

14. Submartingales

14.1 Submartingales

Definition 14.1. Consider a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and a filtration $\mathcal{F}_0 \subset \mathcal{F}_1 \subset \dots \subset \mathcal{F}$. Suppose $X_n \in \mathcal{F}_n$ and $\mathbb{E}|X_n| < \infty$. If for all $m \geq n$, $\mathbb{E}[X_m | \mathcal{F}_n] \geq X_n$, then we say that $(X_n, \mathcal{F}_n)_{n \geq 0}$ is a submartingale. If $\mathbb{E}[X_m | \mathcal{F}_n] \leq X_n$, $(X_n, \mathcal{F}_n)_{n \geq 0}$ is called a supermartingale.

The same proof as in Theorem 12.1 shows that the martingale transform w.r.t. a predictable sequence (A_n) , which is bounded and non-negative, of a submartingale or supermartingale remains as a submartingale or supermartingale, respectively.

Theorem 14.1 (MTT). If (A_n) is predictable w.r.t. (\mathcal{F}_n) , non-negative and bounded, and $(X_n, \mathcal{F}_n)_{n \geq 0}$ is a submartingale (supermartingale), then $(\widetilde{X}_n, \mathcal{F}_n)_{n \geq 0}$ is a submartingale (supermartingale).

Example 14.1. In a casino game, let X_n be the amount of money you win at time n if you had bet one dollar at each time, starting with $X_0 = 0$. Recall that a predictable sequence (A_n) is a gambling strategy so that the winnings at time n is

$$\widetilde{X}_n = \sum_{k=1}^n A_k (X_k - X_{k-1}).$$

Suppose that $M_n = X_n - X_{n-1} \in \{-1, 1\}$ has distribution Bern(p). Your friend claims that a “sure-win” strategy is to choose $A_1 = 1$ and for $n \geq 2$,

$$A_n = \begin{cases} 2A_{n-1} & \text{if } M_{n-1} = -1, \\ 1 & \text{if } M_{n-1} = 1. \end{cases}$$

Assuming that $p > 0$, $\{M_n = 1 \text{ i.o.}\}$ has probability one. Once $M_n = 1$, the above strategy recoups all your previous losses with a winning of $-1 - 2 - \dots - 2^{n-1} + 2^n = 1$. Therefore, this strategy seems to suggest you can always beat the house. But if M_n is a supermartingale (i.e., $\mathbb{E}[M_m | \mathcal{F}_n] \leq M_n$ for $m \geq n$ and this is usually true has the house incorporates some advantages), then M_n is also a supermartingale. This means no strategy can beat the house, in an expectation sense. Many gamblers have gone bankrupt using the above strategy!

Lemma 14.1. Suppose $f : \mathbb{R} \mapsto \mathbb{R}$ is convex, $(X_n, \mathcal{F}_n)_{n \geq 0}$ is an adaptation with $\mathbb{E}|f(X_n)| < \infty$ for all $n \geq 0$. Then if either

- i) $(X_n, \mathcal{F}_n)_{n \geq 0}$ is a martingale; or

ii) $(X_n, \mathcal{F}_n)_{n \geq 0}$ is a submartingale and f is increasing,

then $(f(X_n), \mathcal{F}_n)_{n \geq 0}$ is a submartingale.

Proof. To prove i), from Jensen's inequality, for $n \leq m$, we have $f(X_n) = f(\mathbb{E}[X_m | \mathcal{F}_n]) \leq \mathbb{E}[f(X_m) | \mathcal{F}_n]$. The proof of ii) is similar. \square

Theorem 14.2. *A submartingale $(X_n, \mathcal{F}_n)_{n \geq 0}$ can be decomposed a.s. uniquely as $X_n = Y_n + Z_n$, where $(Y_n, \mathcal{F}_n)_{n \geq 0}$ is a martingale and $(Z_n)_{n \geq 0}$ is predictable with $Z_0 = 0$ and $Z_n \leq Z_{n+1}$ a.s.*

Proof. We first construct a decomposition as follows: Let $Z_0 = 0$,

$$Z_n = \sum_{k=1}^n \mathbb{E}[X_k - X_{k-1} | \mathcal{F}_{k-1}]$$

and $Y_n = X_n - Z_n$. By our construction, $Z_n \in \mathcal{F}_{n-1}$ is predictable and since

$$\mathbb{E}[X_k - X_{k-1} | \mathcal{F}_{k-1}] = \mathbb{E}[X_k | \mathcal{F}_{k-1}] - X_{k-1} \geq 0,$$

we have $Z_n \leq Z_{n+1}$ a.s. Furthermore, $Z_n - Z_{n-1} = \mathbb{E}[X_n | \mathcal{F}_{n-1}] - X_{n-1}$ and we obtain

$$\mathbb{E}[Y_n | \mathcal{F}_{n-1}] = \mathbb{E}[X_n - Z_n | \mathcal{F}_{n-1}] = \mathbb{E}[X_n | \mathcal{F}_{n-1}] - Z_n = X_{n-1} - Z_{n-1} = Y_{n-1},$$

showing that Y_n is a martingale.

To show uniqueness, we proceed by induction. The requirement that $Z_0 = 0$ implies that $Y_0 = X_0$ uniquely. Suppose the decomposition is unique a.s. up to X_{n-1} . Then for any decomposition $X_n = Y_n + Z_n$ meeting the criteria,

$$Z_n = \mathbb{E}[Z_n | \mathcal{F}_{n-1}] = \mathbb{E}[X_n - Y_n | \mathcal{F}_{n-1}] = \mathbb{E}[X_n | \mathcal{F}_{n-1}] - Y_{n-1},$$

because Y_n is a martingale. This implies that Z_n is unique a.s., and hence so is $Y_n = X_n - Z_n$. The proof is now complete. \square

14.2 Doob's Inequalities

Theorem 14.3 (Doob's maximal inequality). *Suppose $(X_n, \mathcal{F}_n)_{n \geq 0}$ is a non-negative submartingale. Let $X_n^* = \max_{0 \leq k \leq n} X_k$. Then for all $\lambda \geq 0$,*

$$\lambda \mathbb{P}(X_n^* \geq \lambda) \leq \mathbb{E} X_n \mathbf{1}_{\{X_n^* \geq \lambda\}} \leq \mathbb{E} X_n. \quad (1)$$

Proof. Let $\tau = \inf\{k : X_k \geq \lambda\}$ be a stopping time. Then $\{X_n^* \geq \lambda\} = \{\tau \leq n\}$ and

$$\lambda \mathbf{1}_{\{\tau \leq n\}} \leq X_\tau \mathbf{1}_{\{\tau \leq n\}} = \sum_{k=0}^n X_k \mathbf{1}_{\{\tau = k\}}. \quad (2)$$

Since $X_k \leq \mathbb{E}[X_n | \mathcal{F}_k] \forall k \leq n$ and $\{\tau = k\} \in \mathcal{F}_k$, $\mathbb{E}X_k \mathbf{1}_{\{\tau=k\}} \leq \mathbb{E}X_n \mathbf{1}_{\{\tau=k\}}$ for all $k \leq n$. Taking expectations in (2), we obtain

$$\begin{aligned} \lambda \mathbb{P}(\tau \leq n) &\leq \mathbb{E} \sum_{k=0}^n X_k \mathbf{1}_{\{\tau=k\}} \\ &\leq \mathbb{E} \sum_{k=0}^n X_n \mathbf{1}_{\{\tau=k\}} \\ &= \mathbb{E}X_n \mathbf{1}_{\{\tau \leq n\}} \\ &= \mathbb{E}X_n \mathbf{1}_{\{X_n^* \geq \lambda\}} \\ &\leq \mathbb{E}X_n. \end{aligned}$$

□

Corollary 14.1. *For $\lambda > 0$ and $p \geq 1$,*

$$\mathbb{P}(X_n^* \geq \lambda) \leq \frac{1}{\lambda^p} \mathbb{E}X_n^p.$$

Proof. From Lemma 14.1, (X_n^p) is a non-negative submartingale. We then apply Theorem 14.3. □

Example 14.2. *Suppose $X_i, i \geq 1$ are independent with $\mathbb{E}X_i = 0$. From Example 12.3, S_n is a martingale. Doob's maximal inequality (or its corollary) recovers Kolmogorov's maximal equality:*

$$\mathbb{P}\left(\max_{1 \leq k \leq n} |S_k| \geq \lambda\right) \leq \frac{1}{\lambda^2} \mathbb{E}S_n^2.$$

Let $p \geq 1$. A r.v. $X \in L^p$ if $\|X\|_p = \{\mathbb{E}|X|^p\}^{1/p} < \infty$. Hölder's inequality says that for $1 \leq p < \infty, p + q = 1$ (i.e., $q = \frac{p}{p-1}$), then for any r.v.s X, Y ,

$$\|XY\|_1 \leq \|X\|_p \|Y\|_q.$$

Lemma 14.2. *Suppose $X, Y \geq 0, \mathbb{E}Y^p < \infty$ for $p > 1$ and for all $\lambda \geq 0$, we have*

$$\lambda \mathbb{P}(X \geq \lambda) \leq \mathbb{E}Y \mathbf{1}_{\{X \geq \lambda\}}.$$

Then,

$$\|X\|_p \leq \frac{p}{p-1} \|Y\|_p. \tag{3}$$

Proof. Let $X_n = X \wedge n$. We use the fact that

$$z^p = p \int_0^z x^{p-1} dx = p \int_0^\infty x^{p-1} \mathbf{1}_{\{z \geq x\}} dx$$

to obtain

$$\begin{aligned}
\mathbb{E}X_n^p &= \mathbb{E}\left[p \int_0^\infty x^{p-1} \mathbf{1}_{\{X_n \geq x\}} dx\right] \\
&\stackrel{\text{Fubini}}{=} p \int_0^\infty x^{p-1} \mathbb{P}(X_n \geq x) dx \\
&\leq p \int_0^\infty x^{p-2} \mathbb{E}[Y \mathbf{1}_{\{X \geq x\}}] dx \quad \text{since } \{X_n \geq x\} \subset \{X \geq x\} \\
&\stackrel{\text{Fubini}}{=} p \mathbb{E}\left[Y \int_0^\infty x^{p-2} \mathbf{1}_{\{X \geq x\}} dx\right] \\
&= \frac{p}{p-1} \mathbb{E}[Y X^{p-1}] \\
&\stackrel{\text{Hölder}}{\leq} \frac{p}{p-1} \|Y\|_p \|X\|_p^{p-1}.
\end{aligned}$$

Therefore, from Fatou's lemma,

$$\|X\|_p^p \leq \liminf_{n \rightarrow \infty} \mathbb{E}X_n^p \leq \frac{p}{p-1} \|Y\|_p \|X\|_p^{p-1},$$

and we obtain (3) (the case $\|X\|_p = 0$ is trivial). \square

Theorem 14.4 (Doob's L^p inequality). *If (X_n, \mathcal{F}_n) is a non-negative submartingale, then for all $p > 1$,*

$$\|X_n^*\|_p \leq \frac{p}{p-1} \|X_n\|_p. \quad (4)$$

Proof. We apply Lemma 14.2 with $X = X_n^*$ and $Y = X_n$, together with Doob's maximal inequality (Theorem 14.3). \square

Theorems 14.3 and 14.4 require (X_n, \mathcal{F}_n) to be non-negative. For a general submartingale (X_n, \mathcal{F}_n) , we can apply these results to (X_n^+, \mathcal{F}_n) since this is a non-negative submartingale from Lemma 14.1.

Theorem 14.4 holds only for $p > 1$. Indeed, there is no corresponding result for $p = 1$ as shown in the following example.

Example 14.3. *Consider the random walk in Example 13.1 with $S_0 = 0$. Take $B = 1$ and $\tau = \inf\{n : S_n = -1\}$. Let $X_n = S_{n \wedge \tau}$. Then using a result in Example 13.1 in the second equality below, we have*

$$\mathbb{E}\left[\max_{m \geq 0} X_m\right] = \sum_{A=1}^{\infty} \mathbb{P}\left(\max_{m \geq 0} X_m \geq A\right) = \sum_{A=1}^{\infty} \frac{1}{A+1} = \infty.$$

The MCT then implies that $\mathbb{E}[\max_{0 \leq m \leq n} X_m] \rightarrow \infty$ as $n \rightarrow \infty$.

14.3 Uniform Integrability

Definition 14.2. A collection of r.v.s $(X_n)_{n \in N}$ is uniformly integrable if

$$\sup_{n \in N} \mathbb{E}|X_n| \mathbf{1}_{\{|X_n| > K\}} \rightarrow 0, \quad (5)$$

as $K \rightarrow \infty$.

If $(X_n)_{n \in N}$ is uniformly integrable, then for K sufficiently large, we have $\sup_{n \in N} \mathbb{E}|X_n| \mathbf{1}_{\{|X_n| > K\}} \leq 1$ and $\sup_n \mathbb{E}|X_n| \leq K + 1 < \infty$ is uniformly bounded. Clearly, the converse is false.

Example 14.4. If $|X_n| \leq Y$, $\forall n \in N$, and $\mathbb{E}Y < \infty$, then

$$\mathbb{E}|X_n| \mathbf{1}_{\{|X_n| > K\}} \leq \mathbb{E}Y \mathbf{1}_{\{Y > K\}} \rightarrow 0,$$

as $K \rightarrow \infty$ from DCT. Therefore $(X_n)_{n \in N}$ is uniformly integrable.

Lemma 14.3. If $X \in L^1$, then $\forall \epsilon > 0$, $\exists \delta > 0$ such that if $\mathbb{P}(A) \leq \delta$, then $\mathbb{E}|X| \mathbf{1}_A \leq \epsilon$.

Proof. If $\mathbb{P}(A) \leq \delta$, we have for all $K > 0$,

$$\mathbb{E}|X| \mathbf{1}_A \leq K\mathbb{P}(A) + \mathbb{E}|X| \mathbf{1}_{\{|X| > K\}} \leq K\delta + \mathbb{E}|X| \mathbf{1}_{\{|X| > K\}}.$$

Choose K sufficiently large so that $\mathbb{E}|X| \mathbf{1}_{\{|X| > K\}} \leq \frac{\epsilon}{2}$ and set $\delta = \frac{\epsilon}{2K}$. Then from above, we have $\mathbb{E}|X| \mathbf{1}_A \leq \epsilon$. \square

Proposition 14.1. Let $X \in L^1(\Omega, \mathcal{F}, \mathbb{P})$. Then $\{\mathbb{E}[X | \mathcal{F}'] : \mathcal{F}' \text{ is a } \sigma\text{-algebra } \subset \mathcal{F}\}$ is uniformly integrable.

Proof. Fix $\epsilon > 0$ and choose $\delta > 0$ as in Lemma 14.3. Pick K large so that $\mathbb{E}|X|/K \leq \delta$. Let $Y = \mathbb{E}[X | \mathcal{F}']$. From Jensen's inequality, $|Y| \leq \mathbb{E}[|X| | \mathcal{F}']$, therefore we have

$$\begin{aligned} \mathbb{E}[|Y| \mathbf{1}_{\{|Y| > K\}}] &\leq \mathbb{E}[\mathbb{E}[|X| | \mathcal{F}'] \mathbf{1}_{\{\mathbb{E}[|X| | \mathcal{F}'] > K\}}] \\ &= \mathbb{E}|X| \mathbf{1}_{\{\mathbb{E}[|X| | \mathcal{F}'] > K\}} \quad \text{since } \{\mathbb{E}[|X| | \mathcal{F}'] > K\} \in \mathcal{F}' \\ &\leq \epsilon, \end{aligned}$$

where the last inequality follows from Lemma 14.3 as $\mathbb{P}(\mathbb{E}[|X| | \mathcal{F}'] > K) \leq \mathbb{E}|X|/K \leq \delta$. \square

Proposition 14.2. Suppose $\varphi : \mathbb{R} \mapsto \mathbb{R}_+$ is such that $\lim_{x \rightarrow \infty} \frac{\varphi(x)}{x} = \infty$. (Examples include $\varphi(x) = x^p$, for $p > 1$ and $\varphi(x) = x \log^+ x$.) If $\mathbb{E}\varphi(|X_n|) \leq C < \infty$, then $(X_n)_{n \in N}$ is uniformly integrable.

Proof. Let $\epsilon_K = \sup\{x/\varphi(x) : x \geq K\}$. Note that $\epsilon_K \rightarrow 0$ as $K \rightarrow \infty$ because for any $\epsilon > 0$, $\exists K$ sufficiently large so that $x/\varphi(x) \leq \epsilon$ for all $x > K$. Then we have

$$\mathbb{E}|X_n| \mathbf{1}_{\{|X_n| > K\}} \leq \epsilon_K \mathbb{E}[\varphi(|X_n|) \mathbf{1}_{\{|X_n| > K\}}] \leq C\epsilon_K \rightarrow 0,$$

as $K \rightarrow \infty$. \square

Lemma 14.4. Suppose $\mathbb{E}|X_n| < \infty$ for all $n \in N$ and $\mathbb{E}|X| < \infty$, then the following are equivalent:

- (i) $X_n \rightarrow X$ in L^1 , i.e., $\mathbb{E}|X_n - X| \rightarrow 0$ as $n \rightarrow \infty$.
- (ii) $(X_n)_{n \in N}$ is uniformly integrable and $X_n \xrightarrow{P} X$.
- (iii) $X_n \xrightarrow{P} X$ and $\mathbb{E}|X_n| \rightarrow \mathbb{E}|X|$.

Proof. We show $(ii) \implies (i) \implies (iii) \implies (ii)$.

$(ii) \implies (i)$: $\forall \epsilon > 0, K > 0$, we have

$$\begin{aligned} \mathbb{E}|X_n - X| &\leq \epsilon + \mathbb{E}|X_n - X| \mathbf{1}_{\{|X_n - X| > \epsilon\}} \\ &\leq \epsilon + \mathbb{E}|X_n| \mathbf{1}_{\{|X_n - X| > \epsilon\}} + \mathbb{E}|X| \mathbf{1}_{\{|X_n - X| > \epsilon\}} \\ &\leq \epsilon + 2K\mathbb{P}(|X_n - X| > \epsilon) + \mathbb{E}|X_n| \mathbf{1}_{\{|X_n| > K\}} + \mathbb{E}|X| \mathbf{1}_{\{|X| > K\}} \end{aligned}$$

and

$$\limsup_{n \rightarrow \infty} \mathbb{E}|X_n - X| \leq \epsilon + \sup_n \mathbb{E}|X_n| \mathbf{1}_{\{|X_n| > K\}} + \mathbb{E}|X| \mathbf{1}_{\{|X| > K\}}.$$

Taking $\epsilon \rightarrow 0$ and $K \rightarrow \infty$ completes the proof.

$(i) \implies (iii)$: From Markov's inequality, for any $\epsilon > 0$, we obtain $\mathbb{P}(|X_n - X| > \epsilon) \leq \epsilon \mathbb{E}|X_n - X| \rightarrow 0$ as $n \rightarrow \infty$. We also have

$$|\mathbb{E}|X_n| - \mathbb{E}|X|| \leq \mathbb{E}||X_n| - |X|| \leq \mathbb{E}|X_n - X| \rightarrow 0,$$

as $n \rightarrow \infty$.

$(iii) \implies (ii)$: For any $\epsilon > 0$, $\exists n_0$ such that $\forall n \geq n_0$, $\mathbb{E}|X_n| \leq \mathbb{E}|X| + \epsilon/2$. Let

$$\phi_K(x) = \begin{cases} x, & \text{for } x \in [0, K-1], \\ 0, & \text{for } x > K, \\ \text{linear}, & \text{for } x \in [K-1, K]. \end{cases}$$

Then from the DCT, for K sufficiently large,

$$\mathbb{E}|X| - \mathbb{E}\phi_K(|X|) \leq \epsilon.$$

Since ϕ_K is continuous, the DCT also yields $\mathbb{E}\phi_K(|X_n|) \rightarrow \mathbb{E}\phi_K(|X|)$ as $n \rightarrow \infty$. Therefore, since $x \geq \phi_K(x) + x \mathbf{1}_{\{x > K\}}$ for all $x \geq 0$, we have

$$\begin{aligned} \mathbb{E}|X_n| \mathbf{1}_{\{|X_n| > K\}} &\leq \mathbb{E}|X_n| - \mathbb{E}\phi_K(|X_n|) \\ &\leq \mathbb{E}|X| - \mathbb{E}\phi_K(|X|) + \epsilon \\ &\leq 2\epsilon, \end{aligned}$$

for all n and K sufficiently large and the proof is complete. \square