \mathrm{Cov}(X_{t_1+h}, X_{t_2+h}).$$

Exercise 5.1.5. Let $\{X_t\}_{t\in\mathbb{N}}$ be independent RVs such that $X_t + 1 \sim \exp(1)$ when t is odd and $X_t \sim N(0,1)$ when t is even. Prove X is weakly stationary but not strictly stationary.

Proof. To prove the weak stationarity, we calculate its mean and covariance:

$$\mathbb{E}X_t = 0$$
$$\mathrm{Cov}(X_{t_1}, X_{t_2}) = \begin{cases} 0 & \forall t_1 \neq t_2 \\ 1 & o.w. \end{cases}$$

Thus, X is weakly stationary.

And it is not strictly stationary because $X_1 \overset{\mathcal{D}}{\neq} X_2$. ☐

Exercise 5.1.6. Let $S_n = \sum_{i=1}^n X_i$ where $X_1, X_2, \ldots$ are i.i.d. RVs with mean 0 and variance σ^2. Prove S is not stationary.

Proof. Notice $\mathrm{Cov}(S_{t_1}, S_{t_2}) = \min(t_1, t_2)\sigma^2 \implies$ not stationary. ☐

Exercise 5.1.7. Let $X_t = Z_t + \theta Z_{t-1},\ t = 1, 2, \ldots,$ where $Z_0, Z_1, \ldots$ are i.i.d RVs with mean 0 and variance σ^2. Prove X is both weakly stationary and strictly stationary.

Proof. It is easy to see the weak stationatity:

$$\mathbb{E}X_t = 0,\ \mathrm{Var}(X_t) = (1+\theta^2)\sigma^2,\ \text{and } \mathrm{Cov}(X_s, X_t) = 0 \text{ for } s \neq t.$$

And we can use the connection between MGFs and fdds to find the strict stationarity. Notice the moment generating function of $(X_1, \ldots, X_n)$ is:

$$\begin{aligned}\mathbb{E}\exp(\sum_{i=1}^n \lambda_i X_i) &= \mathbb{E}\exp\Big(\lambda_n Z_n + (\theta\lambda_n + \lambda_{n-1})Z_{n-1} + \cdots + (\theta\lambda_2 + \lambda_1)Z_1 + \theta\lambda_1 Z_0\Big) \\ &= \mathbb{E}\exp(\lambda_n Z) \cdot \mathbb{E}\exp[(\theta\lambda_n + \lambda_{n-1})Z] \cdot \cdots \cdot \mathbb{E}\exp[(\theta\lambda_2 + \lambda_1)Z] \cdot \mathbb{E}\exp(\theta\lambda_1 Z)\end{aligned}$$

Obviously, it is invariant under index-shift; that is, $\mathbb{E}\exp(\sum_{i=1}^n \lambda_i X_i) = \mathbb{E}\exp(\sum_{i=1}^n \lambda_i X_{i+h})$.

Now consider the random vector $(X_{t_1}, \ldots, X_{t_n})$. It can be divided into several independent disjoint parts in which the index sequence is successive. Then apply for the invariance. ☐

5.2 Continuity of Sample Paths

Definition 5.5. Let $X = (X_t, t \in T)$ be a stochastic process. $\omega \mapsto X_t$ is called a sample path.

Theorem 5.6 (Kolmogorov Continuity Criterion)**.** *Let (X_t) be a stochastic process. If $\forall T^* > 0$, $\exists \alpha, \beta, C > 0$ such that*

$$\mathbb{E}|X_{t+h} - X_t|^\alpha \leq Ch^{1+\beta} \quad \forall h > 0,\ 0 < t < T^* - h$$

then there exists a continuous version of X on $[0, T^*]$.

Example 5.7 (Brownian Motion)**.** Let (B_t) be a Brownian Motion. Take $\alpha = 4$.

$$\begin{aligned}\mathbb{E}|B_{t+h} - B_t|^4 &= 3(\mathbb{E}|B_{t+h} - B_t|^2)^2 \\ &= 3h^2\end{aligned}$$

Note that we use the fact $\mathbb{E}X^4 = 3(\mathbb{E}X^2)^2$ when $X \sim N(0,h)$. Therefore, we can take $\alpha = 4,\ C = 3,\ \beta = 1$ in the criterion. There exists a continuous version of BM.

Exercises

Exercise 5.2.1. Let $\{X_t,\ 0 \le t \le 1\}$ be a family of i.i.d $N(0,1)$ RVs. Show that X cannot have a.s. continuous paths.

Proof. **Note**: X has a.s. continuous paths $\implies$ $\forall \epsilon > 0$, $\mathbb{P}\{\omega : \forall t,\ |X_t - X_{t+\frac{1}{n}}| > 2\epsilon\} \to 0$ as $n \to \infty$.

Because $\{X_t > \epsilon,\ X_{t+\frac{1}{n}} < -\epsilon\} \subset \{|X_t - X_{t+\frac{1}{n}}| > 2\epsilon\}$, it suffices to prove $\mathbb{P}\{X_t > \epsilon,\ X_{t+\frac{1}{n}} < -\epsilon\}$ doesn't converge to 0. And by i.i.d.

$$
\begin{aligned}
\mathbb{P}\{X_t > \epsilon,\ X_{t+\frac{1}{n}} < -\epsilon\} &= \mathbb{P}\{X_t > \epsilon\}\mathbb{P}\{X_{t+\frac{1}{n}} < -\epsilon\} \\
&= [1 - \Phi(\epsilon)]\Phi(-\epsilon)
\end{aligned}
$$

where Φ is the CDF of $N(0,1)$. Thus, X cannot have a.s. continuous paths. □

Exercise 5.2.2. Let $\{X_t,\ 0 \le t \le 1\}$ be a mean 0 Gaussian process with $\mathbb{E}(X_{t+h} - X_t)^2 = h^\gamma,\ \gamma > 0$. Show that X must be a.s. continuous.

Proof. **Note**: X has a.s. continuous paths $\impliedby$ for all $\epsilon > 0$, $\mathbb{P}\{\omega : \forall t,\ |X_t - X_{t+h}| > \epsilon\} \to 0$ as $h \to 0$.

$$
\begin{aligned}
\mathbb{P}\{\omega : |X_t - X_{t+h}| > \epsilon\} &= \mathbb{P}\Big\{\omega : \frac{X_t - X_{t+h}}{h^{\gamma/2}} > \frac{\epsilon}{h^{\gamma/2}}\Big\} + \mathbb{P}\Big\{\omega : \frac{X_t - X_{t+h}}{h^{\gamma/2}} < -\frac{\epsilon}{h^{\gamma/2}}\Big\} \\
&= 1 - \Phi\big(\frac{\epsilon}{h^{\gamma/2}}\big) + \Phi\big(-\frac{\epsilon}{h^{\gamma/2}}\big) \\
&\longrightarrow 0 \quad \text{as } h \to 0
\end{aligned}
$$

Thus, X has a.s. continuous paths. □

5.3 Stopping Times

Definition 5.8. Let $\mathbb{T}$ be an index set, and $\mathcal{F}$ be a filtration on $\mathbb{T}$.

- A random time $T : \Omega \to \mathbb{T} \cup \{+\infty\}$ is called a stopping time of $\mathcal{F}$ if
$$\{T \le t\} \in \mathcal{F}_t$$
for all $t \in \mathbb{T}$.
- The σ-field of the past before T is defined as
$$\mathcal{F}_T = \{A \in \mathcal{F}_\infty : \forall t \in \mathbb{T},\ A \cap \{T \le t\} \in \mathcal{F}_t\}.$$

Remark.

- T is a stopping time of $\mathcal{F}$ if and only if
$$\{T < t\} \in \mathcal{F}_t$$
for all t. This is also equivalent to saying that $T \wedge t$ is $\mathcal{F}_t$-measurable for every $t > 0$.
- T is a stopping time of $\mathcal{F}$, then
$$\mathcal{F}_T = \{A \in \mathcal{F}_\infty : \forall t \in \mathbb{T},\ A \cap \{T < t\} \in \mathcal{F}_t\}.$$

Exercises

Exercise 5.3.1. Let T and S be stopping times of $\mathcal{F}$. Show the following properties:

(a) T is $\mathcal{F}_T$-measurable.

(b) Let $A \in \mathcal{F}_\infty$. Define
$$T^A(\omega) = \begin{cases} T(\omega) & \omega \in A\ , \\ +\infty & \omega \notin A\ . \end{cases}$$
Show that $A \in \mathcal{F}_T$ if and only if T^A is a stopping time.

(c) If $S \le T$, then $\mathcal{F}_S \subset \mathcal{F}_T$.

(d) $S \vee T$ and $S \wedge T$ are also stopping times.
Furthermore, $\mathcal{F}_{S\wedge T} = \mathcal{F}_S \cap \mathcal{F}_T$, $\{S \le T\} \in \mathcal{F}_{S\vee T}$, and $\{S = T\} \in \mathcal{F}_{S\vee T}$.

(e) Let (X_t) be a stochastic process. Show that $\omega \mapsto X_T(\omega)$ defined a $\mathcal{F}_T$-measurable map.

Proof. (a) Recall that $\mathcal{F}_T = \{A \in \mathcal{F}_\infty : \forall t \in \mathbb{T},\ A \cap \{T \le t\} \in \mathcal{F}_t\}$. Because $\{T \le t\} \in \mathcal{F}_t$ is given in the definition of the stopping time, $A = \{T \le t\} \in \mathcal{F}_T$.

(b) We just need to notice that

$$\begin{aligned}\{T^A \le t\} &= \Big(A \cap \{T^A \le t\}\Big) \bigcup \Big(A^c \cap \{T^A \le t\}\Big)\\ &= \Big(A \cap \{T \le t\}\Big) \bigcup \Big(A^c \cap \emptyset\Big)\\ &= A \cap \{T \le t\}.\end{aligned}$$

(c) $S \le T$ implies $\{T \le t\} \subset \{S \le t\}$. So for $A \in \mathcal{F}_S$, we have

$$A \cap \{T \le t\} = \big(A \cap \{S \le t\}\big) \cap \{T \le t\} \in \mathcal{F}_t.$$

(d) It is easy to see that $S \vee T$ and $S \wedge T$ are stopping times:

$$\begin{aligned}\{S \vee T \le t\} = \{S \le t\} \cup \{T \le t\} \in \mathcal{F}_t\\ \{S \wedge T \le t\} = \{S \le t\} \cap \{T \le t\} \in \mathcal{F}_t\end{aligned}$$

To show $\mathcal{F}_{S\wedge T} = \mathcal{F}_S \cap \mathcal{F}_T$, we firstly notice that $\mathcal{F}_{S\wedge T} \subset \mathcal{F}_S \cap \mathcal{F}_T$ by (c); thus, it suffices to prove that $\mathcal{F}_S \cap \mathcal{F}_T \subset \mathcal{F}_{S\wedge T}$. And notice that

$$A \cap \{S \wedge T \le t\} = A \cap \{S \le t\} \cap \{T \le t\} \in \mathcal{F}_t.$$

To show $\{S \le T\} \in \mathcal{F}_{S\vee T}$, we need to notice that not done

$$\begin{aligned}\{S \le T\} \cap \{T \le t\} =\\ \{S \le T\} \cap \{S \le t\} =\end{aligned}$$

And to show $\{S = T\} \in \mathcal{F}_{S\vee T}$, note that $\{S = T\} = \{S \le T\} \cap \{S \ge T\}$. □

Exercise 5.3.2.

(a) Let (T_n) be a monotone sequence of stopping times of $\mathcal{F}$, then $T = \lim T_n$ is also a stopping time.

(b) For any stopping time T, construct a sequence of stopping times that decreases to T.

(c) Let (T_n) be a sequence of stopping times of $\mathcal{F}$, then $\sup T_n$ is also a stopping time; however, $\inf T_n$ is not, in general.

Exercise 5.3.3. Let $N_t = \sum_{n=1}^{\infty} \mathbf{1}_{[0,t]} \circ T_n$ be a counting process where $0 = T_0 < T_1 < T_2 < \dots$ are some random times and $\lim\limits_{n\to\infty} T_n = +\infty$. For fixed $a, b \in \mathbb{R}_+$, define

$$T = \inf\{t \ge a : N_t = N_{t-a}\}$$

and

$$L = \inf\{t \ge 0 : N_t = N_b\}.$$

(a) Show that T_i and T are stopping times.

(b) Show that L is not a stopping time.

(c) Compute $\mathbb{P}(T < \infty)$ if N is a Poisson process with intensity λ.

Proof. (a) First, we show that T_i is a stopping time for all i. Notice that

$$\{T_i \le t\} = \{N_t \ge i\} \in \mathcal{F}_t.$$

Then, we show T is a stopping time.

Option 1.

Observing the definiton of T, we notice that for every $\omega \in \Omega$,

$$T = T_k + a$$

for some k. And $T = T_k + a$ means the length of the first k intervals is less than a and the length of the $(k+1)$-th interval is larger than a; that is,

$$\{T = T_k + a\} = \{T_1 - T_0 \le a, \dots, T_k - T_{k-1} \le a\} \cup \{T_{k+1} - T_k > a\}.$$

Moreover, we have

$$\{T = T_k + a\} \cap \{T_k + a \le t\} \in \mathcal{F}_t,$$

by noting that

$$\begin{aligned}\{T_1 - T_0 \le a, \dots, T_k - T_{k-1} \le a\} \cap \{T_k + a \le t\} &= \{T_1 \le a, \dots, T_k \le ka\} \cap \{T_k \le t - a\} \\ &\in \mathcal{F}_{(t-a)\wedge a} \subset \mathcal{F}_t.\end{aligned}$$

Therefore, we have

$$\begin{aligned}\{T \le t\} &= \bigcup_{n \in \mathbb{N}_0} \Big(\{T = T_k + a\} \cap \{T \le t\}\Big) \\ &\in \mathcal{F}_t.\end{aligned}$$

Option 2.

For each t we have $T_k(\omega) \le t < T_{k+1}(\omega)$ for some k. Thus, we can define

$$A_t(\omega) = t - T_k(\omega).$$

Then each path of A is strictly increasing and right-continuous. Moreover, A is adapted to $\mathcal{F}$.

Notice that $T = \inf\{t \ge 0 : A_t \ge a\}$. Therefore, T is a stopping time of $\mathcal{F}$.

$\square$

-Galmarino's test-

Theorem. *Let (X_t) be a process, $\mathcal{F}$ be a σ-algebra generated by (X_t), and T be a RV. Then thw following are equivalent*

(i) T is a stopping time w.r.t. $\mathcal{F}$.

(ii) $\forall t \ge 0\ \forall \omega, \omega' \in \Omega$

$$T(\omega) \le t \text{ and } \forall s \le t\ X_s(\omega) = X_s(\omega') \implies T(\omega) = T(\omega'). \tag{3}$$

Exercise 5.3.4. Show the Galmarino's test as follows:

(a) Define $a_t : \omega(s) \mapsto \omega(s \wedge t)$. Show $\mathcal{F}_t = a_t^{-1}(\mathcal{F})$ for all $t \ge 0$.

(b) Let Y be a RV. Then Y is measurable w.r.t. $\mathcal{F}_t$ if and only if

$$Y = Y \circ a_t.$$

(c) Show this theorem.

Exercise 5.3.5. Let N be a Poisson process with intensity λ. Is $T = \sup\{n \in \mathbb{N} : N_n = 0\}$ a stopping time?

Exercise 5.3.6. Let $(X_t)_{t \in \mathbb{R}_+}$ be a continuous stochastic process started at 0. For any $b \geq 0$, define

$$T = \inf\{t \geq 0 : X_t > b\}.$$

Is T a stopping time?

Proof. No, in general. Choose ω and ω' such that $X_t(\omega) = X_t(\omega') = b$, $X_{t+}(\omega) > b$ and $X_{t+}(\omega') < b$. Then $T(\omega) = t$ while $T(\omega') > t$.

Figure 1: To be added

□

5.4 Total Variation and Quadratic Variation

Definition 5.9.

- Let $[a, b]$ be an interval of $\mathbb{R}$. A countable family $\mathcal{A} \subset 2^{[a,b]}$ is called a subdivision of $[a, b]$ if
  a) Every element in $\mathcal{A}$ is of form $(s, t]$.
  b) $\cup \mathcal{A} = (a, b]$.
  c) If $U_1 \neq U_2$ in $\mathcal{A}$, then $U_1 \cap U_2 = \emptyset$.
- Let $f : \mathbb{R}_+ \to \mathbb{R}$ be right-continuous, $p > 0$, and $\mathcal{A}$ be a subdivision of $[a, b]$. Define

$$\mathscr{V}_p = \sup_{\mathcal{A}} \sum_{(s,t] \in \mathcal{A}} |f(t) - f(s)|^p.$$

  It is called the p-variation of f on $[a, b]$. For $p = 1$, it is called the total variation. For $p = 2$, it is called the quadratic variation.
- f is said to have bounded p-variation if $\mathscr{V}_p < \infty$.

Definition 5.10 (Quadratic variation for real-valued processes)**.** Let Y be a real-valued process. Define

$$\langle Y, Y \rangle_t = \lim_{\delta^{(n)} \to 0} \sum_{i=1}^{K_n - 1} |Y_{t_{i+1}^{(n)}} - Y_{t_i^{(n)}}|^2,$$

where the limit is defined using convergence in probability.

Example 5.11 (Quadratic variation for Brownian motion)**.** We will see that $\langle B, B \rangle_t = t$. Define

$$S_n = \sum_i |B_{t_{i+1}^{(n)}} - B_{t_i^{(n)}}|^2$$

and take $\{\Delta^{(n)}\}$ as a sequence of partitions of interval of $[a, b]$.

(i) Because $B_{t_{i+1}^{(n)}} - B_{t_i^{(n)}} \sim N(0, t_{i+1}^{(n)} - t_i^{(n)})$, we have

$$\mathbb{E} S_n = \sum_i \mathbb{E}|B_{t_{i+1}^{(n)}} - B_{t_i^{(n)}}|^2 = \sum_i (t_{i+1}^{(n)} - t_i^{(n)}) = b - a.$$

(ii) If $X \sim N(0,t)$, $\mathbb{E}X^4 = 3t^2$; and (B_t) is a Lévy process. Thus,

$$\begin{aligned}
\mathbb{E}S_n^2 &= \mathbb{E}\Big(\sum_i |B_{t_{i+1}^{(n)}} - B_{t_i^{(n)}}|^2\Big)^2 \\
&= \mathbb{E}\sum_i |B_{t_{i+1}^{(n)}} - B_{t_i^{(n)}}|^4 + 2\sum_{i<j}\mathbb{E}\Big\{(B_{t_{i+1}^{(n)}} - B_{t_i^{(n)}})^2(B_{t_{j+1}^{(n)}} - B_{t_j^{(n)}})^2\Big\} \\
&= \sum_i 3(t_{i+1}^{(n)} - t_i^{(n)})^2 + 2\sum_{i<j}(t_{i+1}^{(n)} - t_i^{(n)})(t_{j+1}^{(n)} - t_j^{(n)}) \\
&= 2\sum_i (t_{i+1}^{(n)} - t_i^{(n)})^2 + \sum_i\sum_j (t_{i+1}^{(n)} - t_i^{(n)})(t_{j+1}^{(n)} - t_j^{(n)}) \\
&= 2\sum_i (t_{i+1}^{(n)} - t_i^{(n)})^2 + (b-a)^2 \\
&\le 2\delta^{(n)}(b-a) + (b-a)^2 \\
&\longrightarrow (b-a)^2
\end{aligned}$$

(iii) Then we have

$$\mathbb{E}\big(S_n - (b-a)\big)^2 = \mathrm{Var}S_n^2 = \mathbb{E}S_n^2 - (b-a)^2 \to 0,$$

which implies that $S_n \to b-a$ in L^2 and in probability. To prove $\langle B, B\rangle_t = t$, we need to choose $[a,b] = [0,t]$.

Example 5.12 (Total variation for Brownian motion)**.** For almost every $\omega \in \Omega$, we will see the path $\omega := W(\omega)$ has infinite total variation, where W is a Brownian motion.

Let v^* be the total variation of ω; that is

$$v^* = \sup_{\mathcal{A}} \sum_{(s,t]\in\mathcal{A}} |\omega(s) - \omega(t)|.$$

Let $\mathcal{A}_n$ be a sequence of subdivision. Then notice that

$$\begin{aligned}
\sum |\omega(t) - \omega(s)|^2 &\le \sup|\omega(t) - \omega(s)| \sum |\omega(t) - \omega(s)| \\
&\le \sup|\omega(t) - \omega(s)| \cdot v^*
\end{aligned}$$

Letting $n \to \infty$, by computing its quadratic variation, we have

$$\sum |\omega(t) - \omega(s)|^2 \to b-a,$$

and by the continuity of sample path, we have

$$\sup|\omega(t) - \omega(s)| \to 0.$$

Therefore, v^* cannot be finite.

Exercises

Exercise 5.4.1. For each $n \in \mathbb{N}$, let $\mathcal{A}$ be the subdivision of $[a,b]$ that consists of 2^n intervals of the same length. Then

$$V_n = \sum_{(s,t]} |B_t - B_s|^2$$

converges to $b-a$ almost surely.

Exercise 5.4.2.

(a) Find the total variation and the quadratic variation of the Poisson process N.

(b) Find the quadratic variation of $N_t - \lambda t$.

(c) Find the quadratic variation of $N_{\int_0^t f(s)\mathrm{d}s}$.

Proof. (a) First, we compute its **total variation**.

Let $\{\mathcal{A}_n\}$ be a sequence subdivision of $[a, b]$ such that $\|\mathcal{A}_n\| \to 0$. Define

$$S_n = \sum_{(s,t] \in \mathcal{A}_n} |N_t - N_s|.$$

Simplify it:

$$S_n = N_b - N_a.$$

Letting $n \to \infty$ and $[a, b] = [0, t]$, the total variation of N is N itself.

Second, we compute its **quadratic variation**.

Notice that

$$[N]_t = \sum_{0 \le s \le t} (\Delta X_s)^2$$

where $\Delta X_s := X_s - X_{s-}$ is the jump of N at s. And re-write N as

$$N_t = \sum_{i=1}^{\infty} \mathbf{1}_{[0,t]} \circ T_i.$$

Then $\Delta N_t = \sum_{i=1}^{\infty} \mathbf{1}_{\{t\}} \circ T_i$. Therefore,

$$\begin{aligned}
[N]_t &= \sum_{0 \le s \le t} (\Delta N_s)^2 = \sum_{0 \le s \le t} \Delta N_s \\
&= \sum_{0 \le s \le t} (\sum_{i=1}^{\infty} \mathbf{1}_{\{s\}} \circ T_i) = \sum_{i=1}^{\infty} (\sum_{0 \le s \le t} \mathbf{1}_{\{s\}} \circ T_i) \\
&= \sum_{i=1}^{\infty} \mathbf{1}_{[0,t]} \circ T_i = N_t
\end{aligned}$$

(b) It is easy to see

$$[N_t - \lambda t]_t = \sum_{0 \le s \le t} (\Delta(N_s - \lambda s))^2 = \sum_{0 \le s \le t} (\Delta N_s)^2 = N_t.$$

□

6 Discrete and Continuous Time Markov Chains

6.1 Characterization

Definition 6.1. Let $(\Omega, \mathcal{H}, \mathbb{P})$ be a probability space, and $\mathcal{F} = (\mathcal{F}_t)$ be a filtration on it. Let $X = (X_t)$ be a stochastic process with some state space $(E, \mathcal{E})$ and be adapted to $\mathcal{F}$.

- X is Markovian if for every t, $u > t$, and $f \in \mathcal{E}_+$,
$$\mathbb{E}(f \circ X_u | \mathcal{F}_t) = \mathbb{E}(f \circ X_u | X_t).$$
- For $t \leq u$, define the transition function on $(E, \mathcal{E})$ as
$$P_{t,u}(x, A) = \mathbb{P}(X_u \in A \mid X_t = x).$$
- Chapman-Kolmogorov equation. As the product of transition kernels,
$$P_{s,t} P_{t,u} = P_{s,u}.$$
- Let X be Markovian and admit $(P_{t,u})$ as its transition function, then it is called time-homogeneous if $P_{t,u}$ is only dependent on $u - t$; that is
$$P_{t,u} = P_{u-t}.$$

Remark. In the time-homogenuous case, we can re-write Chapman-Kolmogorov equation as
$$P_t P_u = P_{t+u}, \quad t, u \in \mathbb{R}_+;$$
and usually, we call X a Markov process with transition function (P_t).

And suppose X is a Markov chain, then $Q = P_{t,t+1}$ is free of t. Thus,
$$P_{t,u} = Q^n, \quad u - t = n \in \mathbb{N};$$
and usually, we call X a Markov chain with transition kernel Q.

Exercises

Exercise 6.1.1.

(a) Let Y be a Lévy process and π_t be the distribution of Y_t. Define $X = X_0 + Y$ where X_0 is a RV independent of Y. Show X is a Markov process and compute its transition function.

(b) Give an example of Markov process which doesn't have independent increments.

Proof. (a) Let $A - x = \{a - x : a \in A\}$. We have

$$\begin{aligned}
&\mathbb{P}(X_{t_n} \in A | X_{t_{n-1}} = s_{n-1}, \ldots, X_{t_1} = s_1) \\
&= \mathbb{P}(X_{t_n} - X_{t_{n-1}} \in A - s_{n-1} | X_{t_{n-1}} = s_{n-1}, X_{t_{n-1}} - X_{t_{n-2}} = s_{n-1} - s_{n-2}, \ldots, X_{t_{n-1}} - X_{t_1} = s_{n-1} - s_1) \\
&= \mathbb{P}(Y_{t_n} - Y_{t_{n-1}} \in A - s_{n-1} | X_{t_{n-1}} = s_{n-1}, Y_{t_{n-1}} - Y_{t_{n-2}} = s_{n-1} - s_{n-2}, \ldots, Y_{t_{n-1}} - Y_{t_1} = s_{n-1} - s_1) \\
&= \mathbb{P}(Y_{t_n} - Y_{t_{n-1}} \in A - s_{n-1} | X_{t_{n-1}} = s_{n-1}) \quad \text{(indep. increments)} \\
&= \mathbb{P}(X_{t_n} \in A | X_{t_{n-1}} = s_{n-1})
\end{aligned}$$

Therefore, X is a Markov process. And it is easy to see
$$P_t(A, x) = \mathbb{P}(X_{u+t} \in A | X_u = x) = \mathbb{P}(Y_{t+u} - Y_u \in A - x | X_u = x) = \pi_t(A, x).$$
is the transition function of X.

(b) Ornstein–Uhlenbeck process.

□

Exercise 6.1.2. Let (X_n) be a time-homogenuous Markov chain with a discrete state space $(E, \mathcal{E})$ and with a transition kernel Q. If the distribuiton of X_n is μ_n, find the distribution of X_{n+k}.

6.2 Markov Chains: Classification of States

In this section, we are only interested in the time-homogenuous Markov chains with a discrete state space. In this case, we can re-write P_t as

$$P_t(x, A) = \mathbb{P}(X_t \in A \mid X_0 = x) = \sum_{y \in A} \mathbb{P}(X_t = y \mid X_0 = x).$$

Definition 6.2. Let (X_n) be a time-homogenuous Markov chain with a discrete state space.

- The <u>transition matrix</u> is defined as $\boldsymbol{P} = (p_{ij})$, where

$$p_{ij} = \mathbb{P}(X_{n+1} = j | X_n = i)$$

  means the probability from the state i to j in one step.

- The <u>k-step transition matrix</u> is defined as $\boldsymbol{P(n, n+k)} = (p_{ij}(n, n+k))$, where

$$p_{ij}(n, n+k) = \mathbb{P}(X_{n+k} = j | X_n = i)$$

  means the probability from the state i to j in k steps.

Remark. With this notation, we can re-write the transition kernel as

$$Q(i, J) = \sum_{j \in J} p_{ij};$$

so obviously, $\boldsymbol{P}^k = \boldsymbol{P(n, n+k)}$, which is the matrix form of C-K equation.

Definition 6.3. Let (X_n) be a time-homogenuous Markov chain with a discrete state space.

- Let $\mu_i^{(n)} = \mathbb{P}(X_n = i)$ be the mass function of X_n. And they form a row vector $\boldsymbol{\mu}^{(n)}$.
- The probability that the first visit to state j, starting from i, takes place at the nth step, is

$$f_{ij}(n) = \mathbb{P}(X_1 \neq j, \ldots, X_{n-1} \neq j, X_n = j | X_0 = i).$$

- The probability that the chain ever vists j is

$$f_{ij} = \sum_{n=1}^{\infty} f_{ij}(n).$$

Remark. The transition matrix $\boldsymbol{P}$ and the initial mass function $\boldsymbol{\mu}^{(0)}$ determine the chain. Many questions about the chain can be expressd in therms of these quantities.

Definition 6.4. Let (X_n) be a time-homogenuous Markov chain with a discrete state space.

a) For any state i:

  - State i is called <u>persistent (or recurrent)</u> if

$$\mathbb{P}(X_n = 1,\ \exists n \geq 1 \mid X_0 = i) = 1.$$

  - State i is called <u>transient</u> if

$$\mathbb{P}(X_n = 1,\ \exists n \geq 1 \mid X_0 = i) < 1.$$

b) Define $T_j = \min\{n \geq 1 : X_n = j\}$ be the time of the first visit to j.For a **persistent state** i:

  - State i is called <u>null</u> if

$$\mu_i := \mathbb{E}(T_i | X_0 = i) = \infty.$$

- State i is called non-null (or positive) if

$$\mu_i := \mathbb{E}(T_i | X_0 = i) < \infty.$$

c) Define $d(i) = \gcd\{n : p_{ii}(n) > 0\}$.

- State i is called periodic if

$$d(i) > 1.$$

- State i is called aperiodic if

$$d(i) = 1.$$

d) A state is called ergodic if it is persistent, non-null, and aperiodic.

Theorem 6.5. *Let (X_n) be a time-homogenuous Markov chain with a discrete state space.*

a) For any state j:

- *State j is persistent if*

$$\sum_n p_{jj}(n) = \infty.$$

- *State j is transient if*

$$\sum_n p_{jj}(n) < \infty.$$

b) A persistent state is null if and only if $p_{ii}(n) \to 0$ as $n \to \infty$.

6.3 Markov Chains: Classification of Chains

In this section, we are only interested in the Markov chains with a discrete state space.

Definition 6.6.

- We say i communicates with j, $i \to j$, if $p_{ij}(m) > 0$ for some $m \geq 0$.
- We say i intercommunicates with j, $i \leftrightarrow j$, if $i \to j$ and $j \to i$.

Remark. If $i \leftrightarrow j$, then

- They have the same period.
- i is transient $\iff$ j is transient.
- i is null persistent $\iff$ j is null persistent.

Definition 6.7. A set C of states is called:

- closed if $p_{ij} = 0$ for all $i \in C,\ j \notin C$,
- irreducible if $i \leftrightarrow j$ for all $i, j \in C$.

6.4 Stationary distributions and the limit theorem

6.5 Markov Chains: Examples

In this section, we will mainly focus on the Markov chains with a discrete state space; however, some examples of Markov chains with a non-discrete state space are also given.

Remark. If the state space $(E, \mathcal{E})$ is standard, we can construct every Markov chain in this way. And φ is called the structure function and (Z_n) is called the driving variables.

Example 6.8 (Random walks). Let $E = D = \mathbb{R}^d$, and $\varphi(x, z) = x + z$. Then

$$\begin{aligned} X_{n+1} &= \varphi(X_n, Z_{n+1}) \\ &= X_n + Z_{n+1} \\ &= \sum_{i=1}^{n+1} Z_i \end{aligned}$$

is called a random walk on $\mathbb{R}^d$.

Example 6.9 (Gauss-Markov chains). Let $E = D = \mathbb{R}^d$, and $\varphi(x, z) = Ax + Bz$, where A and B are some $d \times d$ matrices. Assume $Z_i \sim N_d(0, \mathbf{I}_{d\times d})$ is a sequence of i.i.d. RVs. Then the resulting chain is called a Gauss-Markov chain.

6.6 Markov Processes: Examples

Example 6.10 (Markov chains subordinated to Poisson). Let $(Y_n)_{n\in\mathbb{N}}$ be a Markov chain with state space $(E, \mathcal{E})$ and transition kernel Q. Let (N_t) be a Poisson process with rate c, independent of (Y_n). Suppose that

$$X_t = Y_{N_t}, \quad t \in \mathbb{R}_+.$$

Then, X is a Markov process, by the strong Markov property of Y.

And the transition function is

$$\begin{aligned} P_t(x, A) &= \mathbb{P}(X_t \in A \mid X_0 = x) \\ &= \mathbb{P}(Y_{N_t} \in A \mid Y_0 = x) \\ &= \sum_{n=0}^{\infty} \mathbb{P}(Y_n \in A \mid Y_0 = x, N_t = n) \cdot \mathbb{P}(N_t = n \mid Y_0 = 0) \\ &= \sum_{n=0}^{\infty} \frac{e^{-ct}(ct)^n}{n!} Q^n(x, A). \end{aligned}$$

Example 6.11 (Delayed uniform motion). Let T be an exponentially distributed RV. Define $X_t = (t - T)^+$. X can be depicted as the motion of a particle. Firstly, this particle stays at the origin for T of time. Then, it moves upward at unit speed.

First, we show that X is a Markov process.

Then, we compute its transition kernel.

Finally, we can see X has no strong Markov property.

7 Poisson Processes

7.1 Characterization

Definition 7.1.

- **Counting processes**

  $N = (N_t)_{t\in\mathbb{R}_+}$ is called a counting process, if for a.e. ω, the path $t \mapsto N_t(\omega)$ is an increasing right-continuous step function with $N_0(\omega) = 0$ and whose every jump size is one.

- **Poisson processes**

  $N = (N_t)_{t\in\mathbb{R}_+}$ is called a Poisson process with rate c if it is a counting process, and $\forall s, t \in \mathbb{R}_+$, $N_{s+t} - N_s \sim \text{Poisson}(ct)$ is independent of $\mathcal{F}_s$.

Remark. N can be written as

$$N_t(\omega) = \sum_{k=1}^{\infty} \mathbf{1}_{[0,t]} \circ T_k(\omega),$$

where T is an increasing sequence of RVs.

Theorem 7.2. *For fixed $c \in (0, \infty)$, the following are equivalent:*

a) N is a Poisson counting process with rate c.

b) ***Martingale connection***

  N is a counting process and $\tilde{N} = (N_t - ct)_{t\in\mathbb{R}_+}$ is a martingale.

c) (T_k) is an increasing sequence of stopping times, and the differences $(T_k - T_{k-1})_{k\in\mathbb{N}}$ are i.i.d. with the distribution $\text{Exp}(c)$*.*

d) ***Characterization as a Lévy process.***

  N is both a counting process and a Lévy process.

Proof.

- *a)* $\Rightarrow$ *b)*: Notice that for $s \le t$,

$$\begin{aligned}\mathbb{E}(\tilde{N}_t|\mathcal{F}_s) &= \mathbb{E}(N_t - ct|\mathcal{F}_s)\\ &= \mathbb{E}(N_t - N_s|\mathcal{F}_s) + N_s - ct\\ &= c(t-s) + N_s - ct = \tilde{N}_s.\end{aligned}$$

  Therefore, $\tilde{N}$ is a martingale.

  b) $\Rightarrow$ *c)*: First, we notice that $\{N_{T_k+t} - N_{T_k} = 0\} = \{T_{k+1} - T_k > t\}$. (Recall that T_k means the arrival time of the kth visitor.)

  By the stronge Markov property, $N_{T_k+t} - N_{T_k}$ is a Poisson distribution with rate ct, and is independent of $\mathcal{F}_{T_k}$. And

$$\mathbb{P}(N_{T_k+t} - N_{T_k} = 0) = e^{-ct};$$

  that is,

$$\mathbb{P}(T_{k+1} - T_k \le t) = 1 - e^{-ct},$$

  which is the CDF of the exponential distribution with parameter c.

- *a)* $\Rightarrow$ *d)*: Trivial.

$\square$

Proposition 7.3. *Let N be a Poisson process with intensity λ. Then $(T_1, \dots, T_n) \overset{D}{=} (U_{(1)}, \dots, U_{(n)})$.*

Exercises

Exercise 7.1.1.

(a) Let N be a Poisson process with rate c. Compute the mean and the covariance function of N.

(b) Let $N^{(1)}$ and $N^{(2)}$ be two independent Poisson processes with rate c_1 and c_2. Prove $N^{(1)} + N^{(2)}$ is a Poisson process with rate $c_1 + c_2$.

Exercise 7.1.2. Let $N^{(1)}$ and $N^{(2)}$ be two independent Poisson processes with rate c_1 and c_2. Define $X_t = N_t^{(1)} - N_t^{(2)}$.

(a) Compute the mean and the covariance function of X.

(b) Is X a Poisson process?

(c) Is X a Lévy process?

(d) Is X a Markov process? If so, compute its transition semigroup.

(e) Is X a martingale?

Proof.

(a) $\mathbb{E}X_t = (c_1 - c_2)t$; and $\mathbb{E}X_t X_s = (c_1 + c_2) \cdot t \wedge s$.

(b) No, obviously.

(c) Yes. If X is a Lévy process, then cX is a Lévy process. If X and Y are two independent Lévy processes, then $X + Y$ is a Lévy process.

(d) Yes, even better. Because X is a Lévy process, it has strong Markov property.

(e) Let $\mathcal{F}$ be the natural filtration generated by X.

$$\begin{aligned}\mathbb{E}(X_t \mid \mathcal{F}_s) &= \mathbb{E}(X_t - X_s \mid \mathcal{F}_s) + X_s \\ &= \mathbb{E}((N_t^{(1)} - N_s^{(1)}) - (N_t^{(2)} - N_s^{(2)}) \mid \mathcal{F}_s) + X_s \\ &= (c_1 - c_2)(t - s) + X_s\end{aligned}$$

Therefore, X is a martingale if and only if $c_1 = c_2$.

$\square$

Exercise 7.1.3. Let N be a Poisson process with intensity c and $\mathcal{F}$ be the filtration generated by N. Show that (a) $(N_t - ct)^2 - ct$ is a martingale w.r.t $\mathcal{F}$. (b) $\exp\big(\ln(1-u)N_t + uct\big)$, for any $u \in (0,1)$, is a martingale w.r.t $\mathcal{F}$.

Proof. Use $N_t = (N_t - N_s) + N_s$; then $N_t - N_s$ is independent of $\mathcal{F}_s$, and N_s is measurable w.r.t $\mathcal{F}_s$.

(a) First, notice that

$$\mathbb{E}(N_t^2 | \mathcal{F}_s) = c(t-s) + N_s^2 - 2N_s \cdot c(t-s).$$

Therefore,

$$\begin{aligned}\mathbb{E}((N_t - ct)^2 - ct | \mathcal{F}_s) &= \mathbb{E}(N_t^2 | \mathcal{F}_s) - 2ct \cdot \mathbb{E}(N_t | \mathcal{F}_s) + c^2 t^2 - ct \\ &= (N_s - cs)^2 - cs\end{aligned}$$

(b) We use $N_t = (N_t - N_s) + N_s$ again.

$$\begin{aligned}\mathbb{E}\Big(\exp\big(\ln(1-u)N_t + uct\big)\Big|\mathcal{F}_s\Big) &= \mathbb{E}\Big(\exp\big(\ln(1-u)(N_t - N_s) + \ln(1-u)(N_s)\big) \cdot \exp(uct)\Big|\mathcal{F}_s\Big) \\ &= e^{uct} \cdot e^{\ln(1-u)N_s} \cdot \mathbb{E}\Big(e^{\ln(1-u)(N_t - N_s)}\Big|\mathcal{F}_s\Big) \\ \text{(Use the MGF of Poisson dist.)} &= e^{uct} \cdot e^{\ln(1-u)N_s} \cdot e^{c(t-s)(-u)} \\ &= \exp\big(\ln(1-u)N_s + ucs\big)\end{aligned}$$

$\square$

7.2 Strong Markov Properties

Theorem 7.4. *Let N be a Poisson process with intensity c, and S be a finite stopping time. Then*

$$\mathbb{E}\Big(e^{-r\cdot(N_{S+t}-N_S)}\Big|\mathcal{F}_S\Big) = \sum_{k=0}^{\infty} \frac{e^{-ct}(ct)^k}{k!} e^{-rk};$$

i.e. $N_{S+t} - N_S$ is independent of $\mathcal{F}_S$ and $N_{S+t} - N_S \stackrel{D}{=} N_t$.

Exercises

Exercise 7.2.1 (Total unpredictability of jumps)**.** Let S be a stopping time such that $0 \leq S < T$ almost surely. Then $S = 0$ almost surely.

7.3 Compound Poisson

Definition 7.5. Let N be a Poisson process with intensity λ, and Y be a sequence of i.i.d. RVs. Then

$$X_t = \sum_{k=1}^{N_t} Y_k$$

is called a compoind Poisson process.

8 Brownian Motion

8.1 Basic Properties

Definition 8.1. The following two definitons are equivalent:

- A stochastic process X is called a Brownian motion if
  a) X is continuous;
  b) X has stationary independent increments;
  c) $B_0 = 0$, $\mathbb{E}B_t = 0$, and $\mathbb{E}B_t^2 = t$.
- A stochastic process X is called a Brownian motion if
  a) X is continuous;
  b) X is Gaussian;
  c) $B_0 = 0$, $\mathbb{E}B_t = 0$, and $\mathrm{Cov}(B_t, B_s) = \min(s,t)$.

Proposition 8.2. *Let $(B_t)_{t\in\mathbb{R}^+}$ be a BM. Then the following processes are also BMs:*

- *Symmetry.* $(-B_t)_{t\in\mathbb{R}^+}$
- *Scaling.* $(c^{-1/2}B_{ct})_{t\in\mathbb{R}^+}$
- *Time inversion.* $(tB_{1/t})_{t\in\mathbb{R}^+}$

Exercises

Exercise 8.1.1. Show $Z_t = B_{T-t} - B_T$ is a BM, where T is a constant and $0 \le t \le T$.

Proof.

- $Z_0 = 0$, $\mathbb{E}Z_t = 0$, and $\mathbb{E}Z_t^2 = \mathbb{E}B_{T-t}^2 - 2\mathbb{E}B_{T-t}B_t + \mathbb{E}B_T^2 = (T-t) - 2\min(T-t, T) + T = t$.
- Continuous paths: $B_{T-t} - B_T$ is continuous in t.
- Independent increments: Assume $t_0 < t_1 < \cdots < t_n$,

$$\begin{aligned} Z_{t_n} - Z_{t_{n-1}} &= B_{T-t_n} - B_{T-t_{n-1}} \\ Z_{t_{n-1}} - Z_{t_{n-2}} &= B_{T-t_{n-1}} - B_{T-t_{n-2}} \\ &\cdots \\ Z_{t_1} - Z_{t_0} &= B_{T-t_1} - B_{T-t_0} \end{aligned}$$

  Because $B_{T-t_n} - B_{T-t_{n-1}}, \ldots, B_{T-t_1} - B_{T-t_0}$ are independent,
  $\implies \; Z_{t_n} - Z_{t_{n-1}}, \ldots, Z_{t_1} - Z_{t_0}$ are independent.
- Stationary increments: $Z_{t+u} - Z_t = B_{T-t-u} - B_{T-t} \sim N(0,u)$.

□

Exercise 8.1.2. Show that $2B_t - B_s$ for $t > s$ is not independent of $\mathcal{F}_s$.

Proof. We can check the independence by compute its conditional expectation given $\mathcal{F}_s$.

$$\begin{aligned} \mathbb{E}(2B_t - B_s \mid \mathcal{F}_s) &= \mathbb{E}(B_t \mid \mathcal{F}_s) + \mathbb{E}(B_t - B_s \mid \mathcal{F}_s) \\ &= B_s + \mathbb{E}(B_t - B_s) \\ &= B_s \ne 2B_t - B_s \end{aligned}$$

□

Exercise 8.1.3. Calculate $\mathbb{P}(B_t \le 0, t = 0, 1, 2)$.

Proof. We notice that $\mathbb{P}(B_t \leq 0, t = 0, 1, 2) = \mathbb{P}(B_1 \leq 0,\ B_2 \leq 0)$. Thus, it suffices to compute the joint distribution of B_1 and B_2.

Because $\begin{pmatrix} B_2 - B_1 \\ B_1 \end{pmatrix} \sim N_2(0, \begin{pmatrix} 1 & \\ & 1 \end{pmatrix})$,

$\implies \begin{pmatrix} B_1 \\ B_2 \end{pmatrix} = \begin{pmatrix} & 1 \\ 1 & 1 \end{pmatrix} \cdot \begin{pmatrix} B_2 - B_1 \\ B_1 \end{pmatrix} \sim N_2(0, \begin{pmatrix} 1 & 1 \\ 1 & 2 \end{pmatrix})$.

Therefore,

$$\mathbb{P}(B_1 \leq 0,\ B_2 \leq 0) = \int_0^\infty \int_0^\infty \frac{1}{2\pi} e^{-(x^2 + \frac{y^2}{2} - xy)}\ \mathrm{d}x\mathrm{d}y = \frac{3}{8}.$$

$\square$

Exercise 8.1.4. Let T be an exponential RV with parameter λ independent of B. Compute the characteristic function of B_T.

Proof.

$$\begin{aligned} \mathbb{E}e^{isB_T} &= \mathbb{E}(\mathbb{E}(e^{isB_T} \mid T)) \\ &= \mathbb{E}(e^{-Ts^2/2}) \\ &= \int_0^\infty \lambda e^{-\lambda t} \cdot e^{-ts^2/2}\ \mathrm{d}t \\ &= \frac{1}{1 + \frac{s^2}{2\lambda}} \end{aligned}$$

It is easy to see it is the CF of Laplace distribution with mean 0 and variance $\frac{1}{\lambda}$. $\square$

Exercise 8.1.5. For $0 < s < t$, find the distribution of $W_s \big| W_t = x$.

Proof.

- **Option 1**

  First, we should notice that $(W_s | W_t = x) \overset{D}{=} (\bar{W}_s | \bar{W}_t = x)$, where $\bar{W}_t = tW_{1/t}$. It is easy to check by considering their fdds. Then, it suffices to find the distribution of $\bar{W}_s | \bar{W}_t = x$

$$\begin{aligned} \mathbb{P}(\bar{W}_s \leq y \mid \bar{W}_t = x) &= \mathbb{P}\Big(\bar{W}_s - sW_{1/t} + sW_{1/t} \leq y \mid \bar{W}_t = x\Big) \\ &= \mathbb{P}\Big(sW_{1/s} - sW_{1/t} + sW_{1/t} \leq y \mid W_{1/t} = x/t\Big) \\ &= \mathbb{P}\Big(s(W_{1/s} - W_{1/t}) + sx/t \leq y \mid W_{1/t} = x/t\Big) \\ \text{(indep. incre.)} \quad &= \mathbb{P}\Big(s(W_{1/s} - W_{1/t}) + sx/t \leq y\Big) \end{aligned}$$

  Because $W_{1/s} - W_{1/t} \sim N(0, \frac{1}{s} - \frac{1}{t})$, $\implies$ $\bar{W}_s | \bar{W}_t = x \sim N\big(\frac{sx}{t}, s^2(\frac{1}{s} - \frac{1}{t})\big)$

- **Option 2**

  We know for $0 < s < t$, $(W_s, W_t) \sim N_2(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} s & s \\ s & t \end{pmatrix})$. Then we directly know

$$W_s | W_t \sim N(\frac{s}{t} W_t, s^2(\frac{1}{s} - \frac{1}{t})).$$

$\square$

8.2 Martingale Connection

Theorem 8.3. *Let B be a continuous process starting at $B_0 = 0$. The following are equivalent:*

a) $B = (B_t)_{t\in\mathbb{R}^+}$ *is a BM w.r.t* $\mathcal{F}$.

b) For all $r \in \mathbb{R}$, $\{\exp(rB_t - \frac{1}{2}r^2 t)\}_{t\in\mathbb{R}^+}$ *is a* $\mathcal{F}$*-martingale.*

c) $\{B_t^2 - t\}_{t\in\mathbb{R}^+}$ *is a* $\mathcal{F}$*-martingale.*

d) For every twice-differentiable function $f : \mathbb{R} \to \mathbb{R}$ *that is bounded along with its first derivative* f' *and second derivative* f''*, the process*

$$M_t = f \circ B_t - \frac{1}{2}\int_0^t f'' \circ B_t \mathrm{d}s \quad t \in \mathbb{R}_+$$

is an $\mathcal{F}$*-martingale.*

Proof.

- $a) \Rightarrow b)$. Trivial.
- $b) \Rightarrow a)$. To show B is a BM, it suffices to find the distribution of $B_{s+t} - B_s$ where $t > 0$.

$$\mathbb{E}(\exp(r(B_{s+t} - B_s)) \mid \mathcal{F}_s) = \exp(\frac{1}{2}r^2 t)$$

  holds for all $r \in \mathbb{R}_+$. It is the MGF of $N(0, t)$.
- $a) \Rightarrow c)$. Trivial.
- $c) \Rightarrow a)$. Omitted. It is well-known as the Lévy characterization.
- $a) \Leftrightarrow d)$. Omitted.

□

8.3 Strong Markov Properties (SMP)

Definition 8.4. Given a stochastic process (X_t), For all $A \in \mathcal{B}(\mathbb{R})$ and for all $t > 0$, define

$$\mathcal{P}_t(x, A) = \mathbb{P}(X_{t+s} \in A \mid X_s = x).$$

It is called the transition function of (X_t).

Remark. When (X_t) is a time-homogeneous Markov process, $(\mathcal{P}_t)$ forms a semigroup. The relation

$$\mathcal{P}_s\mathcal{P}_t = \mathcal{P}_{s+t}$$

is called Chapman-Kolmogorov equations.

Proposition 8.5.

a) (B_t) *is a time-homogeneous Markov process with the transition function*

$$\int_A \frac{1}{\sqrt{2\pi t}} e^{-(y-x)^2/2t} \, \mathrm{d}y.$$

b) $\mathbb{E}(f(B_t) \mid \mathcal{F}_s) = \mathbb{E}(f(B_t) \mid B_s)$ *for all* $f =$ *bounded and continuous functions.*

Remark. $\frac{1}{\sqrt{2\pi t}} e^{-(y-x)^2/2t}$ is called the transition pdf.

Proof. We only compute its transition function here:

$$
\begin{aligned}
\mathcal{P}_t(x, A) &= \mathbb{P}(B_{t+s} \in A \mid B_s = x) \\
&= \mathbb{P}(B_{t+s} - B_s \in A - x \mid B_s = x) \\
\text{(indep. incre.)} \quad &= \mathbb{P}(B_{t+s} - B_s \in A - x) \\
\text{(Gaussian incre.)} \quad &= \int_{A-x} \frac{1}{\sqrt{2\pi t}} e^{-y^2/2t} \, \mathrm{d}y \\
&= \int_{A} \frac{1}{\sqrt{2\pi t}} e^{-(y-x)^2/2t} \, \mathrm{d}y
\end{aligned}
$$

□

Proposition 8.6.

a) MP says that $\{Y_t = B_{t+s} - B_s\}_{t\geq 0}$ is a standard BM indep. of $\mathcal{F}_s$ for all fixed s.

b) SMP means $\{Y_t = B_{t+S} - B_S\}_{t\geq 0}$ is a standard BM indep. of $\mathcal{F}_S$ for all stopping tims S.

Example 8.7 (Reflected BM)**.** Define

$$
B_t^{(x)} = \begin{cases} B_t & 0 < t \leq T_x \\ 2x - B_t & t > T_x \end{cases}
$$

We can show that $B^{(x)}$ is a standard BM.

- $B_0^{(x)} = 0$.
- For $t > T_x$,

$$
\begin{aligned}
B_t^{(x)} = 2x - B_t &= 2B_{T_x} - B_t \\
&= B_{T_x} - (B_t - B_{T_x}) \\
\text{(symmetry of normal dist.)} &= B_{T_x} + (B_t - B_{T_x})
\end{aligned}
$$

Exercises

Exercise 8.3.1. Compute the transition semigroups:

(a) **Reflected BM**
Let $X = x + B$. Define $R = |X|$. Compute the transition semigroup of R.

(b) **Geometric BM**
Let $X_t = e^{at+bB_t}$. Prove X is a Markov process and compute its transition semigroup.

(c) **BM with a drift**
Let $Y_t = B_t + t\mu$. Compute its transition density function.

Proof. (a) Directly compute it:

$$
\begin{aligned}
\mathcal{P}_t(x, A) &= \mathbb{P}(R_{t+s} \in A \mid R_s = y) \\
&= \mathbb{P}(B_{s+t} \in (A - x) \cup (-x - A) \mid B_s = y - x) \\
&= \int_{(A-x)\cup(-x-A)} \frac{1}{\sqrt{2\pi t}} e^{-(z-y+x)^2/2t} \, \mathrm{d}z
\end{aligned}
$$

If we assume $(A - x) \cap (-x - A) = \emptyset$ (e.g. $A = (x, +\infty)$), $\mathcal{P}_t(x, A)$ can be simplified as

$$
\mathcal{P}_t(x, A) = \int_A \frac{1}{\sqrt{2\pi t}} e^{-(u-y)^2/2t} \, \mathrm{d}u
$$

(b) To prove X is a Markov process, we have two options:

- **Option 1**.
  Note that $B_{s+t} - B_t$ is independent of $\mathcal{F}_t$.

$$\begin{aligned}
&\mathbb{P}(X_{t_n} = x_n \mid X_{t_{n-1}} = x_{n-1}, \dots, X_{t_1} = x_1) \\
=&\mathbb{P}(e^{at_n + bB_{t_n}} = x_n \mid X_{t_{n-1}} = x_{n-1}, \dots, X_{t_1} = x_1) \\
=&\mathbb{P}(e^{a(t_n - t_{n-1}) + b(B_{t_n} - B_{t_{n-1}})} = x_n / X_{t_{n-1}} \mid X_{t_{n-1}} = x_{n-1}, \dots, X_{t_1} = x_1) \\
=&\mathbb{P}(e^{a(t_n - t_{n-1}) + b(B_{t_n} - B_{t_{n-1}})} = x_n / X_{t_{n-1}} \mid X_{t_{n-1}} = x_{n-1}) \\
=&\mathbb{P}(X_{t_n} = x_n \mid X_{t_{n-1}} = x_{n-1})
\end{aligned}$$

- **Option 2**.
  If X is a Markov process and f is injective, then $f(X)$ is also a Markov process.

Now we compute its transition semigroup:

$$\mathbb{P}(X_{t+s} \in A \mid X_s = x) = \mathbb{P}(B_t \in \frac{\ln A - a(t+s)}{b} \mid B_s = \frac{\ln x - as}{b})$$

(c)

$$\begin{aligned}
\mathbb{P}(X_{t+s} \in A \mid X_s = x) &= \mathbb{P}(B_{t+s} + (t+s)\mu \in A \mid B_s + s\mu = x) \\
&= \mathbb{P}(B_{t+s} \in A - (t+s)\mu \mid B_s = x - s\mu)
\end{aligned}$$

□

-Ornstein-Uhlenbeck process-

Exercise 8.3.2. Define

$$X_t = X_0 e^{-at} + be^{-at} B_{e^{2at}-1},$$

where B is independent of X_0 and a, b are strictly positive real number.

(a) Show that (X) is a Markov process and compute its transition semigroup.

(b) Prove it Gaussian if $X_0 = x$ or if X_0 is Gaussian.

(c) Show that, as $t \to \infty$, $X_t \xrightarrow{w} X$ where $X \sim N(0, b^2)$.

(d) If $X_0 \sim N(0, b^2)$, X_t has the same distribution as X_0 for all t.

Proof. (a)

$$\begin{aligned}
&\mathbb{P}(X_{t_n} = x_n \mid X_{t_{n-1}} = x_{n-1}, \dots, X_{t_1} = x_1) \\
=&\mathbb{P}(X_{t_n} - e^{-a(t_n - t_{n-1})} X_{t_{n-1}} = x_n - e^{-a(t_n - t_{n-1})} x_{n-1} \mid X_{t_{n-1}} = x_{n-1}, \dots, X_{t_1} = x_1) \\
=&\mathbb{P}(be^{-at_n} \cdot (B_{e^{2at_n}-1} - B_{e^{2at_{n-1}}-1}) = x_n - e^{-a(t_n - t_{n-1})} x_{n-1} \mid X_{t_{n-1}} = x_{n-1}, \dots, X_{t_1} = x_1) \\
=&\mathbb{P}(be^{-at_n} \cdot (B_{e^{2at_n}-1} - B_{e^{2at_{n-1}}-1}) = x_n - e^{-a(t_n - t_{n-1})} x_{n-1} \mid X_{t_{n-1}} = x_{n-1}) \\
=&\mathbb{P}(X_{t_n} = x_n \mid X_{t_{n-1}} = x_{n-1})
\end{aligned}$$

(b) Trivial. Just compute its fdds.

(c) Obviously, $X_0 e^{-at} \xrightarrow{w} 0$ and $be^{-at} B_{e^{2at}-1} \sim N(0, b^2 - e^{-2at})$ and $be^{-at} B_{e^{2at}-1} \xrightarrow{w} X$. So,

$$X_t \xrightarrow{w} X$$

by Slutsky's theorem.

(d) Again, we use $be^{-at}B_{e^{2at}-1} \sim N(0, b^2 - e^{-2at})$. And it is independent of X_0.

□

Exercise 8.3.3. Define $Y_t = e^{-\alpha t/2}B_{e^{\alpha t}}$ where $\alpha > 0$. (a) Prove Y is stationary. (b) Show that Y has a.s. continuous path.

Proof. Because Y is a Gaussian process, we only need to check its 2nd moment. Obviously, it is stationary. Now, we prove that Y has a.s. continuous path. For almost all ω, $t \mapsto B_t$ is continuous. And $t \mapsto e^{\alpha t}$ is continuous. So

$$t \mapsto e^{-\alpha t/2}B_{e^{\alpha t}}$$

is continuous. □

8.4 Hitting Time and Running Maximum

Definition 8.8.

- Hitting time. $T_x = \inf\{t > 0 : B_t(\omega) \geq x\}$.
- Running maximum. $M_t(\omega) = \max_{0 \leq s \leq t} B_s(\omega)$.

Proposition 8.9 (Properties of T)**.**

- $\mathbb{P}(T_a \leq t) = \mathbb{P}(M_t > a) = \mathbb{P}(|B_t| > a)$.
- *The distribution of T_x is the Inverse Gamma distribution:*

$$f_{T_x}(t) = \frac{x}{\sqrt{2\pi t^3}}e^{-x^2/2t}\mathbf{1}_{\{t>0\}}.$$

- $\mathbb{E}T_x = \infty$ *and* $\mathbb{P}(T_x < \infty) = 1$.

Proof.

- $\mathbb{P}(T_a \leq t) = \mathbb{P}(M_t > a)$ is obvious.
- It suffices to find its Laplace transform. Consider the exponential martingale $N_t^\lambda = e^{\lambda B_t - \frac{\lambda^2}{2}}$ and use the optinal stopping theorem. We can get:

$$\mathbb{E}e^{-\lambda T_a} = e^{-a\sqrt{2\lambda}}$$

- Its expectation is

$$\lim_{\lambda \to 0} e^{-a\sqrt{2\lambda}} \cdot \frac{1}{2}(2\lambda)^{-\frac{1}{2}} = \infty.$$

  And

$$\mathbb{P}(T < \infty) = \lim_{\lambda \to 0} e^{-a\sqrt{2\lambda}} = 1.$$

□

Proposition 8.10.

- *$M - B$ and $|B|$ have the same law.*
- *$2M - B$ is a Bessel process with index* 3.

Exercises

Exercise 8.4.1. $T_a \stackrel{D}{=} a^2 T_1$

Proof. Note that $f_{a^2T_1}(t) = \frac{1}{a^2} f_{T_1}(\frac{t}{a^2}) = f_{T_a}(t)$. □

Exercise 8.4.2.

- Compute
$$\mathbb{P}(T_a \le t, B_t < a) = \mathbb{P}(B_t > a).$$
- Show that
$$\mathbb{P}(M_t > a, B_t \le x) = \int_{2a-x}^{\infty} \frac{1}{\sqrt{2\pi t}} e^{-y^2/2t} \, \mathrm{d}y.$$
And compute its derivative w.r.t. a and x.

Exercise 8.4.3. Define $\tilde{T}_a = \inf\{t > 0 : B_t(\omega) > a\}$. (a) Show that $T_a = \tilde{T}_a$ almost surely. (b) Both of T_a and $\tilde{T}_a$ are stopping times.

Exercise 8.4.4. Let X and Y be two independent BMs, and T be the hitting time processes of Y. Show that (X_{T_a}) is a Cauchy process.

Proof.
- First, we prove that (X_{T_a}) is a Lévy process.
  - For almost every ω, $a \mapsto X_{T_a}$ is right-continuous and left-limited starting from $X_0(\omega) = 0$. This is trivial.
  - $X_{T_{a+u}} - X_{T_a}$ is independent of $\mathcal{F}_{T_a}$ and has the same distribution as X_{T_u}.
- Second, we compute the distribution of X_{T_a}.

$$\begin{aligned}
\mathbb{P}(X_{T_a} \in A) &= \mathbb{P}\Big\{\bigcup_t [(X_t \in A) \bigcap (T_a = t)]\Big\} \\
&= \int_{t \in \mathbb{R}_+} \mathbb{P}(X_t \in A) \, \mathrm{d}F_{T_a} \\
f_{X_{T_a}}(x) &= \int_0^{\infty} \frac{a}{\sqrt{2\pi t^3}} e^{-a^2/2t} \cdot \frac{1}{\sqrt{2\pi t}} e^{-x^2/2t} \, \mathrm{d}t \\
&= \frac{a}{2\pi} \int_0^{\infty} e^{-\frac{x^2+a^2}{2t}} \, \mathrm{d}(-\frac{1}{t}) \\
&= \frac{a}{\pi} \cdot \frac{1}{x^2 + a^2}
\end{aligned}$$

□

Exercise 8.4.5. Let (X, Y) be a BM in $\mathbb{R}^2$ with initial state $(X_0, Y_0) = (0, y)$ for some $y < 0$. Let S be the first time that (X, Y) touches the x-axis. Find the distribution of X_S.

Proof. Let $S = T_{-y}$, the hitting time of Y. As we just computed, X_S has the Cauchy distritbuion with the pdf $f_{X_S}(x) = -\frac{y}{\pi} \cdot \frac{1}{y^2+a^2}$ □

-Arcsin law-

Exercise 8.4.6. Let W be a standard Brownian motion. Define
$$G_t = \sup s \in [0, t] : W_s = 0$$
and
$$D_t = \inf\{u \in (t, \infty) : W_u = 0\}.$$

(a) Show that D_t is a stopping time but G_t is not.

(b) Let A be a RV with $\mathbb{P}(A \le u) = \frac{2}{\pi} \arcsin \sqrt{u}$ where $0 \le u \le 1$. Show that

$$G_t \stackrel{D}{=} tA$$

and

$$D_t \stackrel{D}{=} t/A.$$

(c) Show that

$$\mathbb{P}(W_t \in \mathbb{R} \setminus \{0\},\ \forall t \in [s,u]) = \frac{2}{\pi} \arcsin \sqrt{\frac{s}{u}}.$$

8.5 Path Properties

Definition 8.11. $f : \mathbb{R}_+ \to \mathbb{R}$ is said to be Hölder continuous of order α on $A \subset \mathbb{R}_+$, if there exists a constant k such that

$$|f(t) - f(s)| \le k \cdot |t-s|^\alpha \quad \forall s,t \in A.$$

Proposition 8.12. *For almost every $\omega \in \Omega$, the path $t \mapsto B_t$ has the following properties:*

a) Infinite total variation over every interval;

b) Not Hölder continuous on every interval for $\alpha \ge 1/2$;

c) Nowhere differentiable;

d) Locally Hölder continuous of order α for every $\alpha < 1/2$.

Proof.

a) See Example 6.12.

b) This is a partial proof. Suppose it is Hölder continuous on $[a,b]$ for $\alpha > 1/2$; i.e.

$$|B_t(\omega) - B_s(\omega)| \le k|t-s|^\alpha$$

for all $s,t \in [a,b]$. Then we compute its total variation on $[a,b]$:

$$\sum |B_t(\omega) - B_s(\omega)|^2 \le k^2 \cdot |t-s|^{2\alpha} \le k^2 \cdot (b-a) \cdot \sup |t-s|^{2\alpha-1}.$$

If $2\alpha - 1 > 0$, it implies the total variation of B on $[a,b]$ is 0. It is impossible. However, when $\alpha = 1/2$, this method doesn't work (the proposition is still true).

c) Note that if f is differentiable on $[a,b]$, then f is Hölder continuous on $[a,b]$ for $\alpha = 1$.

d) Check Kolmogorov's moment conditon.

□

Exercises

Exercise 8.5.1. Show that the path of Brownian motion is monotone in no interval.

Proof. First, we show the following fact: Let $f = g - h$. If g and h are increasing on $[a,b]$, then f has bounded variation on $[a,b]$.

Then suppose $B(\omega)$ is monotone on $[a,b]$, then it has bounded variation. Contradiction. □

-Law of the interated logarithm-

Exercise 8.5.2. Let (W_t) be a Brownian motion. The law of the interated logarithm describes the oscillatory behavior of Brownian motion near the time 0 and for vary large time. Define

$$h(t) = \sqrt{2t \log\log(\frac{1}{t})}$$

for $t \in [0,1]$. And it can be shown that for almost every ω,

$$\limsup_{t\to 0} \frac{1}{h(t)} W_t(\omega) = 1 \quad \text{and} \quad \liminf_{t\to 0} \frac{1}{h(t)} W_t(\omega) = -1.$$

Show it by following these steps:

(a) For all $p, q > 0$,

$$\mathbb{P}\Big\{ \sup_{t\le 1} (W_t - \frac{1}{2}pt) > q \Big\} \le e^{-pq}.$$

(b) Define

$$\alpha(\omega) = \limsup_{t\to 0} \frac{1}{h(t)} W_t(\omega).$$

Show that

$$\alpha(\omega) \le 1.$$

(c) By considering the process $(-W_n)$, show that

$$\alpha(\omega) \ge 1.$$

(d) Let $Z \sim N(0,1)$. Then for $b > 0$,

$$\frac{1}{4} \cdot \frac{b^2}{1+b^2} e^{-b^2/2} < \mathbb{P}(Z > b) < \frac{1}{2b} e^{-b^2/2}.$$

(e) Show

$$\liminf_{t\to 0} \frac{1}{h(t)} W_t(\omega) = -1.$$

8.6 Zeros of Brownian motion

Definition 8.13. Fix ω, define

$$C_\omega = \{t \in \mathbb{R}_+ : B_t(\omega) = 0\}.$$

Proposition 8.14. *For almost every ω, we have:*

- C_ω *is perfect and unbounded.*
- $C_\omega^\circ = \emptyset$.
- $\mathrm{Leb}(C_\omega) = 0$.
- C_ω *is uncountable.*