1 Conditional Expectation

Definition. Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space. Let $(X_i)_{i \in I}$ be a collection of random variables defined on this space. Then we define $\sigma(X_i : i \in I) \subseteq \mathcal{F}$ to be the smallest σ-algebra such that all of the X_i are measurable, i.e

$$\sigma(X_i : i \in I) = \sigma(X_i^{-1}(B) : i \in I,\ B \in \mathcal{B}(\mathbb{R})).$$

Definition. If $B \in \mathcal{F}$ has $\mathbb{P}(B) > 0$ then we define

$$\mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}$$

for any $A \in \mathcal{F}$. Furthermore, if X is an integrable random variable we define

$$\mathbb{E}[X|B] = \frac{\mathbb{E}[X \mathbb{1}(B)]}{\mathbb{P}(B)}.$$

Definition. Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space. We say a σ-algebra $\mathcal{G}$ is countably generated if there exist $(B_i)_{i \in I}$ pairwise disjoint (with I countable) such that $\bigcup_{i \in I} B_i = \Omega$ and $\mathcal{G} = \sigma(B_i : i \in I)$.

Let X be an integrable random variable and $\mathcal{G}$ a countably generated σ-algebra. We want to define $X' = \mathbb{E}[X|\mathcal{G}]$. So define

$$X'(\omega) = \mathbb{E}[X|B_i] \text{ whenever } \omega \in B_i.$$

Or equivalently,

$$X'(\omega) = \sum_{i \in I} \mathbb{E}[X|B_i] \mathbb{1}(\omega \in B_i)$$

where we use the convention that $\mathbb{E}[X|B_i] = 0$ if $\mathbb{P}(B_i) = 0$. Then X' is indeed $\mathcal{G}$-measurable (note $\mathcal{G}$ is the set of $\bigcup_{j \in J} B_j$ for $J \subseteq I$).

Note that for any $G \in \mathcal{G}$ we have $\mathbb{E}[X\mathbb{1}(G)] = \mathbb{E}[X'\mathbb{1}(G)]$. Also

$$\mathbb{E}[|X'|] \leq \mathbb{E}\left[\sum_{i \in I} \mathbb{E}[|X||B_i]\mathbb{1}(B_i)\right] = \sum_{i \in I} \mathbb{E}[|X||B_i]\mathbb{P}(B_i) = \mathbb{E}|X| < \infty$$

so X' is integrable.

Theorem (Monotone convergence theorem)**.** *Let $(X_n)_{n \geq 1}$ be a sequence of non-negative random variables with $X_n \uparrow X$ as $n \to \infty$ almost-surely. Then $\mathbb{E}X_n \uparrow \mathbb{E}X$ as $n \to \infty$.*

Proof. See Part II Probability & Measure. □

Theorem (Dominated convergence theorem)**.** *Let $(X_n)_{n \geq 1}$ be a sequence of random variables with $X_n \to X$ as $n \to \infty$ almost-surely and $|X_n| \leq Y$ almost-surely for some Y integrable. Then $\mathbb{E}X_n \to \mathbb{E}X$ as $n \to \infty$.*

Proof. See Part II Probability & Measure. □

Definition (L^p)**.** Let $p \in [1, \infty]$ and f be a measurable function. Define the *L^p-norm*

$$||f||_p = \left(\mathbb{E}[|f|^p]\right)^{1/p} \text{ for } p \in [1, \infty)$$
$$||f||_\infty = \inf\{\lambda : |f| \leq \lambda \text{ a.e}\}.$$

Furthermore write $f \sim g$ if $f = g$ almost everywhere. Then define the L^p-space $\mathcal{L}^p(\Omega, \mathcal{F}, \mathbb{P}) = \{f : ||f||_p < \infty\}/\sim$.

Theorem ($\mathcal{L}^2$ is a Hilbert space)**.** *$\mathcal{L}^2(\Omega, \mathcal{F}, \mathbb{P})$ is a Hilbert space with inner product $\langle U, V\rangle = \mathbb{E}[UV]$. For a closed subspace $\mathcal{H}$, if $f \in \mathcal{L}^2$ there exists a unique $g \in \mathcal{H}$ with $||f - g||_2 = \inf\{||f - h||_2 : h \in \mathcal{H}\}$ and $\langle f - g, h\rangle = 0$ for all $h \in \mathcal{H}$. g is called the orthogonal projection of f on $\mathcal{H}$.*

Proof. See Part II Probability & Measure. □

Theorem (Conditional expectation)**.** *Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space and $\mathcal{G} \subseteq \mathcal{F}$ a sub σ-algebra, $X \in \mathcal{L}^1(\Omega, \mathcal{F}, \mathbb{P})$. Then there exists an integrable random variable Y satisfying*

(a) Y is $\mathcal{G}$-measurable;

(b) for all $A \in \mathcal{G}$, $\mathbb{E}[X\mathbb{1}(A)] = \mathbb{E}[Y\mathbb{1}(A)]$.

Moreover Y is unique, in the sense that if Y' also satisfies (a) and (b), then $Y = Y'$ almost-surely. We call Y a version of the conditional expectation of X given $\mathcal{G}$. We write $Y = \mathbb{E}[X|\mathcal{G}]$ almost-surely. If $\mathcal{G} = \sigma(Z)$ for a random variable Z, then we write $\mathbb{E}[X|Z] = \mathbb{E}[X|\mathcal{G}]$.

Remark. (b) could be replaced by $\mathbb{E}[XZ] = \mathbb{E}[YZ]$ for all Z bounded and $\mathcal{G}$-measurable.

Proof. First we show uniqueness. Suppose Y and Y' both satisfy (a) and (b) and let $A = \{Y > Y'\} \in \mathcal{G}$. Then

$$\mathbb{E}[Y\mathbb{1}(A)] = \mathbb{E}[Y'\mathbb{1}(A)] \Rightarrow \mathbb{E}[(Y-Y')\mathbb{1}(A)] = 0 \Rightarrow \mathbb{P}(Y > Y') = 0 \Rightarrow Y \leq Y' \text{ a.s}$$

and similarly $Y \geq Y'$ a.s.

Now we show existence. First assume $X \in \mathcal{L}^2(\Omega, \mathcal{F}, \mathbb{P})$. Then $\mathcal{L}^2(\Omega, \mathcal{G}, \mathbb{P})$ is a closed subspace of $\mathcal{L}^2(\mathcal{F})$. Hence

$$\mathcal{L}^2(\mathcal{F}) = \mathcal{L}^2(\mathcal{G}) \oplus \mathcal{L}^2(\mathcal{G})^\perp$$

so we can write $X = Y + Z$ for $Y \in \mathcal{L}^2(\mathcal{G})$ and $Z \in \mathcal{L}^2(\mathcal{G})^\perp$. Define $\mathbb{E}[X|\mathcal{G}] = Y$, so Y is $\mathcal{G}$-measurable and for all $A \in \mathcal{G}$

$$\mathbb{E}[X\mathbb{1}(A)] = \mathbb{E}[Y\mathbb{1}(A)] + \underbrace{\mathbb{E}[Z\mathbb{1}(A)]}_{=0} = \mathbb{E}[Y\mathbb{1}(A)].$$

We claim that if $X \geq 0$ almost-surely, then $Y \geq 0$ almost-surely. Indeed, let $A = \{Y < 0\} \in \mathcal{G}$ so $0 \leq \mathbb{E}[X\mathbb{1}(Y < 0)] = \mathbb{E}[Y\mathbb{1}(Y < 0)] \leq 0$ which implies $\mathbb{P}(Y < 0) = 0$.

Assume now that $X \geq 0$ almost-surely. Define $X_n = X \wedge n \leq n$, so $X_n \in \mathcal{L}^2$ for all n. Let $Y_n = \mathbb{E}[X_n|\mathcal{G}]$. Then X_n is an increasing sequence and by the above claim, Y_n is also an increasing sequence almost-surely. Define $Y = \limsup_{n\to\infty} Y_n$, so Y is $\mathcal{G}$-measurable. Also $Y =\uparrow \lim_{n\to\infty} Y_n$ almost-surely. For any $A \in \mathcal{G}$ we have

$$\mathbb{E}[X\mathbb{1}(A)] = \lim_{n\to\infty} \mathbb{E}[X_n\mathbb{1}(A)] = \lim_{n\to\infty} \mathbb{E}[Y_n\mathbb{1}(A)] = \mathbb{E}[Y\mathbb{1}(A)]$$

by the Monotone Convergence Theorem.

Finally, for general X write $X = X^+ - X^-$ and define $\mathbb{E}[X|\mathcal{G}] = \mathbb{E}[X^+|\mathcal{G}] - \mathbb{E}[X^-|\mathcal{G}]$. $\square$

Remark. From the last proof we can see that we can define $\mathbb{E}[X|\mathcal{G}]$ for $X \geq 0$ without assuming integrability of X. It satisfies all the conditions apart from integrability.

Definition. Let $(\mathcal{G}_n)_{n\geq 1}$ be sub σ-algebras of $\mathcal{F}$. We call them *independent* if whenever $G_i \in \mathcal{G}_i$ and $i_1 < i_2 < \ldots < i_k$ we have

$$\mathbb{P}(G_{i_1} \cap \ldots \cap G_{i_k}) = \prod_{j=1}^{k} \mathbb{P}(G_{i_j}).$$

For a random variable X and a σ-algebra $\mathcal{G}$, we say they are *independent* if $\sigma(X)$ is independent of $\mathcal{G}$.

Properties of conditional expectation

Let $X, Y \in \mathcal{L}^1$, $\mathcal{G} \subseteq \mathcal{F}$ a sub σ-algebra. Then

1. $\mathbb{E}[\mathbb{E}[X|\mathcal{G}]] = \mathbb{E}[X]$ (take $A = \Omega$);
2. If X is $\mathcal{G}$-measurable then $\mathbb{E}[X|\mathcal{G}] = X$ almost-surely (X clearly satisfies the conditions);
3. If X is independent of $\mathcal{G}$, then $\mathbb{E}[X|\mathcal{G}] = \mathbb{E}[X]$ almost-surely;
4. If $X \geq 0$ almost-surely then $\mathbb{E}[X|\mathcal{G}] \geq 0$ almost-surely;
5. For $\alpha, \beta \in \mathbb{R}$, $\mathbb{E}[\alpha X + \beta Y|\mathcal{G}] = \alpha\mathbb{E}[X|\mathcal{G}] + \beta\mathbb{E}[Y|\mathcal{G}]$ almost-surely;
6. $|\mathbb{E}[X|\mathcal{G}]| \leq \mathbb{E}[|X||\mathcal{G}]$ almost-surely.

Recall:

Theorem (Fatou's Lemma)**.** *If $X_n \geq 0$ for all n almost-surely, then*

$$\mathbb{E}[\liminf_{n\geq 1} X_n] \leq \liminf_{n\geq 1} \mathbb{E}X_n.$$

Proof. See Part II Probability & Measure. □

Theorem (Jensen's Inequality)**.** *If X is integrable, $\varphi : \mathbb{R} \to \mathbb{R}$ is convex, then*

$$\mathbb{E}[\varphi(X)] \geq \varphi(\mathbb{E}[X]).$$

We consider any analogues of our convergence theorems for conditional expectation.

Theorem (Conditional Monotone Convergence Theorem)**.** *Suppose $X_n \geq 0$ for all n and $X_n \uparrow X$ almost-surely as $n \to \infty$. Let $\mathcal{G}$ be a sub σ-algebra of $\mathcal{F}$. Then $\mathbb{E}[X_n|\mathcal{G}] \uparrow \mathbb{E}[X|\mathcal{G}]$ almost-surely.*

Remark. Note that $\mathbb{E}[X_n|\mathcal{G}] \uparrow \mathbb{E}[X|\mathcal{G}]$ in the almost-sure sense, as these are random variables.

Proof. Let $Y_n = \mathbb{E}[X_n|\mathcal{G}]$ almost-surely. Then Y_n is increasing. Set $Y = \limsup_{n\geq 1} Y_n$. Since Y_n is $\mathcal{G}$-measurable, Y is $\mathcal{G}$-measurable. Also $Y =\uparrow \lim_{n\geq 1} Y_n$ almost-surely. We need to show $\mathbb{E}[Y\mathbb{1}(A)] = \mathbb{E}[X\mathbb{1}(A)]$ for all $A \in \mathcal{G}$. This follows from the usual Monotone Convergence Theorem as

$$\mathbb{E}[Y\mathbb{1}(A)] = \lim_{n\geq 1} \mathbb{E}[Y_n\mathbb{1}(A)] = \lim_{n\geq 1} \mathbb{E}[X_n\mathbb{1}(A)] = \mathbb{E}[X\mathbb{1}(A)].$$

$\square$

Theorem (Conditional Fatou's Lemma)**.** *Let $(X_n)_{n\geq 1}$ be a non-negative sequence of random variables. Then*

$$\mathbb{E}[\liminf_{n\to\infty} X_n|\mathcal{G}] \leq \liminf_{n\to\infty} \mathbb{E}[X_n|\mathcal{G}] \text{ almost-surely.}$$

Proof. Note that $\inf_{k\geq n} X_k \uparrow \liminf_{n\to\infty} X_n$ so by the conditional MCT

$$\lim_{n\to\infty} \mathbb{E}[\inf_{k\geq n} X_k|\mathcal{G}] = \mathbb{E}[\liminf_{n\to\infty} X_n|\mathcal{G}].$$

We also have

$$\mathbb{E}[\inf_{k\geq n} X_k|\mathcal{G}] \leq \mathbb{E}[X_k|\mathcal{G}] \quad \forall k \geq n \text{ almost-surely.}$$

Which implies

$$\mathbb{E}[\inf_{k\geq n} X_k|\mathcal{G}] \leq \inf_{k\geq n} \mathbb{E}[X_k|\mathcal{G}] \quad \forall k \geq n \text{ almost-surely}$$

since k takes countable values (intersection of countable sets of full measure also has full measure). Now taking limits as $n \to \infty$ we are done. $\square$

Theorem (Conditional Dominated Convergence Theorem)**.** *Suppose $X_n \to X$ almost-surely, $|X_n| \leq Y$ almost-surely with Y integrable. Then $\mathbb{E}[X_n|\mathcal{G}] \to \mathbb{E}[X|\mathcal{G}]$ almost-surely.*

Proof. We apply the Conditional Fatou's Lemma. Indeed $-Y \leq X_n \leq Y$ so $X_n + Y \geq 0$ and $Y - X_n \geq 0$ for all n. By Conditional Fatou's Lemma

$$\mathbb{E}[X|\mathcal{G}] + \mathbb{E}[Y|\mathcal{G}] = \mathbb{E}[X+Y|\mathcal{G}] = \mathbb{E}[\liminf_{n\to\infty}(X_n+Y)] \leq \liminf_{n\to\infty} \mathbb{E}[X_n|\mathcal{G}] + \mathbb{E}[Y|\mathcal{G}]$$

and

$$\mathbb{E}[Y|\mathcal{G}] - \mathbb{E}[X|\mathcal{G}] = \mathbb{E}[\liminf_{n\to\infty}(Y - X_n)|\mathcal{G}] \leq \mathbb{E}[Y|\mathcal{G}] + \liminf_{n\to\infty}\left(-\mathbb{E}[X_n|\mathcal{G}]\right).$$

Hence $\limsup_{n\to\infty} \mathbb{E}[X_n|\mathcal{G}] \leq \mathbb{E}[X|\mathcal{G}]$ and $\liminf_{n\to\infty} \mathbb{E}[X_n|\mathcal{G}] \geq \mathbb{E}[X|\mathcal{G}]$ almost-surely.

$\square$

Theorem (Conditional Jensen's Inequality)**.** *Let X be integrable, $\varphi : \mathbb{R} \to \mathbb{R}$ a convex function such that $\varphi(X)$ is integrable or $\varphi(X) \geq 0$. Then $\mathbb{E}[\varphi(X)|\mathcal{G}] \geq \varphi(\mathbb{E}[X|\mathcal{G}])$ almost-surely.*

Proof. We claim that $\varphi(x) = \sup_{i\in\mathbb{N}}(a_i x + b_i)$, $a_i, b_i \in \mathbb{R}$.

Then $\varphi(X) = \sup_{i\in\mathbb{N}}(a_i X + b_i)$. So

$$\mathbb{E}[\varphi(X)|\mathcal{G}] \geq \sup_{n\geq 1}(a_i\mathbb{E}[X|\mathcal{G}] + b_i) \quad \forall i \in \mathbb{N} \text{ almost-surely.}$$

□

Note. We need the supremum in the claim to be over a countable set so we can preserve the almost-sue property of an inequality.

Corollary. *For all $p \in [1, \infty)$ we have*

$$||\mathbb{E}[X|\mathcal{G}]||_p \leq ||X||_p.$$

Proof. Apply conditional Jensen ($x \mapsto x^p$ is convex). □

Theorem (Tower property)**.** *Let X be integrable and $\mathcal{H} \subseteq \mathcal{G} \subseteq \mathcal{F}$ sub σ-algebras. Then*

$$\mathbb{E}[\mathbb{E}[X|\mathcal{G}]|\mathcal{H}] = \mathbb{E}[X|\mathcal{H}] \text{ almost-surely.}$$

Proof. $\mathbb{E}[X|\mathcal{H}]$ is certainly $\mathcal{H}$-measurable so it remains to check

$$\mathbb{E}[\mathbb{E}[X|\mathcal{G}]\mathbb{1}(A)] = \mathbb{E}[\mathbb{E}[X|\mathcal{H}]\mathbb{1}(A)] \quad \forall A \in \mathcal{H}.$$

But since $A \in \mathcal{G}$ whenever $A \in \mathcal{H}$ we have

$$\mathbb{E}[\mathbb{E}[X|\mathcal{G}]\mathbb{1}(A)] = \mathbb{E}[X\mathbb{1}(A)] = \mathbb{E}[\mathbb{E}[X|\mathcal{H}]\mathbb{1}(A)].$$

□

Proposition. Let $X \in \mathcal{L}^1$, $\mathcal{G} \subseteq \mathcal{F}$ a sub σ-algebra, Y bounded and $\mathcal{G}$-measurable. Then

$$\mathbb{E}[XY|\mathcal{G}] = Y\mathbb{E}[X|\mathcal{G}] \text{ almost-surely.}$$

Proof. $Y\mathbb{E}[X\mathcal{G}]$ is certainly $\mathcal{G}$-measurable. Also for any $A \in \mathcal{G}$

$$\mathbb{E}[XY\mathbb{1}(A)] = \mathbb{E}[X \underbrace{(Y\mathbb{1}(A))}_{\substack{\text{bounded,} \\ \mathcal{G}\text{-measurable}}}] = \mathbb{E}[\mathbb{E}[X|\mathcal{G}](Y\mathbb{1}(A))].$$

□

Definition. Let $\mathcal{A}$ be a collection of sets. It is called a *π-system* if whenever $A, B \in \mathcal{A}$ we have $A \cap B \in \mathcal{A}$.

Recall

Theorem (Uniqueness of extension)**.** *Let $(E, \mathcal{E})$ be a measurable space and let $\mathcal{A}$ be a π-system generating $\mathcal{E}$. Let μ, ν be two measures on $(E, \mathcal{E})$ with $\mu(E) = \nu(E) < \infty$. If $\mu = \nu$ on $\mathcal{A}$. then $\mu = \nu$ on $\mathcal{E}$.*

Proof. See Part II Probability & Measure. $\square$

Theorem. *Let $X \in \mathcal{L}^1$, $\mathcal{G}, \mathcal{H} \subseteq \mathcal{F}$ sub σ-algebras. Assume $\sigma(X, \mathcal{G})$ is independent of $\mathcal{H}$. Then*

$$\mathbb{E}[X|\sigma(\mathcal{G}, \mathcal{H})] = \mathbb{E}[X|\mathcal{G}] \text{ almost-surely.}$$

Proof. We need to show $\mathbb{E}[X\mathbb{1}(F)] = \mathbb{E}[\mathbb{E}[X|\mathcal{G}]\mathbb{1}(F)]$ for all $F \in \sigma(\mathcal{G}, \mathcal{H})$. Define $\mathcal{A} = \{A \cap B : A \in \mathcal{G}, B \in \mathcal{H}\}$. This is a π-system generating $\sigma(\mathcal{G}, \mathcal{H})$. If $F = A \cap B$, $A \in \mathcal{G}, B \in \mathcal{H}$ then

$$\begin{aligned}\mathbb{E}[X\mathbb{1}(A \cap B)] &= \mathbb{E}[\quad \underbrace{(X\mathbb{1}(A))}_{\sigma(X,\mathcal{G})\text{measurable}} \quad \mathbb{1}(B)] \\ &= \mathbb{E}[X\mathbb{1}(A)]\mathbb{P}(B) \\ &= \mathbb{E}[\underbrace{\mathbb{E}[X|\mathcal{G}]\mathbb{1}(A)}_{\substack{\mathcal{G} \\ \text{measurable}}}]\mathbb{P}(B) \\ &= \mathbb{E}[\mathbb{E}[X|\mathcal{G}]\mathbb{1}(A)\mathbb{1}(B)].\end{aligned}$$

Assume $X \geq 0$. Define $\mu(F) = \mathbb{E}[X\mathbb{1}(F)]$ and $\nu(F) = \mathbb{E}[\mathbb{E}[X|\mathcal{G}]\mathbb{1}(F)]$ for $F \in \sigma(\mathcal{G}, \mathcal{H})$. Then $\mu = \nu$ on $\mathcal{A}$ by the above and $\mu(\Omega) = \nu(\Omega) < \infty$. Therefore $\mu = \nu$ on $\sigma(\mathcal{G}, \mathcal{H})$. $\square$

Definition. We say $(X_1, \ldots, X_n) \in \mathbb{R}^n$ has the *Gaussian distribution* iff for all $a_1, \ldots, a_n \in \mathbb{R}$

$$a_1 X_1 + \ldots + a_n X_n$$

has the Gaussian distribution in $\mathbb{R}$.

A process $(X_t)_{t \geq 0}$ is called a *Gaussian process* if $\forall t_1 < t_2 < \ldots < t_n$, the vector $(X_{t_1}, \ldots, X_{t_n})$ is a Gaussian random vector.

Example. Let (X, Y) be a Gaussian vector in $\mathbb{R}^2$. We want to compute $\mathbb{E}[X|Y] = \mathbb{E}[X|\sigma(Y)]$. Let $X' = \mathbb{E}[X|Y]$. Since X' is $\sigma(Y)$-measurable it follows X' is a measurable function of Y. So are looking for f Borel such that $\mathbb{E}[X|Y] = f(Y)$ almost-surely. Let $f(y) = ay + b$ for some $a, b \in \mathbb{R}$ to be determined.

Since $\mathbb{E}[X'] = \mathbb{E}[X]$ we have $a\mathbb{E}Y + b = \mathbb{E}X$. Also

$$\begin{aligned} \mathbb{E}[XY] = \mathbb{E}[X'Y] &\implies \mathbb{E}[(X - X')Y] = 0 \\ &\implies \operatorname{Cov}(X - X', Y) = 0 \\ &\implies \operatorname{Cov}(X, Y) = a\operatorname{Var}(Y) \end{aligned}$$

so we have determined a, b. We need to check that for any Z bounded and $\sigma(Y)$-measurable we have $\mathbb{E}[(X - X')Z] = 0$. Write $Z = g(Y)$ and note $\operatorname{Cov}(X - X', Y) = 0$, implying $X - X'$ is independent of Y. Therefore $\mathbb{E}[(X - X')g(Y)] = \mathbb{E}[X - X']\mathbb{E}[g(Y)] = 0$.

Example. Let (X, Y) be a random vector in $\mathbb{R}^2$ with joint density function $f_{X,Y}(x, y)$. Let $h : \mathbb{R} \to \mathbb{R}$ be a Borel function such that $h(X)$ is integrable. We want to compute $\mathbb{E}[h(X)|Y]$. Note

$$\mathbb{E}[h(X)g(Y)] = \int_{\mathbb{R}^2} h(x)g(x)f_{X,Y}(x, y)\mathrm{d}x\mathrm{d}y$$

and write

$$f_Y(y) = \int_{\mathbb{R}} f_{X,Y}(x, y)\mathrm{d}x$$

for the density of Y. So (using the convention $0/0 = 0$)

$$\int_{\mathbb{R}} \left(\int_{\mathbb{R}} h(x)\frac{f_{X,Y}(x, y)}{f_Y(y)}\mathrm{d}x \right) g(y)f_Y(y)\mathrm{d}y$$

define

$$\varphi(y) = \begin{cases} \int_{\mathbb{R}} h(x)\frac{f_{X,Y}(x,y)}{f_Y(y)}\mathrm{d}x & \text{if } f_Y(y) > 0 \\ 0 & \text{otherwise} \end{cases}.$$

Then $\mathbb{E}[h(X)|Y] = \varphi(Y)$ almost-surely.

2 Martingales

2.1 Discrete-time Martingales

Definition. Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space. A *filtration* is a sequence of increasing sub σ-algebras of $\mathcal{F}$, $(\mathcal{F}_n)_{n\geq 0}$, $\mathcal{F}_n \subseteq \mathcal{F}_{n+1}$. We call $(\Omega, \mathcal{F}, (\mathcal{F}_n)_{n\geq 0}, \mathbb{P})$ a *filtered probability space.*

If $X = (X_n)_{n\geq 0}$ is a sequence of random variables on $(\Omega, \mathcal{F}, \mathbb{P})$, define $\mathcal{F}_n^X = \sigma(X_k : k \leq n)$, the *natural filtration* associated with X. We say X is *adapted* to a filtration $(\mathcal{F}_n)$ if X_n is $\mathcal{F}_n$-measurable for all n. X is *integrable* if X_n is integrable for all n.

Definition. Let $(\Omega, \mathcal{F}, (\mathcal{F}_n)_{n\geq 0}, \mathbb{P})$ be a filtered probability space. We say an integrable adapted process $X = (X_n)_{n\geq 0}$ is called a

- *martingale* if

$$\mathbb{E}[X_n|\mathcal{F}_m] = X_m \text{ almost-surely } \forall n \geq m.$$

- *super-martingale* if

$$\mathbb{E}[X_n|\mathcal{F}_m] \leq X_m \text{ almost-surely } \forall n \geq m.$$

- *sub-martingale* if

$$\mathbb{E}[X_n|\mathcal{F}_m] \geq X_m \text{ almost-surely } \forall n \geq m.$$

Remark. If X is a martingale with respect to $(\mathcal{F}_n)$, then it is also a martingale with respect to the natural filtration $(\mathcal{F}_n^X)$.

Example. Let (ξ_i) be a sequence of iid random variables with $\mathbb{E}[\xi_1] = 0$. Let $X_n = \xi_1 + \ldots + \xi_n$, $X_0 = 0$. This is a martingale. We have

$$\mathbb{E}[X_n|\mathcal{F}_{n-1}] = \xi_1 + \ldots + \xi_{n-1} + \mathbb{E}[\xi_n|\mathcal{F}_{n-1}] = \xi_1 + \ldots + \xi_{n-1}$$

by independence.

Example. Let (ξ_i) be a sequence of iid random variables with $\mathbb{E}[\xi_1] = 1$. Let $X_n = \prod_{i=1}^n \xi_i$, $X_0 = 1$. This is a martingale.

Definition. Let $(\Omega, \mathcal{F}, (\mathcal{F}_n)_{n\geq 0}, \mathbb{P})$ be a filtered probability space. A *stopping time* T is a random variable $T : \Omega \to \mathbb{Z}_+ \cup \{\infty\}$ such that $\{T \leq n\} \in \mathcal{F}_n$ for all n.

Note. T being a stopping time is equivalent to $\{T = n\} \in \mathcal{F}_n$ for all n.

Examples.

- Constant times are trivial stopping times;
- Suppose $(X_n)_{n\geq 0}$ is an adapted process taking values in $\mathbb{R}$. For $A \in \mathcal{B}$ define $T_A = \inf\{n \geq 0 : X_n \in A\}$ (with the convention that $\inf \emptyset = \infty$). Then $\{T_A \leq n\} = \bigcup_{k\leq n}\{X_k \in A\} \in \mathcal{F}_n$, so T_A is a stopping time;
- In the setting above, let $L_A = \sup\{n \geq 0 : X_n \in A\}$. This is in general not a stopping time.

Proposition. Let $S, T, (T_n)$ be stopping times. Then $S \wedge T$, $S \vee T$, $\inf T_n$, $\sup T_n$, $\liminf T_n$ and $\limsup T_n$ are also stopping times.

Proof. Follows directly from the definition. $\square$

Definition. If T is a stopping time, we define

$$\mathcal{F}_T = \{A \in \mathcal{F} : A \cap \{T \leq t\} \in \mathcal{F}_t,\ \forall t\}.$$

If $(X_n)_{n\geq 0}$ is a process, write $X_T(\omega) = X_{T(\omega)}(\omega)$ whenever $T(\omega) < \infty$. We define the *stopped process* $X_t^T = X_{T\wedge t}$.

Proposition. Let S and T be stopping times and let X be an adapted process. Then

1. If $S \leq T$, then $\mathcal{F}_S \subseteq \mathcal{F}_T$;
2. $X_T \mathbb{1}(T < \infty)$ is $\mathcal{F}_T$-measurable;
3. X^T is adapted;
4. If X is integrable, then X^T is also integrable.

Proof.

1. Immediate from the definition;
2. Let $A \in \mathcal{B}(\mathbb{R})$. We need to show $\{X_T \mathbb{1}(T < \infty) \in \mathcal{A}\} \in \mathcal{F}_T$. Note that

$$\{X_T \mathbb{1}(T < \infty) \in A\} \cap \{T \leq t\} = \bigcup_{s=0}^{t} \underbrace{\{X_s \in A\}}_{\in \mathcal{F}_s \subseteq \mathcal{F}_t} \cap \underbrace{\{T = s\}}_{\in \mathcal{F}_s} \in \mathcal{F}_t.$$

3. $X_t^T = X_{T\wedge t}$ is $\mathcal{F}_{T\wedge t}$-measurable so $\mathcal{F}_t$-measurable by (1).

4. We have

$$\begin{aligned}\mathbb{E}[|X_t^T|] = \mathbb{E}[|X_{T\wedge t}|] &= \sum_{s=0}^{t-1} \mathbb{E}[|X_s|\mathbb{1}(T=s)] + \mathbb{E}[|X_t|\mathbb{1}(T \geq t)] \\ &\leq \sum_{s=0}^{t} \mathbb{E}[|X_s|] < \infty.\end{aligned}$$

□

Theorem (Optional Stopping Theorem)**.** *Let (X_n) be a martingale.*

1. *If T is a stopping time, then X^T is also a martingale. In particular $\mathbb{E}[X_{T\wedge t}] = \mathbb{E}[X_0]$ for all t;*
2. *If $S \leq T$ are bounded stopping times then $\mathbb{E}[X_T|\mathcal{F}_S] = X_S$ almost-surely, and $\mathbb{E}[X_T] = \mathbb{E}[X_S]$;*
3. *If there exists an integrable random variable Y such that $|X_n| \leq Y$ for all n, and T is finite almost-surely then $\mathbb{E}[X_T] = \mathbb{E}[X_0]$;*
4. *If there exists $M > 0$ such that $|X_{n+1} - X_n| \leq M$ for all n, and T is a stopping time with $\mathbb{E}T < \infty$, then $\mathbb{E}[X_T] = \mathbb{E}[X_0]$.*

Proof.

1. We need to show that for all t we have

$$\mathbb{E}[X_{T\wedge t}|\mathcal{F}_{t-1}] = X_{T\wedge(t-1)}$$

almost-surely. Indeed

$$\begin{aligned}\mathbb{E}[X_{T\wedge t}|\mathcal{F}_{t-1}] &= \mathbb{E}\left[\sum_{s=0}^{t-1} X_s\mathbb{1}(T=s)|\mathcal{F}_{t-1}\right] + \mathbb{E}[X_t\mathbb{1}(T\geq t)|\mathcal{F}_{t-1}] \\ &= \sum_{s=0}^{t-1} X_s\mathbb{1}(T=s) + \mathbb{1}(T\geq t)X_{t-1} \\ &= X_{T\wedge(t-1)}\end{aligned}$$

using the fact that $\mathbb{1}(T\geq t)$ is $\mathcal{F}_{t-1}$-measurable;

2. Suppose $S \leq T \leq n$ and let $A \in \mathcal{F}_S$. We need to show $\mathbb{E}[X_T\mathbb{1}(A)] = \mathbb{E}[X_S\mathbb{1}(A)]$. Note

$$\begin{aligned}X_T - X_S &= (X_T - X_{T-1}) + \ldots + (X_{S+1} - X_S) \\ &= \sum_{k\geq 0}(X_{k+1} - X_k)\mathbb{1}(S \leq k < T) \\ &= \sum_{k=0}^{n}(X_{k+1} - X_k)\mathbb{1}(S \leq k < T). \qquad (T \leq n)\end{aligned}$$

Hence

$$\mathbb{E}[X_T \mathbb{1}(A)] = \mathbb{E}[X_S \mathbb{1}(A)] + \sum_{k=0}^{n} \mathbb{E}[(X_{k+1} - X_k) \underbrace{\mathbb{1}(S \leq k < T)\mathbb{1}(A)}_{\in \mathcal{F}_k}]$$
$$= \mathbb{E}[X_S \mathbb{1}(A)]$$

since $\mathbb{E}[X_{k+1}|\mathcal{F}_k] = X_k$ almost-surely. Taking expectations gives $\mathbb{E}[X_T] = \mathbb{E}[X_S]$;

3. Example Sheet;

4. Example Sheet.

□

Note. Analogous results follow if (X_n) is instead a sub/super-martingale.

Corollary. *If X is a positive super-martingale, T is a stopping time, $T < \infty$ almost-surely, then $\mathbb{E}[X_T] \leq \mathbb{E}[X_0]$.*

Proof. Fatou's lemma gives $\mathbb{E}[\liminf_t X_{T\wedge t}] \leq \liminf_t \mathbb{E}[X_{T\wedge t}] \leq \mathbb{E}[X_0]$. □

Example. Let $(\xi_i)_{i\geq 0}$ be iid with $\mathbb{P}(\xi_0 = 1) = \mathbb{P}(\xi_0 = -1) = 1/2$. Define $X_0 = 0$ and $X_n = \sum_{i=1}^{n} \xi_i$ for $n \geq 1$. Then $(X_n)_{n\geq 0}$ is a martingale. Define $T = \inf\{n \geq 0 : X_n = 1\}$. Then $\mathbb{P}(T < \infty) = 1$ and for all t we have $\mathbb{E}[X_{T\wedge t}] = 0$, while $\mathbb{E}[X_T] = 1$. Hence (4) from the previous theorem tells us $\mathbb{E}T = \infty$.

Example. Consider a SRW on $\mathbb{Z}$, $X_0 = 0$, $X_n = \sum_{i=1}^n \xi_i$ with $(\xi_i)_{i\geq 1}$ iid taking values ± 1 with equal probability. Define $T_c = \inf\{n \geq 0 : X_n = c\}$ and set $T = T_{-a} \wedge T_b$. What is $\mathbb{P}(T_{-a} < T_b)$?

We have that $X_n^T = X_{T\wedge n}$ is a martingale by the optional stopping theorem. Furthermore $|X_{n+1} - X_n| = 1$ for all n. Need to check $\mathbb{E}[T] < \infty$: consider blocks

- $\xi_1, \dots, \xi_{a+b}$
- $\xi_{a+b+1}, \dots, \xi_{2(a+b)}$
- $\xi_{2(a+b)+1}, \dots, \xi_{3(a+b)}$
- $\vdots$

note that the probability the ξ_i in one of these blocks are all equal to either 1 or -1 is $2\cdot 2^{-(a+b)}$. Hence $T \leq (a+b)\text{Geo}(2\cdot 2^{-(a+b)})$ and $\mathbb{E}T \leq (a+b)2^{a+b-1} < \infty$.

So applying the optional stopping theorem to T we have $\mathbb{E}[X_T] = \mathbb{E}[X_0] = 0$. Hence $-a\mathbb{P}(T_{-a} < T_b) + b\mathbb{P}(T_b < T_{-a}) = 0$ and $\mathbb{P}(T_{-a} < T_b) + \mathbb{P}(T_b < T_{-a})$, which gives $\mathbb{P}(T_{-a} < T_b) = \frac{b}{a+b}$.

Martingale convergence theoem

Theorem (Almost-sure martingale convergence theorem)**.** *Let X be a supermartingale bounded in $\mathcal{L}^1$, i.e $\sup_{n\geq 0} \mathbb{E}|X_n| < \infty$. Then there exists a random variable $X_\infty \in \mathcal{L}^1(\mathcal{F}_\infty)$ where $\mathcal{F}_\infty = \sigma(\mathcal{F}_n : n \geq 0)$ such that $X_n \to X_\infty$ almost-surely as $n \to \infty$.*

Before we can prove this we will need some preliminary results.

Doob's upcrossing inequality

For a real sequence $(x_n)_{n\geq 0}$, for an interval $[a,b]$ we want to count the number of times (x_n) crosses below a or above b. Define $T_0(x) = 0$ and define for $k \geq 0$

$$S_{k+1}(x) = \inf\{n \geq T_k(x) : x_n \leq a\} \text{ the } (k+1)\text{st downcrossing}$$
$$T_{k+1}(x) = \inf\{n \geq S_{k+1}(x) : x_n \geq b\} \text{ the } (k+1)\text{st upcrossing.}$$

Also let $N_n([a,b],x) = \sup\{k \geq 0 : T_k(x) \leq n\}$, the number of up crossings up to time N. Then as $n \to \infty$, $N_n([a,b],x) \uparrow N([a,b],x) = \sup\{k \geq 0 : T_k(x) < \infty\}$.

Lemma. *Let $x = (x_n)_{n\geq 0}$ be a real sequence. Then x converges in $\overline{\mathbb{R}} = \mathbb{R} \cup \{\pm\infty\}$ if and only if for all $a < b$, $a, b \in \mathbb{Q}$ we have $N([a,b],x) < \infty$.*

Proof. If x converges then suppose there is $a < b$ with $N([a,b],x) = \infty$. Then

$$\liminf x_n \leq a < b \leq \limsup x_n$$

a contradiction.

Conversely, if x doesn't converge we have $\liminf x_n < \limsup x_n$ so there are $a < b$ (with $a, b \in \mathbb{Q}$) with $\liminf x_n < a < b < \limsup x_n$ and hence $N([a,b],x) = \infty$. $\square$

Now we can prove

Theorem (Doob's upcrossing inequality)**.** *Let X be a supermartingale and $a < b$. Then for all n,*

$$(b-a)\mathbb{E}[N_n([a,b],X)] \leq \mathbb{E}[(X_n - a)^-].$$

Proof. We have $(T_k)_{k\geq 0}$, $(S_k)_{k\geq 0}$ stopping times. Then

$$\sum_{k=1}^{n}(X_{T_k\wedge n} - T_{S_k \wedge n}) = \sum_{k=1}^{N_n([a,b],X)} \underbrace{(X_{T_k} - X_{S_k})}_{\geq b-a} + \underbrace{(X_n - X_{S_{N_n+1}})\mathbb{1}(S_{N_n+1} \leq n)}_{\geq (X_n - a)\vee 0 = -(X_n-a)^-}.$$

Note $T_k \wedge n, S_k \wedge n$ are stopping times with $T_k \wedge n \geq S_k \wedge n$. Then by the optional stopping theorem $\mathbb{E}[X_{T_k\wedge n}] \leq \mathbb{E}[X_{S_k \wedge n}]$. So taking expectations we have

$$0 \geq (b-a)\mathbb{E}[N_n] - \mathbb{E}[(X_n - a)^-].$$

$\square$

Now we are ready to prove

Theorem (Almost-sure martingale convergence theorem)**.** *Let X be a supermartingale bounded in $\mathcal{L}^1$, i.e $\sup_{n\geq 0}\mathbb{E}|X_n| < \infty$. Then there exists a random variable $X_\infty \in \mathcal{L}^1(\mathcal{F}_\infty)$ where $\mathcal{F}_\infty = \sigma(\mathcal{F}_n : n \geq 0)$ such that $X_n \to X_\infty$ almost-surely as $n \to \infty$.*

Proof. Let $a, b \in \mathbb{Q}$ be such that $a < b$. Then

$$\begin{aligned}
\mathbb{E}[N_n([a,b],X)] &\leq (b-a)^{-1}\mathbb{E}[(X_n - a)^-] \\
&\leq (b-a)^{-1}\mathbb{E}[|X_n| + a] \\
&\leq (b-a)^{-1}\left(\sup_{n\geq 0}\mathbb{E}[|X_n|] + 1\right).
\end{aligned}$$

We know $N_n([a,b],X) \uparrow N([a,b],X)$ as $n \to \infty$, so by monotone convergence, $\mathbb{E}[N([a,b],X)] < \infty$. Set

$$\Omega_0 = \bigcap_{\substack{a<b \\ a,b\in\mathbb{Q}}} \{N([a,b],X) < \infty\} \in \mathcal{F}_\infty$$

so $\mathbb{P}(\Omega_0) = 1$ as the intersection of almost-sure events. On Ω_0, X converges by a previous lemma. Set

$$X_\infty = \begin{cases} \lim_{n\to\infty} X_n & \text{on } \Omega_0 \\ 0 & \text{on } \Omega \setminus \Omega_0 \end{cases}.$$

So X_∞ is $\mathcal{F}_\infty$-measurable, and $X_n \to X_\infty$ almost surely. Also

$$\mathbb{E}[|X_\infty|] = \mathbb{E}[\liminf_n |X_n|] \leq \liminf_n \mathbb{E}[|X_n|] < \infty$$

by Fatou. □

Corollary. *Let X be a positive super-martingale. Then X converges almost-surely.*

Proof. $\mathbb{E}[|X_n|] = \mathbb{E}[X_n] \leq \mathbb{E}[X_0]$. So apply the previous. □

Doob's inequalities

Theorem (Doob's maximal inequality)**.** *Let X be a non-negative submartingale. Set $X_n^* = \sup_{0 \leq k \leq n} X_k$. Then for all $\lambda \geq 0$*

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

Proof. Let $T = \inf\{k \geq 0 : X_k \geq \lambda\}$. Then T is a stopping time and $\{X_n^* \geq \lambda\} = \{T \leq n\}$. By the optional stopping theorem we have $\mathbb{E}[X_{T \wedge n}] \leq \mathbb{E}[X_n]$ and note

$$\begin{aligned}\mathbb{E}[X_n] \geq \mathbb{E}[X_{T \wedge n}] &= \mathbb{E}[X_T \mathbb{1}(T \leq n)] + \mathbb{E}[X_n \mathbb{1}(T > n)] \\ &\geq \lambda \mathbb{P}(T \leq n) + \mathbb{E}[X_n \mathbb{1}(T > n)].\end{aligned}$$

Therefore

$$\lambda \mathbb{P}(X_n^* \geq \lambda) = \lambda \mathbb{P}(T \leq n) \leq \mathbb{E}[X_n \mathbb{1}(T \leq n)] = \mathbb{E}[X_n \mathbb{1}(X_n^* \geq \lambda)].$$

□

Theorem. *Doob's $\mathcal{L}^p$-inequality Let $p > 1$ and let X be a martingale or a non-negative submartingale. Set $X_n^* = \sup_{0 \leq k \leq n} |X_k|$. Then*

$$\|X_n^*\|_p \leq \frac{p}{p-1} \|X_n\|_p.$$

Proof. By Jensen's inequality it is enough to prove for X a non-negative submartingale. Let $k > 0$ and note

$$(y \wedge k)^p = \int_0^k p x^{p-1} \mathbb{1}(y \geq x) \mathrm{d}x$$

so

$$\begin{aligned}\|X_n^* \wedge k\|_p^p &= \mathbb{E}[(X_n^* \wedge k)^p] \\ &= \mathbb{E}\left[\int_0^k p x^{p-1} \mathbb{1}(X_n^* \geq x) \mathrm{d}x\right] \\ &= \int_0^k p x^{p-1} \mathbb{P}(X_n^* \geq x) \mathrm{d}x && \text{(Fubini)} \\ &\leq \int_0^k p x^{p-1} x^{-1} \mathbb{E}[X_n \mathbb{1}(X_n^* \geq x)] \mathrm{d}x && \text{(Doob's max inequality)} \\ &= \mathbb{E}\left[\int_0^k p x^{p-2} \mathbb{1}(X_n^* \geq x) \mathrm{d}x X_n\right] && \text{(Fubini)} \\ &= \mathbb{E}\left[X_n \frac{p}{p-1} (X_n^* \wedge k)^{p-1}\right] \\ &\leq \frac{p}{p-1} \|X_n\|_p \|X_n^* \wedge k\|_p^{p-1}. && \text{(Hölder)}\end{aligned}$$

Therefore $\|X_n^* \wedge k\|_p \leq \frac{p}{p-1}\|X_n\|_p$. Taking $k \to \infty$ gives the result by monotone convergence.

□

Theorem ($\mathcal{L}^p$-convergence theorems)**.** *Let X be a martingale, $p > 1$. The following are equivalent*

1. *X is bounded in $\mathcal{L}^p$, i.e* $\sup_{n\geq 0}\|X_n\|_p < \infty$.
2. *X converges almost-surely and in $\mathcal{L}^p$ to a limit $X_\infty \in \mathcal{L}^p$.*
3. *There exists $Z \in \mathcal{L}^p$ such that $X_n = \mathbb{E}[Z|\mathcal{F}_n]$ almost-surely.*

Proof. (1⇒2) If X is bounded in $\mathcal{L}^p$ then it its bounded in $\mathcal{L}^1$. Hence there exists X_∞ such that $X_n \to X_\infty$ almost-surely as $n \to \infty$. Furthermore

$$\mathbb{E}|X_\infty|^p = \mathbb{E}[\liminf_n |X_n|^p] \leq \liminf_n \mathbb{E}[|X_n|^p] < \infty \qquad \text{(Fatou)}$$

so $X_\infty \in \mathcal{L}^p$. Define $X_n^* = \sup_{0\leq k\leq n}|X_k|$, $X_\infty^* = \sup_{k\geq 0}|X_k|$. Then $|X_n - X_\infty| \leq 2X_\infty^*$ for all n. By dominated convergence it is enough to show $X_\infty^* \in \mathcal{L}^p$. Doob's $\mathcal{L}^p$ inequality gives

$$\|X_n^*\|_p \leq \frac{p}{p-1}\|X_n\|_p \leq \frac{p}{p-1}\sup\_n \geq 0\|X_n\|_p.$$

So by monotone convergence $\|X_\infty^*\|_p < \infty$.

(2⇒3) Set $Z = X_\infty$. Need to show $X_n = \mathbb{E}[X_\infty|\mathcal{F}_n]$ almost-surely. We have for $m \geq n$ that

$$\begin{aligned}
\|X_n - \mathbb{E}[X_\infty|\mathcal{F}_n]\|_p &= \|\mathbb{E}[X_m|\mathcal{F}_n] - \mathbb{E}[X_\infty|\mathcal{F}_n]\|_p \\
&\leq \|X_m - X_\infty\|_p && \text{(conditional Jensen)} \\
&\to 0 \text{ as } m \to \infty.
\end{aligned}$$

(3⇒1) By conditional Jensen. □

Proof. A martingale of the form $X_n = \mathbb{E}[Z|\mathcal{F}_n]$ for $Z \in \mathcal{L}^p$ is called a *martingale closed in $\mathcal{L}^p$*. □

Corollary. *If $Z \in \mathcal{L}^p$, $X_n = \mathbb{E}[Z|\mathcal{F}_n]$ almost-surely then $X_n \to \mathbb{E}[Z|\mathcal{F}_\infty]$ almost-surely and in $\mathcal{L}^p$, where $\mathcal{F}_\infty = \sigma(\mathcal{F}_n : n \geq 0)$.*

Proof. By the theorem we have $X_n \to X_\infty$ almost-surely and in $\mathcal{L}^p$. We need to show $X_\infty = \mathbb{E}[Z|\mathcal{F}_\infty]$ almost-surely.

- X_∞ is certainly $\mathcal{F}_\infty$-measurable.

- So we check that for all $A \in \mathcal{F}_\infty$ we have $\mathbb{E}[Z\mathbb{1}(A)] = \mathbb{E}[X_\infty \mathbb{1}(A)]$. Note that $\bigcup_{n\geq 0} \mathcal{F}_n$ is a π-system generating $\mathcal{F}_\infty$ so it suffices to check for A in this π-system. Indeed for such A, there exists $N \geq 0$ such that $A \in \mathcal{F}_N$. Now let $n \geq N$ so

$$\begin{aligned}\mathbb{E}[Z\mathbb{1}(A)] &= \mathbb{E}[\mathbb{E}[Z|\mathcal{F}_N]\mathbb{1}(A)] \\ &= \mathbb{E}[X_N \mathbb{1}(A)] \to \mathbb{E}[X_\infty \mathbb{1}(A)] \text{ as } n \to \infty.\end{aligned}$$

□

Uniform integrability

Recall that a collection $(X_i)_{i\in I}$ of random variables is said to be *uniformly integrable* if

$$\sup_{i\in I} \mathbb{E}[|X_i||1(|X_i| > \alpha)] \to 0 \text{ as } \alpha \to \infty.$$

Equivalently, $(X_i)_{i\in I}$ is uniformly integrable (UI) if it is bounded in $\mathcal{L}^1$ and for all $\varepsilon > 0$ there exists $\delta > 0$ such that for all $A \in \mathcal{F}$ with $\mathbb{P}(A) < \delta$ we have

$$\sup_{i\in I} \mathbb{E}[|X_i|\mathbb{1}(A)] < \varepsilon.$$

Remark. If $(X_i)_{i\in I}$ is bounded in $\mathcal{L}^p$ for $p > 1$ then it is uniformly integrable.

Lemma. *Let $(X_n)_{n\geq 1}, X$ be in $\mathcal{L}^1$ and $X_n \to X$ almost-surely as $n \to \infty$. Then $X_n \to X$ in $\mathcal{L}^1$ if and only if $(X_n)_{n\geq 1}$ is uniformly integrable.*

Proof. See Part II Probability & Measure. □