

Math 639: Lecture 11

Convergence of Martingales

Bob Hough

March 3, 2017

Submartingales

Theorem

If X_n is a submartingale and N is a stopping time with $\text{Prob}(N \leq k) = 1$ then

$$E[X_0] \leq E[X_N] \leq E[X_k].$$

Submartingales

Proof.

- $X_{N \wedge n}$ is a submartingale, so

$$E[X_0] = E[X_{N \wedge 0}] \leq E[X_{N \wedge k}] = E[X_N].$$

- Let $K_n = \mathbf{1}_{N < n}$. Since K_n is predictable, $(K \cdot X)_n = X_n - X_{N \wedge n}$ is a submartingale, so

$$E[X_k] - E[X_N] = E[(K \cdot X)_k] \geq E[(K \cdot X)_0] = 0.$$



Doob's inequality

Theorem (Doob's inequality)

Let X_m be a submartingale,

$$\bar{X}_n = \max_{0 \leq m \leq n} X_m^+,$$

$\lambda > 0$, and $A = \{\bar{X}_n \geq \lambda\}$. Then

$$\lambda \text{Prob}(A) \leq E[X_n \mathbf{1}_A] \leq E[X_n^+].$$

Doob's inequality

Proof.

- Let $N = \inf\{m : X_m \geq \lambda \text{ or } m = n\}$. Since $X_N \geq \lambda$ on A ,

$$\lambda \text{Prob}(A) \leq E[X_N \mathbf{1}_A] \leq E[X_n \mathbf{1}_A].$$



Example

- Let $S_n = \xi_1 + \cdots + \xi_n$ where the ξ_m are independent and have $E[\xi_m] = 0$, $\sigma_m^2 = E[\xi_m^2] < \infty$.
- We have $X_n = S_n^2$ is a submartingale.
- Choosing $\lambda = x^2$ in the previous theorem, we get Kolmogorov's maximal inequality

$$\text{Prob} \left(\max_{1 \leq m \leq n} |S_m| \geq x \right) \leq x^{-2} \text{Var}(S_n).$$

L^p maximum inequality

Theorem

If X_n is a submartingale, then for $1 < p < \infty$,

$$E[\bar{X}_n^p] \leq \left(\frac{p}{p-1} \right)^p E[X_n^+]^p.$$

L^p maximum inequality

Proof.

Calculate

$$\begin{aligned} E[|\bar{X}_n \wedge M|^p] &= \int_0^\infty p\lambda^{p-1} \text{Prob}(\bar{X}_n \wedge M \geq \lambda) d\lambda \\ &\leq \int_0^\infty p\lambda^{p-1} \left(\lambda^{-1} \int X_n^+ \mathbf{1}(\bar{X}_n \wedge M \geq \lambda) dP \right) d\lambda \\ &= \int X_n^+ \int_0^{\bar{X}_n \wedge M} p\lambda^{p-2} d\lambda dP \\ &= \frac{p}{p-1} \int X_n^+ (\bar{X}_n \wedge M)^{p-1} dP \\ &\leq \frac{p}{p-1} E[|X_n^+|^p]^{\frac{1}{p}} E[|\bar{X}_n \wedge M|^p]^{\frac{p-1}{p}}. \end{aligned}$$

The result follows on letting $M \uparrow \infty$. □

L^1 maximum inequality

Theorem

Let X_n be a submartingale and $\log^+ x = \max(\log x, 0)$.

$$E[\bar{X}_n] \leq (1 - e^{-1})^{-1} [1 + E[X_n^+ \log^+(X_n^+)]] .$$

Proof.

Exercise. □

L^p convergence theorem

Theorem

If X_n is a martingale with $\sup E[|X_n|^p] < \infty$ where $p > 1$, then $X_n \rightarrow X$ a.s. and in L^p .

L^p convergence theorem

Proof.

- $(E[X_n^+])^p \leq (E[|X_n|])^p \leq E[|X_n|^p]$. Hence $X_n \rightarrow X$ a.s.
- By the L^p maximum inequality,

$$E \left[\left(\sup_{0 \leq m \leq n} |X_m| \right)^p \right] \leq \left(\frac{p}{p-1} \right)^p E[|X_n|^p].$$

Letting $n \rightarrow \infty$, $\sup |X_n| \in L^p$, so $E[|X_n - X|^p] \rightarrow 0$ by dominated convergence.



Orthogonality of martingale increments

Theorem

Let X_n be a martingale with $E[X_n^2] < \infty$ for all n . If $m \leq n$ and $Y \in \mathcal{F}_m$ has $E[Y^2] < \infty$, then

$$E[(X_n - X_m)Y] = 0.$$

Orthogonality of martingale increments

Proof.

By Cauchy-Schwarz, $E[|(X_n - X_m)Y|] < \infty$, so

$$E[(X_n - X_m)Y] = E[Y E[(X_n - X_m)|\mathcal{F}_m]] = 0.$$



Conditional variance formula

Theorem

If X_n is a martingale with $E[X_n^2] < \infty$ for all n , then

$$E[(X_n - X_m)^2 | \mathcal{F}_m] = E[X_n^2 | \mathcal{F}_m] - X_m^2.$$

Conditional variance formula

Proof.

Calculate

$$\begin{aligned} E[X_n^2 - 2X_nX_m + X_m^2 | \mathcal{F}_m] &= E[X_n^2 | \mathcal{F}_m] - 2X_m E[X_n | \mathcal{F}_m] + X_m^2 \\ &= E[X_n^2 | \mathcal{F}_m] - X_m^2. \end{aligned}$$



Square integrable martingales

Definition

Let X_n be a martingale with $X_0 = 0$ and $E[X_n^2] < \infty$ for all n . Thus X_n^2 is a sub-martingale. Write $X_n^2 = M_n + A_n$ where M_n is a martingale. A_n is called the *increasing process*. Let $A_\infty = \lim A_n$.

Square integrable martingales

Theorem

We have $E[\sup_m |X_m|^2] \leq 4 E[A_\infty]$.

Proof.

The L^2 maximum inequality gives

$$E \left[\sup_{0 \leq m \leq n} |X_m|^2 \right] \leq 4 E[X_n^2] = 4 E[A_n].$$

The conclusion follows from monotone convergence. □

Square integrable martingales

Theorem

$\lim_{n \rightarrow \infty} X_n$ exists and is finite a.s. on $\{A_\infty < \infty\}$.

Proof.

- Let $a > 0$. Since $A_{n+1} \in \mathcal{F}_n$, $N = \inf\{n : A_{n+1} > a^2\}$.
- Since $A_{N \wedge n} \leq a^2$,

$$E \left[\sup_n |X_{N \wedge n}|^2 \right] \leq 4a^2.$$

- Hence $\lim X_{N \wedge n}$ exists and is finite a.s. Since this holds for all a , the result follows.



Square integrable martingales

Theorem

Let $f \geq 1$ be increasing with $\int_0^\infty f(t)^{-2} dt < \infty$. Then $\frac{X_n}{f(A_n)} \rightarrow 0$ a.s. on $\{A_\infty = \infty\}$.

Square integrable martingales

Proof.

- Let $H_m = f(A_m)^{-1}$ is bounded and predictable so

$$Y_n = (H \cdot X)_n = \sum_{m=1}^n \frac{X_m - X_{m-1}}{f(A_m)}$$

is a martingale.

- The increasing process associated to Y_n satisfies

$$\begin{aligned} B_{n+1} - B_n &= \mathbb{E}[(Y_{n+1} - Y_n)^2 | \mathcal{F}_n] \\ &= \mathbb{E} \left[\frac{(X_{n+1} - X_n)^2}{f(A_{n+1})^2} \middle| \mathcal{F}_n \right] = \frac{A_{n+1} - A_n}{f(A_{n+1})^2}. \end{aligned}$$



Square integrable martingales

Proof.

- Since

$$\sum_{n=0}^{\infty} \frac{A_{n+1} - A_n}{f(A_{n+1})^2} \leq \sum_{n=0}^{\infty} \int_{[A_n, A_{n+1})} f(t)^{-2} dt < \infty.$$

Hence $Y_n \rightarrow Y_\infty$ a.s.

- It follows that $\frac{X_n}{f(A_n)} \rightarrow 0$ a.s. by Kronecker's lemma.



Uniformly integrable random variables

Definition

A collection of random variables $\{X_i : i \in I\}$ is *uniformly integrable* if

$$\lim_{M \rightarrow \infty} \left(\sup_{i \in I} E[|X_i| \mathbf{1}(|X_i| > M)] \right) = 0.$$

Choose M sufficiently large in the definition so that the sup is less than 1. Then

$$\sup_{i \in I} E[|X_i|] \leq M + 1 < \infty.$$

Uniformly integrable random variables

Theorem

Given a probability space $(\Omega, \mathcal{F}_0, \text{Prob})$ and an $X \in L^1$, then $\{E[X|\mathcal{F}] : \mathcal{F} \subset \mathcal{F}_0\}$ is uniformly integrable.

Uniformly integrable random variables

Proof.

- If A_n is a sequence of sets with $\text{Prob}(A_n) \rightarrow 0$, then $E[|X|\mathbf{1}_{A_n}] \rightarrow 0$ by dominated convergence. Hence, for each $\epsilon > 0$ there exists $\delta > 0$ such that $\text{Prob}(A_n) < \delta$ implies $E[|X|\mathbf{1}_{A_n}] < \epsilon$.
- Apply Jensen's inequality to find, for $M > 0$,

$$\begin{aligned} E[|E[X|\mathcal{F}]|\mathbf{1}(|E[X|\mathcal{F}]| > M)] &\leq E[E[|X||\mathcal{F}]\mathbf{1}(|E[X|\mathcal{F}]| > M)] \\ &= E[|X|\mathbf{1}(|E[X|\mathcal{F}]| > M)]. \end{aligned}$$

- Choose M so that $E[|X|] \leq M\delta$ so that

$$\text{Prob}(|E[X|\mathcal{F}]| > M) \leq \frac{E[E[|X||\mathcal{F}]]}{M} = \frac{E[|X|]}{M} \leq \delta.$$

- Thus $E[|E[X|\mathcal{F}]|\mathbf{1}(|E[X|\mathcal{F}]| > M)] \leq \epsilon$ for all \mathcal{F} .



Uniformly integrable random variables

Theorem

If $X_n \rightarrow X$ in probability, then the following are equivalent.

- 1 $\{X_n : n \geq 0\}$ is uniformly integrable.
- 2 $X_n \rightarrow X$ in L^1
- 3 $E[|X_n|] \rightarrow E[|X|] < \infty$.

Uniformly integrable random variables

Proof.

- 1 implies 2:

▶ Let

$$\phi_M(x) = \begin{cases} M & x \geq M \\ x & |x| \leq M \\ -M & x \leq -M \end{cases}$$

Thus

$$|X_n - X| \leq |X_n - \phi_M(X_n)| + |\phi_M(X_n) - \phi_M(X)| + |\phi_M(X) - X|.$$

- ▶ Since $|\phi_M(Y) - Y| \leq |Y|\mathbf{1}(|Y| > M)$, taking expected values

$$\begin{aligned} E[|X_n - X|] &\leq E[|\phi_M(X_n) - \phi_M(X)|] + E[|X_n|\mathbf{1}(|X_n| > M)] \\ &\quad + E[|X|\mathbf{1}(|X| > M)]. \end{aligned}$$



Uniformly integrable random variables

Proof.

- - Since $\phi_M(X_n) \rightarrow \phi_M(X)$ in probability, the first term tends to 0.
 - The second term tends to 0 as M tends to ∞ by uniform integrability.
 - $\sup E[|X_n|] < \infty$ implies $E[|X|] < \infty$, which implies $E[|X|\mathbf{1}(|X| > M)]$.
- 2 implies 3: Jensen gives

$$|E[|X_n|] - E[|X|]| \leq E[||X_n| - |X||] \leq E[|X_n - X|] \rightarrow 0.$$



Uniformly integrable random variables

Proof.

- 3 implies 1:

- ▶ Let ψ_M interpolate linearly between $f(x) = x$ on $[0, M - 1]$ and 0 on $[M, \infty)$.
- ▶ $E[\psi_M(|X_n|)] \rightarrow E[\psi_M(|X|)]$ by convergence in probability.
- ▶ Choose M sufficiently large so that $E[|X|] - E[\psi_M(|X|)] \leq \frac{\epsilon}{2}$. If n is sufficiently large,

$$E[|X_n| \mathbf{1}(|X_n| > M)] \leq E[|X_n|] - E[\psi_M(|X_n|)] < \epsilon.$$



Uniformly integrable random variables

Theorem

For a submartingale, the following are equivalent.

- 1 *It is uniformly integrable.*
- 2 *It converges a.s. in L^1*
- 3 *It converges in L^1 .*

Uniformly integrable random variables

Proof.

- 1 implies 2: Uniform integrability implies $\sup E[|X_n|] < \infty$, so the martingale convergence theorem implies almost sure convergence. The convergence in L^1 follows from the previous theorem.
- 2 implies 3: This is automatic.
- 3 implies 1: Convergence in L^1 implies convergence in probability, so this follows from the previous theorem.



Uniformly integrable random variables

Lemma

If integrable random variables $X_n \rightarrow X$ in L^1 then $E[X_n \mathbf{1}_A] \rightarrow E[X \mathbf{1}_A]$.

Proof.

$$|E[X_m \mathbf{1}_A] - E[X \mathbf{1}_A]| \leq E[|X_m \mathbf{1}_A - X \mathbf{1}_A|] \leq E[|X_m - X|] \rightarrow 0.$$



Uniformly integrable random variables

Lemma

If a martingale $X_n \rightarrow X$ in L^1 , then $X_n = E[X|\mathcal{F}_n]$.

Proof.

- If $m > n$, $E[X_m|\mathcal{F}_n] = X_n$, so if $A \in \mathcal{F}_n$, $E[X_n\mathbf{1}_A] = E[X_m\mathbf{1}_A]$
- Since $E[X_m\mathbf{1}_A] \rightarrow E[X\mathbf{1}_A]$ we have $E[X_n\mathbf{1}_A] = E[X\mathbf{1}_A]$ for all $A \in \mathcal{F}_n$. In particular, $X_n = E[X|\mathcal{F}_n]$.



Uniformly integrable random variables

Theorem

For a martingale, the following are equivalent.

- 1 *It is uniformly integrable*
- 2 *It converges a.s. and in L^1*
- 3 *It converges in L^1*
- 4 *There is an integrable random variable X so that $X_n = E[X|\mathcal{F}_n]$.*

Proof.

The first two implications are as above. For 3 implies 4, this is the previous lemma. 4 implies 1 is a previous theorem. □

Uniformly integrable random variables

Theorem

Suppose $\mathcal{F}_n \uparrow \mathcal{F}_\infty$ and $\mathcal{F}_\infty = \sigma(\bigcup_n \mathcal{F}_n)$. As $n \rightarrow \infty$, $E[X|\mathcal{F}_n] \rightarrow E[X|\mathcal{F}_\infty]$ a.s. and in L^1 .

Uniformly integrable random variables

Proof.

- If $m > n$ then

$$E[E[X|\mathcal{F}_m]|\mathcal{F}_n] = E[X|\mathcal{F}_n],$$

so $Y_n = E[X|\mathcal{F}_n]$ is a martingale.

- Since Y_n is uniformly integrable, Y_n converges a.s. and in L^1 to a limit Y_∞ .
- Observe $E[X|\mathcal{F}_n] = Y_n = E[Y_\infty|\mathcal{F}_n]$, and hence if $A \in \mathcal{F}_n$,

$$\int_A X dP = \int_A Y_\infty dP.$$

Since $E[X|\mathcal{F}_\infty]$ and Y_∞ agree on a π -system in \mathcal{F}_∞ , they are equal there.



Lévy's 0-1 law

Theorem

If $\mathcal{F}_n \uparrow \mathcal{F}_\infty$ and $A \in \mathcal{F}_\infty$ then $E[\mathbf{1}_A | \mathcal{F}_n] \rightarrow \mathbf{1}_A$ a.s.

Dominated convergence

Theorem

Suppose $Y_n \rightarrow Y$ a.s. and $|Y_n| \leq Z$ for all n where $E[Z] < \infty$. If $\mathcal{F}_n \uparrow \mathcal{F}_\infty$ then

$$E[Y_n | \mathcal{F}_n] \rightarrow E[Y | \mathcal{F}_\infty] \text{ a.s.}$$

Dominated convergence

Proof.

- Let $W_N = \sup\{|Y_n - Y_m| : n, m \geq N\}$. Note $E[W_N] < \infty$.
- We have

$$\limsup_{n \rightarrow \infty} E[|Y_n - Y| | \mathcal{F}_n] \leq \lim_{n \rightarrow \infty} E[W_n | \mathcal{F}_n] = E[W_N | \mathcal{F}_\infty].$$

- Since $W_N \downarrow 0$ as $N \uparrow \infty$, $E[W_N | \mathcal{F}_\infty] \downarrow 0$, and Jensen gives

$$|E[Y_n | \mathcal{F}_n] - E[Y | \mathcal{F}_n]| \leq E[|Y_n - Y| | \mathcal{F}_n] \rightarrow 0 \text{ a.s.}$$

- Since $E[Y | \mathcal{F}_n] \rightarrow E[Y | \mathcal{F}_\infty]$ a.s. this suffices.



Backwards martingales

Definition

A *backwards martingale* is a martingale indexed by the negative integers, that is, X_n , $n \leq 0$, adapted to an increasing sequence of σ -algebras \mathcal{F}_n

$$E[X_{n+1} | \mathcal{F}_n] = X_n, \quad n \leq -1.$$

Backwards martingales

Theorem

$X_{-\infty} = \lim_{n \rightarrow -\infty} X_n$ exists a.s. and in L^1 .

Backwards martingales

Proof.

- Let U_n be the number of upcrossings of $[a, b]$ by X_{-n}, \dots, X_0 .
- $(b - a) E[U_n] \leq E[(X_0 - a)^+]$.
- Letting $n \rightarrow \infty$, $E[U_\infty] < \infty$, so the limit exists almost surely.
- Since $X_n = E[X_0 | \mathcal{F}_n]$, X_n is uniformly integrable, so that the convergence is in L^1 .



Backwards martingales

Theorem

If $X_{-\infty} = \lim_{n \rightarrow -\infty} X_n$ and $\mathcal{F}_{-\infty} = \bigcap_n \mathcal{F}_n$, then $X_{-\infty} = E[X_0 | \mathcal{F}_{-\infty}]$.

Backwards martingales

Proof.

Since $X_n = E[X_0 | \mathcal{F}_n]$, if $A \in \mathcal{F}_{-\infty} \subset \mathcal{F}_n$,

$$\int_A X_n dP = \int_A X_0 dP.$$

Since $E[X_n \mathbf{1}_A] \rightarrow E[X_{-\infty} \mathbf{1}_A]$,

$$\int_A X_{-\infty} dP = \int_A X_0 dP$$

for all $A \in \mathcal{F}_{-\infty}$. □

Backwards martingales

From the previous theorems it follows.

Theorem

If $\mathcal{F}_n \downarrow \mathcal{F}_{-\infty}$ as $n \downarrow -\infty$,

$$E[Y|\mathcal{F}_n] \rightarrow E[Y|\mathcal{F}_{-\infty}] \text{ a.s. and in } L^1.$$

Strong law of large numbers

Example

- Let ξ_1, ξ_2, \dots be i.i.d. with $E[|\xi_i|] < \infty$.
- Let $S_n = \xi_1 + \dots + \xi_n$, let $X_{-n} = \frac{S_n}{n}$, and let

$$\mathcal{F}_{-n} = \sigma(S_n, S_{n+1}, S_{n+2}, \dots) = \sigma(S_n, \xi_{n+1}, \xi_{n+2}, \dots).$$

- Calculate, using symmetry, for $j \leq n + 1$,

$$\begin{aligned} E[\xi_j | \mathcal{F}_{-n-1}] &= \frac{1}{n+1} \sum_{k=1}^{n+1} E[\xi_k | \mathcal{F}_{-n-1}] \\ &= \frac{1}{n+1} E[S_{n+1} | \mathcal{F}_n] = \frac{S_{n+1}}{n+1}. \end{aligned}$$

Strong law of large numbers

Example

- Since $X_{-n} = \frac{S_{n+1} - \xi_{n+1}}{n}$,

$$\begin{aligned} E[X_{-n} | \mathcal{F}_{-n-1}] &= E\left[\frac{S_{n+1}}{n} \middle| \mathcal{F}_{-n-1}\right] - E\left[\frac{\xi_{n+1}}{n} \middle| \mathcal{F}_{-n-1}\right] \\ &= \frac{S_{n+1}}{n} - \frac{S_{n+1}}{n(n+1)} = \frac{S_{n+1}}{n+1} = X_{-n-1}. \end{aligned}$$

- Thus X_{-n} is a backwards martingale, and thus $\lim_{n \rightarrow \infty} \frac{S_n}{n} = E[X_{-1} | \mathcal{F}_{-\infty}]$.
- Since \mathcal{F}_{-n} has first n coordinates exchangeable, $\mathcal{F}_{-\infty} \subset \mathcal{E}$, and thus, by the Hewitt-Savage 0-1 law, $\lim_{n \rightarrow \infty} \frac{S_n}{n} = E[X_{-1}]$ a.s..

de Finetti's Theorem

A sequence X_1, X_2, \dots is said to be *exchangeable* if for each n and permutation π of $\{1, 2, \dots, n\}$, (X_1, \dots, X_n) and $(X_{\pi(1)}, \dots, X_{\pi(n)})$ have the same distribution.

Theorem

If X_1, X_2, \dots are exchangeable, then conditional on \mathcal{E} , X_1, X_2, \dots are independent and identically distributed.

de Finetti's Theorem

Proof.

- Let ϕ be bounded, and introduce

$$A_n(\phi) = \frac{1}{(n)_k} \sum_i \phi(X_{i_1}, \dots, X_{i_k})$$

where the sum runs over distinct sets $1 \leq i_1, \dots, i_k \leq n$ and $(n)_k = n(n-1) \cdots (n-k+1)$.

- Calculate

$$\begin{aligned} A_n(\phi) &= \mathbb{E}[A_n(\phi) | \mathcal{E}_n] = \frac{1}{(n)_k} \sum_i \mathbb{E}[\phi(X_{i_1}, \dots, X_{i_k}) | \mathcal{E}_n] \\ &= \mathbb{E}[\phi(X_1, \dots, X_k) | \mathcal{E}_n]. \end{aligned}$$

- It follows $A_n(\phi) \rightarrow \mathbb{E}[\phi(X_1, \dots, X_k) | \mathcal{E}]$.



de Finetti's Theorem

Proof.

- Let f and g be bounded on \mathbb{R}^{k-1} and \mathbb{R} and calculate

$$\begin{aligned}(n)_{k-1}A_n(f)nA_n(g) &= \sum_{\substack{1 \leq i_1, \dots, i_{k-1} \leq n \\ \text{distinct}}} f(X_{i_1}, \dots, X_{i_{k-1}}) \sum_m g(X_m) \\ &= \sum_{\substack{1 \leq i_1, \dots, i_k \leq n \\ \text{distinct}}} f(X_{i_1}, \dots, X_{i_{k-1}})g(X_{i_k}) \\ &+ \sum_{\substack{1 \leq i_1, \dots, i_{k-1} \leq n \\ \text{distinct}}} \sum_{j=1}^{k-1} f(X_{i_1}, \dots, X_{i_{k-1}})g(X_{i_j}).\end{aligned}$$



de Finetti's Theorem

Proof.

- Let $\phi(x_1, \dots, x_k) = f(x_1, \dots, x_{k-1})g(x_k)$ and $\phi_j(x_1, \dots, x_{k-1}) = f(x_1, \dots, x_{k-1})g(x_j)$.
- Rearranging the above identity,

$$A_n(\phi) = \frac{n}{n-k+1} A_n(f)A_n(g) - \frac{1}{n-k+1} \sum_{j=1}^{k-1} A_n(\phi_j).$$

Letting $n \rightarrow \infty$,

$$E[f(X_1, \dots, X_{k-1})g(X_k)|\mathcal{E}] = E[f(X_1, \dots, X_{k-1})|\mathcal{E}] E[g(X_k)|\mathcal{E}].$$

- The theorem now follows by induction.



Optional Stopping Theorems

Theorem

If X_n is a uniformly integrable submartingale, then for any stopping time N , $X_{N \wedge n}$ is uniformly integrable.

Optional Stopping Theorems

Proof.

- X_n^+ is a submartingale, so $E[X_{N \wedge n}^+] \leq E[X_n^+]$.
- $\sup_n E[X_{N \wedge n}^+] \leq \sup_n E[X_n^+] < \infty$.
- By the martingale convergence theorem $X_{N \wedge n} \rightarrow X_N$ a.s. and $E[|X_N|] < \infty$.
- Now calculate

$$E[|X_{N \wedge n}| \mathbf{1}(|X_{N \wedge n}| > K)] = E[|X_N| \mathbf{1}(|X_N| > K, N \leq n)] \\ + E[|X_n| \mathbf{1}(|X_n| > K, N > n)].$$

Choosing K sufficiently large makes both parts on the right sufficiently small.



Optional Stopping Theorems

Theorem

If X_n is a uniformly integrable submartingale, then for any stopping time $N \leq \infty$ we have $E[X_0] \leq E[X_N] \leq E[X_\infty]$ where $X_\infty = \lim X_n$.

Optional Stopping Theorems

Proof.

Recall $E[X_0] \leq E[X_{N \wedge n}] \leq E[X_n]$. Letting $n \rightarrow \infty$ and noting $X_{N \wedge n} \rightarrow X_N$ and $X_n \rightarrow X_\infty$ in L^1 proves the result. \square

Optional Stopping Theorems

Theorem (Optional stopping theorem)

If $L \leq M$ are stopping times and $Y_{M \wedge n}$ is a uniformly integrable submartingale, then $E[Y_L] \leq E[Y_M]$ and

$$Y_L \leq E[Y_M | \mathcal{F}_L].$$

Optional Stopping Theorems

Proof.

- Set $X_n = Y_{M \wedge n}$ and use $E[X_L] \leq E[X_\infty]$ to obtain $E[Y_L] \leq E[Y_M]$.
- Let $A \in \mathcal{F}_L$ and

$$N = \begin{cases} L & \text{on } A \\ M & \text{on } A^c \end{cases}$$

We have $E[Y_N] \leq E[Y_M]$. Since $N = M$ on A^c ,

$$E[Y_L \mathbf{1}_A] \leq E[Y_M \mathbf{1}_A] = E[E[Y_M | \mathcal{F}_L] \mathbf{1}_A].$$

Set $A_\epsilon = \{Y_L - E[Y_M | \mathcal{F}_L] > \epsilon\}$ gives $\text{Prob}(A_\epsilon) = 0$.

