Chapter 1

1.1 Martingales

p.s. for a probability space.
r.v. for a random variable.

Definition 1.1
For a p.s. $(\Omega, \mathcal{F}_0, P)$ a σ-field $\mathcal{F} \subset \mathcal{F}_0$ and a r.v. $X \in \mathcal{F}_0$ with $E|X| < \infty$. We define the conditional expectation of X given $\mathcal{F}$, $E(X|\mathcal{F})$ to be any r.v. Y that has
a. $Y \in \mathcal{F}$.
b. $\int_A XdP = \int_A YdP$ for all $A \in \mathcal{F}$. and Y is said to be a version of $E(X|\mathcal{F})$.
♣

Lemma 1.1
If Y satisfies (a),(b) above, then it is integrable.
♡

Proof

We know
$$\int_{\{Y>0\}} YdP = \int_{\{Y>0\}} XdP < \infty \int_{\{Y<0\}} YdP = \int_{\{Y<0\}} XdP < \infty$$
and hence $\int |Y|dP$ finite.

Lemma 1.2
If Y' also satisfies (a),(b) in Def.1.1., then $Y = Y'$ a.s.
♡

Proof

Assume $E_n = \{Y' - Y > n^{-1}\}, F_n = \{Y - Y' > n^{-1}\}, n \in \mathbb{N}$, then we know
$$n^{-1}P(E_n) \leq \int_{E_n} (Y - Y')dP = \int_{E_n} YdP - \int_{E_n} Y'dP = 0$$
and hence $P(E_n) = 0$ for any $n \in \mathbb{N}$, similarly, we know $P(F_n) = 0$ for any $n \in \mathbb{N}$, therefore, $Y = Y'$ a.s.

Theorem 1.1
If $X_1 = X_2$ on $B \in \mathcal{F}$ then $E(X_1|\mathcal{F}) = E(X_2|\mathcal{F})$ a.s. on B.
♡

Proof

For any $E \subset B$, we have
$$0 = \int_{\{E(X_1|\mathcal{F}) - E(X_2|\mathcal{F}) > n^{-1}\} \cap E} (X_1 - X_2)dP \geq n^{-1}P(\{E(X_1|\mathcal{F}) - E(X_2|\mathcal{F}) > n^{-1}\} \cap E)$$
and the rest is similar.

Theorem 1.2
$E(X|\mathcal{F})$ exists.
♡

Proof

Define $\nu(E) = \int_E XdP$ for $E \in \mathcal{F}$ and we know $\nu \ll P$ and hence there exists $Y \in \mathcal{F}$ such that
$$\int_E YdP = \nu(E) = \int_E XdP$$
for all $E \in \mathcal{F}$ by Radon-Nikodym's Theorem.

Example 1.1 a. If $X \in \mathcal{F}$, then $E(X|\mathcal{F}) = X$.

b. If X is independent to $\mathcal{F}$, i.e. $P(\{X \in B\} \cap A) = P(X \in B)P(A)$, then X is independent to χ_A for any $A \in \mathcal{F}$ and hence $E(X|\mathcal{F}) = EX$.

c. Suppose $\Omega_1, \Omega_2, \cdots$ is a finite or infinite partition of Ω into disjoint sets, with $P(\Omega_i) > 0, i \geq 1$ and then let $\mathcal{F} = \sigma(\Omega_1, \Omega_2, \cdots)$ and then

$$E(X|\mathcal{F}) = \frac{E(X;\Omega_i)}{P(\Omega_i)} \quad \text{on } \Omega_i$$

d. Suppose X, Y have joint density $f(x, y)$ i.e.,

$$P((X,Y) \in B) = \int_B f(x,y)dxdy \quad \text{for } B \in \mathcal{R}^2$$

then if $E|g(X)| < \infty$, then $E(g(X)|Y) = h(Y)$, where

$$h(y) = \int g(x)f(x,y)dx / \int f(x,y)dx$$

on $\{(x, y), \int f(x, y)dx > 0\}$, and hence a.s.

e. Suppose X and Y are independent, let ϕ be a function with $E|\phi(X,Y)| < \infty$ and let $g(x) = E(\phi(x, Y))$, then $E(\phi(X,Y)|X) = g(X)$.

Proof

c. By the $\pi - \lambda$ theorem, it suffices to show that

$$\int_A XdP = \int_A YdP$$

for any $A \in \{\bigcup_{1 \leq i \leq n} \Omega_i\}$ where Y was defined as above.

d. Firstly, we recall any simple function $\phi \geq 0$ will cause $\int \phi(x,y)dy$ is measurable since $\int \phi(x,y)dy = \nu(E_y)$ when $\phi = \chi_E$ and then we know for any $g \geq 0$, $\int g(x)f(x,y)dy$ is measurable and then $\int g(x)f(x,y)dy$ is measurable for general g, then we will know $h(Y) \in \sigma(Y)$.

Consider $A \in \sigma(Y)$, where $A = \{Y \in B\}$, then

$$E(h(Y);A) = \int_{Y \in B} h(y)f(x,y)dxdy = \int_B \int h(y)f(x,y)dxdy = \int_B \int g(x)f(x,y)dxdy = E(g(X);A)$$

and the conclusion goes.

e. We know $g(X) \in \sigma(X)$ and then for any $A = \{X \in B\}$, we will know

$$E(g(X);A) = \int_B g(x)dx = \int_B \int \phi(x,y)dydx = E(\phi(X,Y);A)$$

and hence $E(\phi(X,Y)|X) = g(X)$.

Definition 1.2

Denote

$$P(A|\mathcal{G}) = E(1_A|\mathcal{G})$$
$$P(A|B) = P(A \cap B)/P(B)$$

and $E(X|Y) = E(X|\sigma(Y))$.

♣

Theorem 1.3

For the first two parts, we assume $E|X|, E|Y| < \infty$.

(a) $E(aX + Y|\mathcal{F}) = aE(X|\mathcal{F}) + E(Y|\mathcal{F})$.

(b) If $X \leq Y$ *then* $E(X|\mathcal{F}) \leq E(Y|\mathcal{F})$.

(c) If $X_n \geq 0$ *and* $X_n \uparrow X$ *with* $EX < \infty$ *then* $E(X_n|\mathcal{F}) \uparrow E(X|\mathcal{F})$.

♡

Theorem 1.4

If ϕ *is convew and* $E|X|, E|\phi(X)| < \infty$ *then*

$$\phi(E(X|\mathcal{F})) \leq E(\phi(X)|\mathcal{F})$$

♡

Proof

Let $S = \{(a,b) : a, b \in \mathbb{Q}, ax + b \leq \phi(x) \text{ for all } x\}$, then $\phi(x) = \sup\{ax + b : (a,b) \in S\}$. And we know

$$E(\phi(X)|\mathcal{F}) \geq aE(X|\mathcal{F}) + b$$

and hence $E(\phi(X)|\mathcal{F}) \geq \phi(E(X|\mathcal{F}))$.

Theorem 1.5

Conditional expectation is a contraction in L^p, $p \geq 1$. ♡

Proof

By Theorem 1.5., we have $|E|(X|\mathcal{F})|^p \leq E(|X|^p|\mathcal{F})$, then we know

$$E(|E(X|\mathcal{F})|^p) \leq E(E(|X|^p|\mathcal{F})) = E|X|^p$$

Theorem 1.6

If $\mathcal{F} \subset \mathcal{G}$ and $E(X|\mathcal{G}) \in \mathcal{F}$, then $E(X|\mathcal{F}) = E(X|\mathcal{G})$. ♡

Theorem 1.7

If $\mathcal{F}_1 \subset \mathcal{F}_2$ then
(i) $E(E(X|\mathcal{F}_1)|\mathcal{F}_2) = E(X|\mathcal{F}_1)$
(ii) $E(E(X|\mathcal{F}_2)|\mathcal{F}_1) = E(X|\mathcal{F}_1)$ ♡

Proof

For $A \in \mathcal{F}_1$, we know

$$\int_A E(E(X|\mathcal{F}_1)|\mathcal{F}_2)dP = \int_A E(X|\mathcal{F}_1)dP = \int_A XdP$$
$$\int_A E(E(X|\mathcal{F}_2)|\mathcal{F}_1)dP = \int_A E(X|\mathcal{F}_2)dP = \int_A XDP$$

therefore, the equalities go.

Theorem 1.8

If $X \in \mathcal{F}$ and $E|Y|, E|XY| < \infty$ then

$$E(XY|\mathcal{F}) = XE(Y|\mathcal{F})$$

♡

Proof

For any $X, Y \geq 0$, assume $\phi_n \uparrow X$ simple, then we know $\phi_n Y \uparrow XY$ and then

$$\int_A E(\chi_B Y|\mathcal{F}) = \int_A \chi_B Y dP = \int_{AB} Y dP = \int_{AB} E(Y|\mathcal{F})dP = \int_A \chi_B E(Y|\mathcal{F})$$

for any $A, B \in \mathcal{F}$ and hence $E(\chi_B Y|\mathcal{F}) = \chi_B E(Y|\mathcal{F})$ for any $B \in \mathcal{F}$, therefore, we know $E(\phi_n Y|\mathcal{F}) = \phi_n E(Y|\mathcal{F})$. By theorem 1.3 we know $E(\phi_n T|\mathcal{F}) \uparrow E(XY|\mathcal{F})$ and hence $E(XY|\mathcal{F}) = XE(Y|\mathcal{F})$, so for any $X \in \mathcal{F}, E|Y| < \infty, E|XY| < \infty$, we can consider the positive and negative parts and the conclusion goes.

Theorem 1.9

Suppose $EX^2 < \infty$. $E(X|\mathcal{F})$ is the variable $Y \in \mathcal{F}$ that minimizes the "mean square error" $E(X-Y)^2$. ♡

Proof

If $Z \in L^2(\mathcal{F})$, then

$$ZE(X|\mathcal{F}) = E(ZX|\mathcal{F})$$

then we know

$$E(ZE(X|\mathcal{F})) = E(E(ZX|\mathcal{F})) = E(ZX)$$

and hence $E(Z(X - E(X|\mathcal{F}))) = 0$ for any $Z \in L^2(\mathcal{F})$.

If $Z = E(X|\mathcal{F}) - Y$, then

$$E(X-Y)^2 = E(X - E(X|\mathcal{F}) + Z)^2 = E(X - E(X|\mathcal{F}))^2 + EZ^2$$

and hence $E(X-Y)^2$ are minimal when $Y = E(X|\mathcal{F})$.

Definition 1.3

Let $(\Omega, \mathcal{F}, P)$ be a probability space, $X : (\Omega, \mathcal{F}) \to (S, \mathcal{S})$ and $\mathcal{G}$ a σ-algebra contained by $\mathcal{F}$. $\mu : \Omega \times \mathcal{S} \to [0,1]$ is said to be a regular conditional distribution for X given $\mathcal{G}$ if
a. For each A, $\omega \to \mu(\omega, A)$ is a version of $P(X \in A|\mathcal{G})$.
b. For a.e. ω, $A \to \mu(\omega, A)$ is a probability measure on $(S, \mathcal{S})$.
When $S = \Omega$ and X is the identity map, μ is called a regular condition probability.

♣

Proposition 1.1

Suppose X and Y have a joint density $f(x,y) > 0$. If

$$\mu(y, A) = \int_A f(x,y)dx \Big/ \int f(x,y)dx$$

then $\mu(Y(\omega), A)$ is a r.c.d for X given $\sigma(Y)$.

♠

Proof

Here we know $X : (\Omega.\mathcal{F}) \to (\mathbb{R}, \mathcal{R})$, so we should check:
a. $\mu(Y(\omega), A) = \int_A f(x, Y(\omega))dx / \int f(x, Y(\omega))dx$ is a version of $P(X \in A|Y)$.
b. For a.e. ω, $\mu_{Y(\omega)}(A) = \mu(Y(\omega), A)$ is a probability measure on $(\mathbb{R}, \mathcal{R})$.

To see the first claim, consider

$$\begin{aligned}
\int_{Y \in B} P(X \in A|Y)dP = \int_{Y \in B} \chi_{X \in A} dP &= \int_B \int_A f(x,y)dxdy \\
&= \int_A \int_B f(x,y)dydx \\
&= \int_B \int_A f(x,y)dxdy
\end{aligned}$$

$$= \int_B \int \int_A f(x,y)dx \Big/ \int f(x,y)dx f(x,y)dxdy = \int_{Y \in B} \mu(Y(\omega), A)dP$$

and the second claim is trivial.

Theorem 1.10

Let $\mu(\omega, A)$ be a r.c.d for X given $\mathcal{F}$. If $f : (S, \mathcal{S}) \to (\mathbb{R}, \mathcal{R})$ has $E|f(X)| < \infty$ then

$$E(f(x)|\mathcal{F}) = \int \mu(\omega, dx) f(x) \quad a.s.$$

♡

Proof

Consider $f = \chi_A$ for some A mrb in $\mathcal{R}$, then $\int \mu(\omega, dx) f(x) = \mu(\omega, A) = P(X \in A|\mathcal{F})$ and hence the equality holds for all simple functions, then the problem goes.

Here we skip some properties of regular conditional distribution and continue to martingale.

Definition 1.4

$\mathcal{F}_n$ is a filtration, i.e. an increasing sequence of σ-fields. A sequence X_n is said to be adapted to $\mathcal{F}_n$ if $X_n \in \mathcal{F}_n$ for all n. If X_n is sequence with
a. $E|X_n| < \infty$.
b. X_n is adapted to $\mathcal{F}_n$.
c. $E(X_{n+1}|\mathcal{F}_n) = X_n$ for all n then X is said to be a martingale (resp to $\mathcal{F}_n$). If we replace the equality into $\leq$ or $\geq$, then X is said to be a supermartingale or submartingale.

♣

Example 1.2 (Random walk)Let $\xi_1, \xi_2, \cdots$ be independent and id.d, $S_n = S_0 + \sum_{i=1}^{n} \xi_i$ where S_0 is a constant. $\mathcal{F}_n = \sigma(\xi_1, \cdots, \xi_n)$ and take $\mathcal{F}_0 = \{\emptyset, \Omega\}$.

a. If $\mu = E\xi_i = 0$ then $S_n, n \geq 0$ is a martingale with respect to $\mathcal{F}_n$.

b. $\mu = E\xi_i = 0$ and $\sigma^2 = \mathrm{var}(\xi_i) < \infty$, then $S_n^2 - n\sigma^2$ is a martingale.

Proof

a. Notice $E|S_n| < \infty, n \geq 0$, for any $A \in \mathcal{F}_n$, then notice

$$E(S_{n+1}|\mathcal{F}_n) = E(\xi_{n+1}|\mathcal{F}_n) + S_n = E\xi_{n+1} + S_n = S_n$$

b. Notice that $E|S_n - n\sigma^2| < \infty$, and

$$E(S_{n+1}^2 - (n+1)\sigma^2|\mathcal{F}) = S_n^2 - (n+1)\sigma^2 + \sigma^2 = S_n^2 - n\sigma^2$$

Example 1.3 Let $Y_1, Y_2, \cdots$ be nonnegative i.i.d r.v.s with $EY_m = 1$. If $\mathcal{F}_n = \sigma(Y_1, \cdots, Y_n)$, then $M_n = \prod_{m \leq n} Y_m$ defines a martingale.

Then assume $\phi(\theta) = Ee^{\theta \xi_i}, Y_i = e^{\theta \xi_i}/\phi(\theta)$, then we know $M_n = e^{\theta S_n}/\phi(\theta)^n$.

Theorem 1.11

If X_n is a (super-/sub-)martingale then for $n > m$, $E(X_n|\mathcal{F}_m) \leq (\geq / =) X_m$.

Proof Notice

$$E(X_{m+k}|\mathcal{F}_m) = E(E(X_{m+k}|\mathcal{F}_{m+k-1})|\mathcal{F}_m) \leq E(X_{m+k-1}|\mathcal{F}_m)$$

the rest proof is similar.

Theorem 1.12

If X_n is a martingale w.r.t. $\mathcal{F}_n$ and ϕ is a convex function with $E|\phi(X_n)| < \infty$ for all n then $\phi(X_n)$ is a submartingale w.r.t. $\mathcal{F}_n$. Consequently, if $p \geq 1$ and $E|X_n|^p < \infty$ for all n, then $|X_n|^p$ is a submartingale w.r.t. $\mathcal{F}_n$.

Proof Notice

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

and the problem goes.

Theorem 1.13

If X_n is a submartingale w.r.t. $\mathcal{F}_n$ and ϕ is an increasing convex function with $E|\phi(X_n)| < \infty$ for all n, then $\phi(X_n)$ is a submartingale w.r.t. $\mathcal{F}_n$. Consequently

a. If X_n is a submartingale then $(X_n - a)^+$ is a submartingale.

b. If X_n is a supermartingale then $\min(X_n, a)$ is a supermartingale.

Proof Notice

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

then (a) is easy to be checked and hence (b) is correct.

Definition 1.5

Let $\mathcal{F}_n, n \geq 0$ be a filtration. $H_n, n \geq 1$ is said to be a predictable sequence if $H_n \in \mathcal{F}_{n-1}$ for all $n \geq 1$.

Definition 1.6

We denote

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

Theorem 1.14

Let $X_n, n \geq 0$ be a supermartingale. If $H_n \geq 0$ is predictable and each H_n is bounded then $(H \cdot X)_n$ is a supermartingale.

Proof Consider

$$E((H \cdot X)_{n+1}|\mathcal{F}_n) = E(\sum_{m=1}^{n+1} H_m(X_m - X_{m-1})|\mathcal{F}_n) = (H \cdot X)_n + E(X_{n+1}|\mathcal{F}_n) - X_n \leq (H \cdot X)_n$$

Definition 1.7

A r.v. N is said to be a stopping time if $\{N = n\}$ in $\mathcal{F}_n$ for all $n > \infty$.

Theorem 1.15

If N is a stoppiing time and X_n is a supermartingale, then $X_{N \wedge n}$ is a supermartingale.

Proof Consider

$$E(X_{N\wedge n+1}|\mathcal{F}_n) = E(X_{n+1}\chi_{N \geq n+1} + \sum_{k=0}^{n} X_k \chi_{N=k}|\mathcal{F}_n) \leq \chi_{N\geq n+1} X_n + \sum_{k=0}^{n} X_k \chi_{N=k} = X_{N\wedge n}$$

Definition 1.8

Suppose $X_n, n \geq 0$ is a submartingale. Let $a < b, N_0 = -1$ and for $k \geq 1$ let

$$N_{2k-1} = \inf\{m > N_{2k-2}, X_m \leq a\}$$
$$N_{2k} = \inf\{m > N_{2k-1}, X_m \geq b\}$$

The N_j are stopping times so

$$H_m = \begin{cases} 1 & \text{if } N_{2k-1} < m \leq N_{2k} \text{ for some } k \\ 0 & \text{otherwise} \end{cases}$$

defines a predictable sequence.

Proof

Notice

$$\{N_{2k-1} = n\} = \bigcup_{0\leq m\leq n-1} \{N_{2k-2} = m\} \cap (\bigcap_{n-1-m\geq k\geq 0} \{X_{m+k} > a\}) \cap \{X_n \leq a\}$$

and

$$\{N_{2k} = n\} = \bigcup_{0\leq m\leq n-1} \{N_{2k-1} = m\} \cap (\bigcap_{n-1-m\geq k\geq 0} \{X_{m+k} < b\}) \cap \{X_n \geq b\}$$

and hence N_{2k-1}, N_{2k} are stopping times by induction.

And notice

$$\{N_{2k-1} < m \leq N_{2k} \text{ for some } k\} = \bigcup_{k\geq 0} \{N_{2k-1} \leq m-1\} \cap \{N_{2k} \geq m\} \in \mathcal{F}_{m-1}$$

and hence H_m is predictable.

Theorem 1.16

(Upcoming inequality) If $X_m, m \geq 0$, is a submartingale then

$$(b-a)EU_n \leq E(X_n - a)^+ - E(X_0 - a)^+$$

where $U_n = \sup\{k, N_{2k} \leq n\}$.

Proof

Here we assume $Y_m = a + (X_m - a)^+$ and we have

$$(b-a)U_n \le (H \cdot Y)_n$$

let $K_m = 1 - H_m$ and then we know that $(K \cdot X)_n$ is a submartingale and then

$$E(K \cdot X)_n \ge E(K \cdot X)_0 = 0$$

so we know

$$E(H \cdot Y)_n \le E(Y_n - Y_0) = E(X_n - a)^+ - E(X_0 - a)^+$$

since $Y_n - Y_0 = (H \cdot Y)_n + (K \cdot Y)_n$

Theorem 1.17

(Martingale convergence theorem) If X_n is a submartingale with $\sup EX_n^+ < \infty$ then as $n \to \infty$, X_n converges a.s. to a limit X with $E|X| < \infty$.

♡

Proof

We know $(X-a)^+ \le X^+ + |a|$, then we know

$$EU_n \le (|a| + EX_n^+)/(b-a)$$

so $\sup X_n^+$ will imply than $EU < \infty$ where $U = \lim U_n$ and hence for all rational a, b, we know

$$P(\{\liminf X_n < a < b < \limsup X_n\}) = 0$$

and hence $\lim X_n$ exists a.s. and $EX^+ \le \liminf EX_n^+ < \infty$ and hence $X < +\infty$ a.s. and notice

$$EX_n^- = EX_n^+ - EX_n \le EX_n^+ - EX_0$$

and hence $EX^- \le \liminf EX_n^- \le \liminf EX_n^+ - EX_0 < \infty$ therefore $E|X| < \infty$.

Theorem 1.18

If $X_n \ge 0$ is a supermartingale then as $n \to \infty$, $X_n \to X$ a.s. and $EX \le EX_0$.

♡

Proof

Let $Y_n = -X_n$ and hence a submartingale with $EY_n^+ = 0$, then we know $X_n \to X$ a.s. and we also have

$$EX \le \liminf EX_n^+ \le EX_0$$

Proposition 1.2

The theorem 1.18. provide a method to show that a.s. convergence does not guarantee convergence in L^1.

♠

Proof

Let S_n be a symmetric simple random walk with $S_0 = 1$ and $P(\xi_i = 1) = P(\xi_i = -1) = \frac{1}{2}$, let $N = \inf\{n : S_n = 0\}$ and $X_n = S_{N \wedge n}$. Then we know X_n nonnegative and $EX_n = EX_0 = 1$ since X_n is a martingale, then we know $X_n \to X$ where X is some r.v. and hence $X = 0$, because there is no way to converge to others and hence X_n do not converge to X in L^1.

Proposition 1.3

Convergence in probability do not guarantee convergence a.s.

♠

Proof

Let $X_0 = 0$ and $P(X_k = 1 | X_{k-1} = 0) = P(X_k = -1 | X_{k-1} = 0) = \frac{1}{2k}$, $P(X_k = 0 | X_{k-1} = 0) = 1 - \frac{1}{k}$ and $P(X_k = kX_{k-1} | X_{k-1} \ne 0) = \frac{1}{k}$, $P(X_k = 0 | X_{k-1} \ne 0) = 1 - \frac{1}{k}$, then we know $X_k \to 0$ in probability, but $P(X_k = 0, k \ge K)$ and it picks discrete values and hence X_k can not converge to 0 a.s.

Theorem 1.19

Let $X_1, X_2, \cdots$ be a martingale with $|X_{n+1} - X_n| \leq M < \infty$. Let

$$C = \{\lim X_n \textit{ exists and is finite}\}$$
$$D = \{\limsup X_n = +\infty \textit{ and } \liminf X_n = -\infty\}$$

Then $P(C \cup D) = 1$. ♡

Proof We may assume that $X_0 = 0$ and then for $K \geq 0$ denote

$$N = \inf\{n, X_n \leq -K\}$$

then we know $X_{n\wedge N}$ is a martingale since

$$E(X_{(n+1)\wedge N}|\mathcal{F}_n) = E(X_{n+1}\chi_{N\geq n+1} + X_N\chi_{N\leq n}|\mathcal{F}_n) = X_N\chi_{N\leq n} + X_n\chi_{N\geq n+1} = X_{n\wedge N}$$

and $X_{n\wedge N} \geq -K - M$ and hence $X_{n\wedge N} + K + M \geq 0$ and we may know $X_{n\wedge N}$ will converges to X a.s. with X finite. So if $\liminf X_n > -\infty$, then we know there exists K large enough such that $N = \infty$ and hence X_n will converges to a finite limit on $\{\liminf X_n > -\infty\}$. For $\limsup X_n$ consider $N = \inf\{x, X_n \geq K\}$ with $K + M - X_{n\wedge N}$ will converges and the $\lim X_n$ will exists and be finite on $\{\limsup X_n = +\infty\}$ and hence the conclusion holds.

Theorem 1.20

(Doob's decomposition) Any submartingale $X_n, n \geq 0$ can be written in a unique way as $X_n = M_n + A_n$ where M_n is a martingale and A_n is a predictable increasing sequence with $A_0 = 0$. ♡

Proof If so we know

$$E(X_{n+1}|\mathcal{F}_n) = M_n + A_{n+1} = X_n - A_n + A_{n+1}$$

and hence set

$$A_n = \sum_{k=1}^{n}(E(X_k|\mathcal{F}_{k-1}) - X_{k-1})$$

and

$$M_k = X_k - A_k$$

then it is easy to check A_n is predictable increasing sequence and

$$E(M_{n+1}|\mathcal{F}_n) = E(X_{n+1} - \sum_{k=1}^{n+1}(E(X_k|\mathcal{F}_{k-1}) - X_{k-1})|\mathcal{F}_n) = X_n - A_n = M_n$$

Theorem 1.21

(Second Borel-Cantelli lemma) Let $\mathcal{F}_n, n \geq 0$ be a filtration with $\mathcal{F}_0 = \{\emptyset, \Omega\}$ and let $B_n, n \geq 1$ a sequence of events with $B_n \in \mathcal{F}_n$. Then

$$\{B_n, i.o.\} = \{\sum_{n=1}^{\infty} P(B_n|\mathcal{F}_{n-1}) = \infty\}$$

♡

Proof We know

$$\sum_{i=1}^{\infty}\chi_{B_i} = \infty$$

on $\{B_n \ i.o.\}$ and we know

$$\chi_{B_n} = M_n + \sum_{k=1}^{n}(E(\chi_{B_k}|\mathcal{F}_{k-1}) - \chi_{B_{k-1}})$$

and hence

$$M_n = \sum_{i=1}^{n}\chi_{B_i} - \sum_{i=1}^{n}E(\chi_{B_i}|\mathcal{F}_{i-1})$$

is a martingale. Then we know

$$EM_n = EX_0 < \infty$$

which means M_n is a martingale with bounded increments and we know

$$\{B_n \ i.o.\} = \{\sum P(B_n|\mathcal{F}_{n-1}) = \infty\}$$

on both part of Ω.

Example 1.4 (Polya's Urn Scheme) An urn contains r red and g green balls. At each time we draw a ball out, then replact it with c balls with the same color. Let X_n be the fraction of green balls after the n^{th} draw.

Proof

X_n is a martingale because assume $\mathcal{F}_n$ is is consisting by $E_{i,j} = \{$There are i green balls and j red balls in the urn.$\}$ and it suffices to show that

$$\frac{j}{i+j} P(E_{i,j}) = \int_{E_{i,j}} E(X_{n+1}|\mathcal{F}_n)$$

where we know

$$X_{n+1} = \begin{cases} (j+c)/(i+j+c) & \text{with probability } j/(i+j) \\ (j)/(i+j+c) & \text{with probability } i/(i+j) \end{cases}$$

and the equality is easy to be checked. Since $X_n \geq 0$, then we know X_n will converges to X.

Theorem 1.22

Assume μ is a finite measure and ν a probability measure on $(\omega, \mathcal{F})$ with $\mathcal{F}_n \uparrow \mathcal{F}$,i.e. $\sigma(\bigcup \mathcal{F}_n) = \mathcal{F}$ and μ_n, ν_n are the restrictions on $\mathcal{F}_n$ of μ, ν. Suppose $\mu_n \leq \nu_n$ for all n. Let $X_n = \frac{d\mu_n}{d\nu_n}$ and let $X = \limsup X_n$, then

$$\mu(A) = \int_A X d\nu + \mu(A \cap \{X = \infty\})$$

for any $A \in \mathcal{F}$.

Proof

We should show a lemma at first.

Lemma 1.3

X_n defined on $(\Omega, \mathcal{F}, \nu)$ is a martingale w.r.t. $\mathcal{F}_n$.

Proof

For any $A \in \mathcal{F}_n$, we know

$$\int_A X_n d\nu = \int_A X_n d\nu_n = \mu_n(A) = \mu(A)$$

and which means $\int_A X_n d\nu = \int_A X_{n+1} d\nu$ for any $A \in \mathcal{F}_n$.

Now let's come back to the proof of the original theorem.

Now we know X_n is a nonnegative martingale on $(\Omega, \mathcal{F}, \nu)$ and hence $X_n \to X$ ν-a.s. Without loss of the generality, we may assume μ is a probability measure and let $\rho = (\mu + \nu)/2$, then we know $\mu \ll \nu \ll \rho$ and similarly define ρ_n and $Y_n = d\mu_n/d\rho_n, Z_n = d\nu_n/d\rho_n$ and $Y_n + Z_n = 2, Y_n, Z_n \geq 0$ ρ_n-a.s. By the lemma, we will know that Y_n, Z_n are bounded martingales and we may assume they have limits Y, Z.

Notice for $A \in \mathcal{F}_n$, we have

$$\mu(A) = \int_A Y_n d\rho \to \int_A Y d\rho$$

by the DCT and hence $\mu(A) = \int_A Y d\rho$ for all $A \in \bigcup_m \mathcal{F}_m$ and we will know $\mu(A) = \int_A Y d\rho$ for $A \in \mathcal{F}$ by the $\pi - \lambda$ theorem and hence $Y = d\mu/d\rho$, then we will know $Z = d\nu/d\rho$. Then notice

$$0 = \int_{\{Z_n = 0\}} Z_n d\rho_n = \nu_n(\{Z_n = 0\})$$

and hence $\int_{Z_n=0} Y_n d\rho_n = \mu_n(\{Z_n = 0\}) = 0$, which means $Y_n = 0$ ρ-a.s. on $\{Z_n = 0\}$ which means $Z_n > 0$ a.s. since

$\{Y_n = Z_n = 0\}$ is ρ-null. Then we know $X_n = Y_n/Z_n$ ρ-a.s. and hence $X = Y/Z$ ρ-a.s. and hence ν-a.s.

Let $W = (1/Z)\chi_{Z>0}$ and then $1 = ZW + \chi_{Z=0}$ and we have

$$\mu(A) = \int_A YWZd\rho + \int_A \chi_{Z=0}Yd\rho = \int_A Xd\nu + \mu(A \cap \{X = \infty\})$$

since $\nu(\{Z = 0\}) = \int_{\{Z=0\}} Zd\rho = 0$ and $\{X = \infty\} = \{Z = 0\}$ ρ-a.s. and hence μ-a.s.

Definition 1.9

Let $\xi_i^n, i, n \geq 1$ be i.i.d. nonnegative integer-valued r.v.s and define

$$Z_{n+1} = \begin{cases} \xi_1^{n+1} + \cdots \xi_{Z_n}^{n+1} & Z_n > 0 \\ 0 & Z_n = 0 \end{cases}$$

where $Z_0 = 1$ and Z_n is called a $Galton-Watson$ process, $p_k = P(\xi_i^n = k)$ is called the offspring distribution. ♣

Lemma 1.4

Let $\mathcal{F}_n = \sigma(\xi_i^m : i \geq 1, 1 \leq m \leq n)$ and $\mu = E\xi_i^m \in (0, \infty)$, then Z_n/μ^n is a martingale w.r.t. $\mathcal{F}_n$. ♡

Proof We know

$$E(Z_{n+1}/\mu^{n+1}|\mathcal{F}_n) = E(\sum \chi_{Z_n=k} \sum_{i=1}^{k} \xi_i^{n+1})/\mu^{n+1} = k\chi_{Z_n=k}/\mu^n = Z_n/\mu^n$$

Theorem 1.23

If $\mu < 1$ then $Z_n = 0$ for all n sufficiently large, so $Z_n/\mu^n \to 0$. ♡

Proof

$E(Z_n/\mu^n) = E(Z_0) = 1$ and hence

$$P(Z_n > 0) \leq \mu^n$$

and hence

$$P(Z_n > 0\, i.o.) = 0$$

by the Borel-Cantelli's theorem, which means $Z_n = 0$ for all n sufficiently large almost surely.

Theorem 1.24

If $\mu = 1$ and $P(\xi_i^m = 1) < 1$, then $Z_n = 0$ for all n sufficiently large. ♡

Proof

$2P(Z_n > 1) \leq \mu^n$ and hence $Z_n \leq 1$ for all n sufficiently large almost surely, and the $Z_n = 0$ for all n sufficiently large will not happen iff $Z_n = 1$ for all n sufficiently large, which owns the probability of 0 and hence the conclusion holds.

Definition 1.10

For $s \in [0, 1]$, let $\phi(s) = \sum_{k\geq 0} p_k s^k$ and ϕ is called the $generating\ function$ for the offspring distribution p_k. ♣

Theorem 1.25

Suppose $\mu > 1$. If $Z_0 = 1$ then $P(Z_n = 0$ for some $n) = \rho$ which is the only solution of $\phi(\rho) = \rho$ in $[0, 1)$. ♡

Proof

Firstly let us show the existence. We can calculate

$$\phi'(s) = \sum kp_k s^{k-1}$$

by some methods in real analysis and hence $\phi'(s) > h + \epsilon$ for some $\epsilon > 0$ near 1 and hence there have to be a point in

$[0, 1)$ such that $\phi(\rho) = \rho$ since $\phi(0) \geq 0$. And ϕ' is increasing strictly on $[0, 1)$ guaranteeing that the point is unique.

Then consider $\theta_m = P(Z_m = 0)$, then $\theta_m = \phi(\theta_{m-1})$ which can be implied by consider $Z_1 = k$ separately.

Then notice $\theta_0 = 0$ and then $\theta_m \leq \rho$ may implie that $\theta_{m+1} = \phi(\theta_m) \leq \phi(\rho) \leq \rho$ and hence $\phi(\theta_m) \geq \theta_m$, which means θ_m is increasing, then we know $\theta_m \uparrow \rho$.