

Lec 2: Conditional Expectation and Martingales

- 1) A simple motivating example
- 2) Conditioning and Prediction
- 3) Classical conditional probability
- 4) Abstract conditional expectation
- 5) Basic properties
- 6) Conditional expectation and L^2 projection

Martingales

- 1) Filtrations and semi-martingales.
- 2) Martingale Transforms, Doob Martingales
- 3) Martingale decompositions
- 4) Stopping times and optional stopping
- 5) Maximal inequalities
- 6) Martingale convergence
- 7) Zero-One law
- 8) Option pricing and Black-Scholes.

Let $X \sim \text{Bin}(100, 1/2)$ represent outcomes of coin toss. Player 2 is supposed to guess the value of X . What should his guess be?

Obviously 50. But in what sense is this the best guess? Let's suppose your guess is g , and you want to minimize the L^2 norm between X and g .

$$\begin{aligned} \mathbb{E}[|X - g|^2] &= \|X - g\|_2^2 \\ &= \mathbb{E}[(X - \mathbb{E}X + \mathbb{E}X - g)^2] \end{aligned}$$

$$= \overbrace{\text{Var}(X)}^{6^2} + (\mu - g)^2 = f(g)$$

$f(g)$ takes its minimum value at:

Ex: What if I define some "reasonable" distance function $d(X, g)$. What happens then? Start with the p norms and graduate to $d(X, g) = \varphi(X - g)$ where φ is some convex function.

Now suppose I give you "EXTRA INFORMATION"? Say Y is the # of heads found in the first 10 coin tosses, what should your guess be?

Let's call our guess g . How do we minimize

$$E((X - g)^2 | Y)$$

POLL

What should our guess be for X ?

$$\begin{array}{c} A \\ 50 - Y \end{array}$$

$$\begin{array}{c} B \\ 45 + Y \end{array}$$

$$\begin{array}{c} C \\ 50 \end{array}$$

Well, the remaining 90 turns are independent of the first 10. So we should guess $g = 45 + Y$

We will call $E[X|Y] = g$.
Our "best guess" for X given Y is the conditional expectation

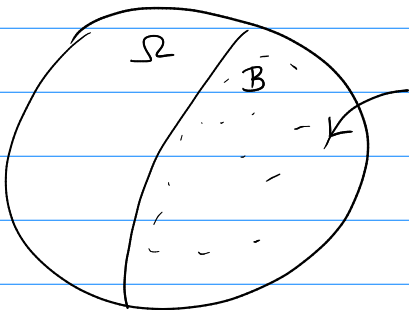
Ex (from Le Gall)

let $\Omega = \{1, 2, \dots, 6\}$ $P(\omega) = \frac{1}{6}$.

$$Y(\omega) = \begin{cases} 1 & \omega \text{ is odd} \\ 0 & \text{otherwise} \end{cases}$$

let $X(\omega) = \omega$

$$E[X|Y] = \begin{cases} \sum_{i \in \{1,3,5\}} i P(X=i | Y \in \{1,3,5\}) = \frac{1+3+5}{3} = 3 \\ 4 \end{cases}$$



$$E[X|B] = \sum_{y \in B} P(X=y | B) y$$

Classical conditioning

For 2 events A and B , $P(B) \neq 0$

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

So for a discrete random variable $X \in \{a_0, a_1, \dots\}$

$$\begin{aligned} E[X|B] &= \sum_{i=0}^{\infty} a_i P(X=a_i|B) \\ &= \sum_{i=0}^{\infty} a_i \frac{P(X=a_i \cap B)}{P(B)} \end{aligned}$$

If X is continuous

$$E[X|B] = \frac{1}{P(B)} \int X \mathbf{1}_B dP$$

★ Can you prove the above?

So certainly, we want some notion of conditional expectation that falls with the above.

Now suppose Y is discrete. Then what should $E[X|Y]$ be? let $Y \in \{b_0, b_1, \dots\}$

$$\begin{aligned} E[X|Y=b_i] &= \sum_j a_j P(X=a_j | Y=b_i) \\ &= f(b_i) \end{aligned}$$

So $E[X|Y] = f(Y)$ some function of Y .

BUT if Y is continuous, then $P(Y=z) = 0$ for any z , then you cannot divide by $P(Y=z)$

POLL

Similarly, what should $E[X|1_B]$ be?

A

B

$$\frac{1}{P(B^c)} \int X 1_{B^c} dP + \frac{1}{P(B)} \int X 1_B dP$$

$$1_B E[X|B] + 1_{B^c} E[X|B^c]$$

- 1) We defined conditional prob on events.
- 2) Conditional expectation on events
- 3) " " on discrete rvs.

We learned $E[X|Y] = f(Y)$ a random variable,

What we have learned is that we can condition on r.v.s ; thus we can condition on the σ algebra associated with Y itself. So our abstract version of conditional expectation will condition on σ -algebras.

Prop let $X \in L^1$, Y discrete. Then

$$E[|E[X|Y]|] \leq E[|X|]$$

That is $E[X|Y] \in L^1(\Omega, \sigma(Y), P)$

$$\begin{aligned} \text{Pfs: } E[|E[X|Y]|] &= \sum_{i=0}^{\infty} P(Y=b_i) |E[X|Y=b_i]| \\ &= \sum_{i=0}^{\infty} P(\cancel{Y=b_i}) \frac{|E[X 1_{\{Y=b_i\}}]|}{P(\cancel{Y=b_i})} \leq \sum_{i=0}^{\infty} E[|X| 1_{\{Y=b_i\}}] \end{aligned}$$

and the rest follows from MCT or Fubini.

Prob

Let $Z: \Omega \rightarrow \mathbb{R}$ be bounded & $\mathcal{G}(Y)$ measurable, then

$$E[Z X] = E[Z E[X|Y]]$$

Pf:

Let $\mathcal{Z}(Y) = Z$.

$$E[\mathcal{Z}(Y) E[X|Y]]$$

$$= \sum_{i=0}^{\infty} \mathcal{Z}(b_i) E[X|Y=b_i] P(Y=b_i)$$

$$= \sum_{i=0}^{\infty} \mathcal{Z}(b_i) E[X 1_{\{Y=b_i\}}] = E\left[\sum_{i=0}^{\infty} \mathcal{Z}(b_i) X 1_{\{Y=b_i\}}\right]$$

Using $E[X|Y] \in L^1$ and Fubini/DOM.

$$= E[\mathcal{Z}(Y) X]$$

— ★ Important.

□

How should I think about this?

Choose $\mathcal{Z}(Y) = 1_{[b_k - \epsilon, b_k + \epsilon)}^{(Y)}$ and can reconstruct $E[X|Y]$ using this property (if b_k is not an accumulation pt of Y)

$$E[\mathcal{Z} E[X|Y]] = E[X 1_{\{b_k - \epsilon, b_k + \epsilon\}}^{(Y)}]$$

Consequence:

If $\sigma(Y) = \sigma(Y')$ then $E[X|Y] = E[X|Y']$ a.s.

$$E[Z E[X|Y']] = E[ZX] = E[Z E[X|Y]] \text{ from prev.}$$

choose $Z = 1_{E[X|Y'] > E[X|Y]}$ and apply a standard argument.

Remark: $E[X|Y]$ only depends on $\sigma(Y)$!

So how does one define $E[X|Y]$ for general Y ?

$$\text{Note, } E[X|1_B] = 1_B E[X|B] + 1_{B^c} E[X|B^c]$$

$$\text{If } Y \text{ simple } Y = \sum a_i 1_{B_i}$$

$$\Rightarrow E[X|Y] = \sum_{i=1}^n E[X|B_i] 1_{B_i}$$

Can one somehow take a limit here? People usually take the reverse approach nowadays. So we will revisit this.

Space (Ω, \mathcal{F}, P) . Subalgebra: $\mathcal{G} \subset \mathcal{F}$

Prop 8.1 (from Khoshnevisan): If $X \in L^1(P)$ then

there exists an a.s.-unique random variable

$$E[X|\mathcal{G}] \in L^1(P) \text{ st}$$

- 1) \mathcal{G} measurable
- 2) Defining property: $\forall Z$ that is \mathcal{G} -meas.

$$E\left[Z E[X|\mathcal{G}]\right] = E[Z X]$$

★ Ex: If X is G -measurable then $X = E[X|G]$ a.s.

Def: $E[X|Y] := E[X|\sigma(Y)]$

Pf: Will define a new meas.-space with a signed measure (Ω, G, ν) :

$$\nu(A) = \int X 1_A dP$$

Restrict P to G and thus $\nu \ll P$ (definition of integral)

If $P(A) = 0$,

$$|\nu(A)| \leq \int |X| 1_A dP = 0$$

Similarly, one checks that ν is finite.

Radon-Nikodym theorem says there exists an \tilde{X} st for any g that is G -measurable and integrable,

$$\int Z d\nu = \int Z \tilde{X} dP$$

Choose $Z = 1_{\{\tilde{X} > 0\}}$ and the finiteness of ν shows $\tilde{X} \in L^1(\mathcal{G}, P)$

Using simple functions and bounded convergence we can also get

$$\int Z d\nu = \int Z X dP$$

$$\Rightarrow \int Z d\nu = \int Z \tilde{X} dP = \int Z X dP$$

★

$\mu(\emptyset) = 0$

μ countably additive

μ cannot take both $+\infty$ and $-\infty$

Le Gall's version of signed meas. at least seems a bit stronger.

we call $\tilde{x} =: E[X|G]$ and

★1 is the defining property.

Remarks: $E[X|G]$ is a random variable

$E[X|Y]$ is an r.v. that is a function of Y

Rem: (Exercise) $X \geq 0$ a.s. $\Rightarrow E[X|G] \geq 0$ a.s.

Theorem • (Ω, \mathcal{F}, P) $G \subset \mathcal{F}$

1) Basic properties

$$a) E[E[X|G]] = E[X] \quad (Z=1)$$

$$b) E[X|\mathcal{F}] = X \quad (Z = 1_{\{X > E[X|\mathcal{F}]\}})$$

information (pointing to \mathcal{F})

$$c) E[X|\{\emptyset, \Omega\}] = E[X] \quad (\text{constant fn, and choose } Z=1)$$

trivial σ -algebra (pointing to $\{\emptyset, \Omega\}$)

2) Linearity

If $X_1, X_2, \dots, X_n \in L^1(P)$ and
 $a_1, a_2, \dots, a_n \in \mathbb{R}$ a.s.

$$E\left[\sum_{j=1}^n a_j X_j \mid G\right] = \sum_{j=1}^n a_j E[X_j | G]$$

$$\text{Pf: } E[ZE[aX_1 + bX_2] | G] = E[Z(aX_1 + bX_2)]$$

$$= a E[ZE[X_1 | G]] + b E[ZE[X_2 | G]]$$

3) Jensen: If φ is convex and $\varphi(x) \in L^1(\mathcal{P})$

$$\varphi(E[X|G]) \leq E[\varphi(X)|G] \quad \left(\begin{array}{l} \text{In particular} \\ \varphi(x) = |x| \end{array} \right)$$

$$\text{Pf: } \varphi(x) = \sup_{a,b} \{ax+b : ay+b \leq \varphi(y) \forall y\}$$

$$\text{In fact } \varphi(x) = \sup_{a,b \in \mathbb{Q}^2} \{ax+b : ay+b \leq \varphi(y) \forall y\}$$

$$\text{Call } E_\varphi = \{(a,b) \in \mathbb{Q}^2 : ay+b \leq \varphi(y) \forall y\}$$

One inequality is obvious. The other follows from the existence of the supporting line

$$\varphi(x) \geq \varphi(x_0) + (x-x_0)c_{x_0}$$

Fix a,b st for any $ay+b \leq \varphi(y) \forall y$. Then

$$\varphi(X(\omega)) \geq aX(\omega)+b \quad \text{for any fixed } z \in C_b$$

$$E[z E[\varphi(X)|G]] \geq E[z(aX(\omega)+b)]$$

$$\geq a E[zX] + b = a E[z E[X|G]] + b$$

$$= E[z(a E[X|G] + b)] \quad \forall a,b \in \mathbb{Q}^2 \text{ st } ay+b \leq \varphi(y) \forall y$$

$$\begin{aligned} \text{One needs to write } & \sup E[z(a E[X|G] + b)] \\ &= E[z \sup(a E[X|G] + b)] \\ &= E[z \varphi(E[X|G])] \end{aligned}$$

But how does one pass the sup inside?

Instead we use $\mathbb{E}G_{a,b}$: since $\varphi(x) \geq ax+b$

$$\mathbb{E}[\varphi(x)|G] \geq a\mathbb{E}[x|G] + b \quad \text{a.s.}$$

This is true $\forall (a,b) \in E_\varphi$, a countable set.

$$\Rightarrow \mathbb{E}[\varphi(x)|G] \geq \sup_{a,b \in E_\varphi} a\mathbb{E}[x|G] + b = \varphi(\mathbb{E}[x|G]) \quad \text{a.s.}$$

We want to prove the MCT but this is hard to do since we can

have $x_n \in L^1$, $x_n \uparrow x$ but $x \notin L^1$. So $\mathbb{E}[x_n|G]$ is well defined, but $\mathbb{E}[x|G]$ is not defined.

So let us define $\mathbb{E}[x|G]$ $\forall x \geq 0$, not just $x \in L^1$.

Def: let $x \geq 0$ $\mathbb{E}[x|G] := \lim_{n \rightarrow \infty} \mathbb{E}[x \wedge n | G]$. ★2

$x \wedge n$ is bounded and $\mathbb{E}[x \wedge n | G] \geq \mathbb{E}[x \wedge m | G]$ a.s. $\forall n \geq m$. So $\mathbb{E}[x \wedge n | G]$ is a.s. increasing, and so the

limit in ★2 exists.

MCT. Suppose $x_n \geq 0$ and $x_n \uparrow x$ a.s. Then

$$\lim_{n \rightarrow \infty} \mathbb{E}[x_n | G] = \mathbb{E}[x | G]$$

4) Fatou, BCT, DCT

5) Conditional Hölder

$$|E[XY|G]| \leq E[|X|^p|G]^{1/p} E[|Y|^q|G]^{1/q}$$

6) Conditional Minkowski holds (triangle inequality for L^p norms)

Does it tally with the classical notion of conditional expectation? (Use the defining property and go back to basics)

Let B be a set st $P(B) \neq 0$. Then

$$E[X|1_B] = E[X|\underbrace{\{B, B^c, \Omega\}}_G]$$

POLL

What is the set of G measurable fns?

A

$$\{1_B, 1_{B^c}, 1_\Omega\}$$

B

$$a 1_B + b 1_{B^c}, a, b \in \mathbb{R}$$

Thus

$$E[X|1_B] = E[X|\delta(1_B)] = p 1_B + q 1_{B^c}$$

The defining property says for $\xi = a 1_B + c 1_{B^c}$

$$E[\xi E[X|1_B]] = a p P(B) + b q P(B^c)$$

$$= E[a X 1_B + b X 1_{B^c}]$$

$$\Rightarrow p = \frac{E[X 1_B]}{P(B)} \quad q = \frac{E[X 1_{B^c}]}{P(B^c)}$$

*

$$\text{Ex: } E[X|Y] = \sum 1_{\{Y=a_i\}} E[X|Y=a_i]$$

L^2 -projection

Prop 8.4: $X \in L^2(P)$, $G \subset \mathcal{F}$. Then for every r.v. Y that is G -meas.

$$E[(X - E[X|G])^2] \leq E[(X - Y)^2]$$

$$\| \quad \|_2 \leq \| \quad \|_2$$

$$\text{Let } H = L^2(\Omega, \mathcal{F}, P)$$

$$M = L^2(\Omega, G, P) \quad M \subset H$$

Let $\pi: H \rightarrow M$ be the L^2 orthogonal projection operator. It satisfies

$$1) \pi^2 = \pi$$

$$2) (X - \pi X, Y) = 0 \quad \forall X \in H, Y \in M$$

$$\text{Then } \pi f = E[f|G]$$

$$(X, Y) = (\pi X, Y)$$

$$\int XY \, dP = \int \pi X Y \, dP$$

Ex: Show that the L^2 orthogonal projection operator onto a subspace is unique (up to a.s. equivalence)

By the defining property, this shows $\pi X = E[X|G]$ a.s.

Theorem 8.5 (Tower Property)

Let $G_1 \subset G_2 \subset \mathcal{F}$ be subalgebras
and suppose $X \in L^1(P)$

$$E[E[X|G_2] | G_1] = E[X|G_1]$$

↑
information interpretation

Pf:

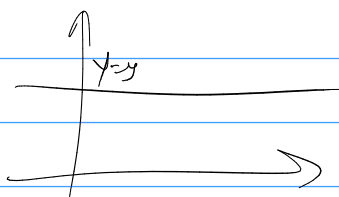
Take $Z \in G_1$ meas. Then it's definitely G_2 meas as well.

$$\text{LHS: } E[Z E[E[X|G_2] | G_1]] = E[Z E[X|G_2]] = E[ZX]$$

$$\text{RHS: } E[Z E[X|G_1]] = E[ZX]$$

Let X, Y be RVs w/ joint density $f(x, y)$ s.t. $\int_{\mathbb{R}} f(x, y) dx > 0 \forall y$, $E(X) < \infty$. What is $E(X|Y)$? Given $X \in L^1(\Omega)$

Intuitively



given Y , best guess for X is its expected value on the line corresponding to the value of Y .

$$E(X|Y) = h(Y) \quad \text{where} \quad h(y) = \int x f(x, y) dx / \int f(x, y) dx$$

~~Def:~~ $h(Y)$ is $\mathcal{G}(Y)$ -m.l.e. $\forall A \in \mathcal{G}(Y)$, $h \in L^1$ by previous.

$\mathcal{G}(Y)$ - smallest σ -alg. s.t. $Y: \Omega \rightarrow \mathbb{R}$ is m.l.e. : $\mathcal{G}(Y) = Y^{-1}(\mathcal{B})$
 $\Rightarrow \exists B \in \mathcal{B}$ s.t. $A = Y^{-1}(B)$ i.e. $(x, y) \in A \iff y \in B$.

$$E[1_A h(Y)] = \int \int 1_B(y) h(y) f(x, y) dx dy \stackrel{?}{=} E[X 1_A]$$

$$= \int \int 1_B(y) x f(x, y) dx dy \stackrel{\text{Fubini}}{=} \int 1_B(y) \int x f(x, y) dx dy$$

$$= \int 1_B(y) h(y) \int f(x, y) dx dy = \int \int 1_B(y) h(y) f(x, y) dx dy$$

which is what we wanted to show.

Prop: If X and Y are rvs, and let Y be G meas. If X, Y are bounded or $YX \in L^1$ then

$$E[YX|G] = Y E[X|G] \quad \text{a.s.}$$

Pf: Let Z be G meas and bdd. Assume $X, Y \geq 0$. Let $Y_n = Y \wedge n$

$$E[Z E[Y_n X|G]] = E[Z Y_n X]$$

since $Z Y_n$ is bounded.

$$E[Z Y_n E[X|G]] = E[Z Y_n X]$$

$\Rightarrow E[Y_n X|G] = Y_n E[X|G]$ and using conditional MCT.

$$\lim_{n \rightarrow \infty} E[Y_n X|G] = E[YX|G] = Y E[X|G]$$

The integrable case follows from $X = X^+ - X^-$

Prop: $G_1, G_2 \subset \Sigma$ are sub σ -fields. They are independent iff $\forall B \in G_2$ we have

$$E[1_B | G_1] = P(B)$$

Pf: (\Rightarrow) let G_1, G_2 be indep and Z be bdd and G_2 meas.

$$E[Z 1_B] \stackrel{\text{indep.}}{=} E[Z] P(B) \stackrel{P(B) \text{ is a const}}{=} E[Z P(B)]$$

$$= E[Z E[1_B | G_1]]$$

By prev. $P(B) = E[1_B | G_1]$

a.s.

$$\Leftarrow \text{If } A \in \mathcal{G}_1 \quad P(A \cap B) = E[1_A 1_B] = E[1_A E[1_B | \mathcal{G}_1]] \\ = P(B) E(1_A)$$

□

Martingales

Example/motivation:

Let X_0, X_1, X_2, \dots be a s/c of RVs on Ω
 Z - any RV on Ω

We start on day zero & gain new information every day & observe the RV X_n on day n .

The information we have on day n can be represented by a σ -alg \mathcal{F}_n .
 We'll have $\mathcal{F}_0 \subseteq \mathcal{F}_1 \subseteq \dots$

eg. if the only info we gain on day n is the value of X_n ,
 we'll have $\mathcal{F}_n = \sigma(X_0, \dots, X_n)$.

E.g.: X_n - value of a stock on day n .

Say we're on day n . What's the best guess for X_{n+1} ?

i.e. $E(X_{n+1} | \text{info we have on day } n)$

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

assuming no insider info, dividends, etc,

best guess for $E(X_{n+1} | \mathcal{F}_n)$ should be X_n .

(\mathcal{F}_n doesn't need to be $\mathcal{F}_n = \sigma(X_0, X_1, \dots, X_n)$.)

eg. maybe we're also keeping track of other stocks daily,

say Y_0, Y_1, Y_2, \dots

Z_0, Z_1, Z_2, \dots

so $\mathcal{F}_n = \sigma(X_0, \dots, X_n, Y_0, \dots, Y_n, Z_0, \dots, Z_n)$.

Defn: A stochastic process is a collection of RVs on (Ω, \mathcal{F}, P)

if $\mathcal{F}_1 \subseteq \mathcal{F}_2 \subseteq \dots \subseteq \mathcal{F}$ are sub σ -algebras, then

$\{\mathcal{F}_n\}_{n=1}^{\infty}$ is called a filtration.

The process $\{X_n\}_{n=1}^{\infty}$ is adapted to the filtration $\{\mathcal{F}_n\}_{n=1}^{\infty}$

if X_n is \mathcal{F}_n -m'le $\forall n \geq 1$.

(think of it as, if have the info \mathcal{F}_n , then know the value of X_n).

Ex: $\mathcal{F}_n = \sigma(X_1, \dots, X_n)$. Then $\{X_n\}_{n=1}^{\infty}$ is always adapted to $\{\mathcal{F}_n\}_{n=1}^{\infty}$

Def: A stochastic process $X = \{X_n\}_{n=1}^{\infty}$ is a martingale wrt the filtration $\mathcal{F} = \{\mathcal{F}_n\}_{n=1}^{\infty}$ if

- 1) X_n is adapted to \mathcal{F}
- 2) $X_n \in L^1(P) \quad \forall n \geq 1$
- 3) $E[X_{n+1} | \mathcal{F}_n] = X_n$ a.s. $\forall n \geq 1$.

X is a submartingale if

$$3') E[X_{n+1} | \mathcal{F}_n] \geq X_n \text{ a.s. } \forall n \geq 1$$

X is a supermartingale if

$$3'') E[X_{n+1} | \mathcal{F}_n] \leq X_n \text{ a.s. } \forall n \geq 1$$

Rule: Martingale "the best guess for X_{n+1} given present info is X_n "

Super vs sub: If a supermartingale agrees w/ a "fair" martingale now, then in the past it would tend to be larger

Rule: martingale \Leftrightarrow super & subm

Ex: Simple RW. X_1, X_2, \dots iid $P(X_i = 1) = P(X_i = -1) = \frac{1}{2}$
(example of fair game)

$S_k = X_1 + \dots + X_k$ - cumulative fortune after k steps.

$$E[X_k | X_1, \dots, X_{k-1}] \stackrel{\text{indep}}{=} E[X_k] = 0$$

so $E[S_k | X_1, \dots, X_{k-1}] = S_{k-1}$ so $S = \{S_n\}_{n=1}^{\infty}$ is a martingale wrt the filtration $\mathcal{F} = \{\mathcal{F}_n\}_{n=1}^{\infty}$ w/ $\mathcal{F}_n = \sigma(X_1, \dots, X_n)$.

Rule: Only needed indep & $E[X_i] = 0 \quad \forall i$, to get S martingale wrt \mathcal{F} . No need for identically distributed

Ex: If \mathcal{F} is a filtration & $Y \in L^1(P)$, $X_n := E[Y | \mathcal{F}_n]$ is a martingale (these are called Doob martingales).

There are called "closed" by Le Gall.

Defn A stoch. pr. $\{A_i\}_{i=1}^\infty$ is previsible wrt filtration $\mathcal{F} = \{\mathcal{F}_n\}_{n=1}^\infty$ if A_n is \mathcal{F}_{n-1} m.e. $\forall n \geq 1$, where $\mathcal{F}_0 = \{\emptyset, \Omega\}$.
Prn Previsible is also called predictable.

Ex X_1, X_2, X_3, \dots indep. $E X_i = 0$ (fair game).

$S_n = X_1 + \dots + X_n$ - winnings after n th round.

Of course S_n - martingale

What if we change the bets every day?

If we bet A_n on day n , our overall winnings will be

$$\begin{aligned} Y_n &= Y_{n-1} + A_n X_n = Y_{n-1} + A_n (S_n - S_{n-1}) \\ &= Y_0 + \sum_{i=1}^n A_i (S_i - S_{i-1}) \end{aligned}$$

Some \uparrow starting amount

How much we bet can only be based on info we had up to that point so $A_n \in \mathcal{F}_{n-1}$, i.e. $A = \{A_n\}_{n=1}^\infty$ is previsible.
 more generally

Martingale transforms

let $\{S_n\}_{n=1}^\infty$ be a martingale wrt filtration $\mathcal{F} = \{\mathcal{F}_n\}_{n=1}^\infty$.

let $S_0 = 0$, $Y_0 = 0$ & $A = \{A_n\}_{n=1}^\infty$ previsible wrt \mathcal{F} .

Define pr. Y by $Y_n := Y_0 + \sum_{j=1}^n A_j (S_j - S_{j-1}) \quad \forall n \geq 0$.

Exercise : Y is a martingale

Y is called a martingale transform of S .

Le Gall writes if (A_n) previsible, (X_n) is a Martingale,

$$(A \bullet X)_n = \sum_{i=1}^n A_i (X_i - X_{i-1}) \quad " = \quad \int A dx$$

Prop: If (X_n) is a super(sub)martingale and (H_n) previsible and nonnegative
Then $(H \bullet X)_n$ is a super(sub)martingale.

Example: $\Omega = \{-1, +1\}^{\mathbb{Z}_+}$, $P = \mu^{\otimes \mathbb{Z}_+}$ (product meas.)
let $Y_n(\omega) = \omega_n$ represent the outcome of the game.
If it's fair $E[Y_n(\omega)] = 0$.

Then $S_n = \sum_{i=1}^n Y_i$ is a martingale.

If $H_n = f(Y_1, \dots, Y_{n-1})$ is a previsible "bet" then if you win you gain $H_n(S_n - S_{n-1}) = H_n$ and if you lose you

gain $H_n(S_n - S_{n-1}) = -H_n$. Thus your net winnings after

n games is $(H \bullet S)_n$.

Another transform :

Prop: let $\varphi: \mathbb{R} \rightarrow \mathbb{R}$ be convex, and let X_n be \mathcal{F}_n adapted.

1) If (X_n) is a martingale, and $E|\varphi(X_n)| < \infty$ then $\varphi(X_n)$ is a submartingale.

2) If $(X_n)_{n \in \mathbb{Z}_+}$ is a submartingale and φ is increasing then $\varphi(X_n)$ is a submartingale.

Pf: 1) $E[\varphi(X_{n+1}) | \mathcal{F}_n] \geq \varphi(E[X_{n+1} | \mathcal{F}_n]) = \varphi(X_n)$ ★1

↑

This needs the L^1 condition to be defined. If $\varphi: \mathbb{R} \rightarrow \mathbb{R}_+$ as in the Gall, then can drop $E|\varphi(X_n)| < \infty$. Recall that we defined $E[X | \mathcal{F}] := \lim_{n \rightarrow \infty} E[X \wedge n | \mathcal{F}]$ if $X \geq 0$.

2) Similarly, if X_n is only a submartingale, the last step has $E[X_{n+1} | \mathcal{F}_n] \geq X_n$ then we get ★1.

Properties of martingales

Lemma If X is a subm. w.r.t filtration \mathcal{F} , then X is a subm. w.r.t the filtration generated by X itself, i.e.

$$E[X_{n+1} | X_1, \dots, X_n] \geq X_n \text{ a.s.}$$

Pf: know $E[X_{n+1} | \mathcal{F}_n] \geq X_n \quad \forall n$.

$X_n - \mathcal{F}_{n-m}$'s $\forall n$ & $\mathcal{F}_1 \subseteq \dots \subseteq \mathcal{F}_{n-1} \subseteq \mathcal{F}_n \Rightarrow \sigma(X_1, \dots, X_n) \subseteq \mathcal{F}_n$.

$$E[E[X_{n+1}|F_n] | X_1, \dots, X_n] \geq E[X_n | X_1, \dots, X_n]$$

$$\overset{||}{E[X_{n+1} | X_1, \dots, X_n]} \geq X_n$$

△.

Lemma: If X is a martingale & ψ is convex s.t. $\psi(X_n) \in L^1(P) \forall n$
 then $\psi(X)$ is a subm. If X subm & ψ -non-decr. convex,
 & $\psi(X_n) \in L^1(P) \forall n$, then $\psi(X)$ is also subm.

Pf: Conditional Jensen

$$E[\psi(X_{n+1}) | F_n] \geq \psi E[X_{n+1} | F_n] = \psi(X_n). \text{ if } X \text{ martingale}$$

If X -subm & ψ -non-decr, then

$$E[X_{n+1} | F_n] \geq X_n$$

$$\text{so } \psi(E[X_{n+1} | F_n]) \geq \psi(X_n)$$

△

Cor: If X -martingale, then X^+ , $|X|^p$, e^X are subm.

if they stay in $L^1(P) \forall n$.

If X -subm, then X^+ , e^X also subm if in $L^1(P) \forall n$.

If X -subm, $|X|$ might not be.

$$\text{e.g. } X_k = -\frac{1}{k}.$$

Thm (Doob's decomposition thm).

Any submartingale X can be written as

$$X_n = Y_n + Z_n \text{ where } Y \text{ is a martingale \&}$$

Z is a non-neg. predictable a.s. increasing process

$$\text{w/ } Z_n \in L^1(P) \forall n$$

Pf Set $X_0 = 0$ & $d_j = X_j - X_{j-1}$ so $X_n = d_1 + \dots + d_n$.

Suppose have Y_n, Z_n , want to find out Y_{n+1}, Z_{n+1} .

Let $e_{n+1} = Y_{n+1} - Y_n$, $f_{n+1} = Z_{n+1} - Z_n$. Have $d_{n+1} = e_{n+1} + f_{n+1}$

Must have Z_{n+1} & F_n -me & $E(e_{n+1} | F_n) = 0$

$$E(d_{n+1} | F_n) = E(e_{n+1} | F_n) + E(f_{n+1} | F_n)$$

$$\text{need} = 0 + f_{n+1}$$

so should take $f_{n+1} = E(d_{n+1} | F_n)$

$$e_{n+1} = d_{n+1} - E(d_{n+1} | F_n).$$

Thus $Z_n = \sum_{k=1}^n E(d_k | \mathcal{F}_{k-1})$

$$Y_n = X_n - Z_n$$

Hint: Check these work. △

Another decomp. thm

Defn: $\{X_i\}_{i=1}^\infty$ is bdd on $L^1(P)$ if $\sup_n \|X_n\|_1 < \infty$

Thm: (Krickeberg's decomposition).

If X is a subm. bdd on $L^1(P)$ then can write it as

$$X_n = Y_n - Z_n \text{ w/ } Y_n \text{ - mart.}, Z_n \text{ - non-neg. superm.}$$

Pf

Set $Y_n = \lim_{m \rightarrow \infty} E[X_m | \mathcal{F}_n]$. Does the limit exist?

Yes sure it is as decreasing
(X is a subm.)
Let $m \geq n$. $E[X_{m+1} | \mathcal{F}_n] \geq E[X_m | \mathcal{F}_n] \geq E[X_n | \mathcal{F}_n] = X_n$
(use tower property) So $Y_n \geq X_n \Rightarrow Z_n = Y_n - X_n$
is non-neg.

Check Y_n - martingale. Certainly adapted.

$$E Y_n = \lim_{m \rightarrow \infty} E[E[X_m | \mathcal{F}_n]] = \lim_{m \rightarrow \infty} E X_m \stackrel{\text{subm}}{=} \sup_n E X_n \stackrel{X \text{ bdd on } L^1(P)}{<} \infty$$

$$E[Y_{n+1} | \mathcal{F}_n] = E\left[\lim_{m \rightarrow \infty} E[X_{m+1} | \mathcal{F}_{n+1}] \mid \mathcal{F}_n\right] \stackrel{\text{w'd l m.c.t.}}{=} \lim_{m \rightarrow \infty} E[E[X_{m+1} | \mathcal{F}_{n+1}] | \mathcal{F}_n]$$

$$= \lim_{m \rightarrow \infty} E[X_{m+1} | \mathcal{F}_n] = Y_n$$

So Y_n - mart. $\Rightarrow Z_n$ - superm. △

Prk: Y & Z are L^1 -bdd.

Pf: $Y_n = X_n + Z_n$ $Z_n \geq 0$

$$E|Y_n| \leq \underbrace{\sup_k E|X_k|}_{\text{indep of } n, \text{ finite}} + E Z_n.$$

$$|E Z_n| = |E(Y_n - X_n)| = |E Y_n - E X_n| \leq |E Y_n| + \sup_k E|X_k|.$$

$\stackrel{\text{indep of } n, \text{ finite}}{\text{finite}}$ △

Doob + Krickeberg: submartingales are bounded above and below by martingales.

Thm: \forall bdd L^1 -bdd subm or bdd above & below by martingales.

Pf: Doob - \forall subm bdd below by mart.

Krickeberg - $\forall L^1$ -bdd subm bdd above by mart. \triangle

Stopping times

Def: A stopping time wrt a filtration \mathcal{F} is a RV $T: \Omega \rightarrow \mathbb{N} \cup \{\infty\}$ st. $\{T \leq k\} \in \mathcal{F}_k \forall k \in \mathbb{N}$
(equiv. $\{T \leq k\} \in \mathcal{F}_k \forall k \in \mathbb{N}$)

$$\{T = +\infty\} = \bigcap_{n \in \mathbb{Z}_+} \{T \leq n\}^c \quad \text{Each of them are } \mathcal{F}_n \text{ meas.}$$

$$\Rightarrow \{T = +\infty\} \in \mathcal{F}_\infty$$

Ex 1) $T = k$ a.s. is a stopping time since $\{T = k\} \Delta \Omega = \emptyset$

2) If $A \in \mathcal{B}(\mathbb{R})$, $T_A = \inf \{n: X_n \in A\}$ is a stopping time.

$$\{T_A = k\} = \{X_1 \notin A, \dots, X_{k-1} \notin A, X_k \in A\} \in \mathcal{F}_k$$

Actually, every stopping time can be expressed as a 1st visit time.

If T -stopping time, define

$$X_j^T(\omega) := \mathbb{1}_{\{T \leq j\}}(\omega).$$

Then T is the 1st time the Stoch. pr. $\{X_j^T\}_{j \geq 1}$ visits $A = \{1\}$

This may not be that useful in general.

3) $L_A = \sup \{n: X_n \in A\}$ is not in general.

$$\{L_A = k\} = \{X_k \in A, X_{k+1} \notin A, \dots\}$$

4) S, T stopping times $\{\max(S, T) = k\} = \{S = k, T \leq k\} \cup \{T = k, S \leq k\} \in \mathcal{F}_k$

Hint: Check that if $\{T_i\}_{i=1}^n$ are stopping times then so are $\bigvee_{i=1}^n T_i$ and $\max_{i=1}^n T_i$

Stopped σ -algebras

$$\mathcal{F}_T := \{A \in \mathcal{F} \mid A \cap \{T \leq k\} \in \mathcal{F}_k \text{ for all } k \in \mathcal{N}\}.$$

(note that \mathcal{F}_T is not a random σ -alg, you don't choose $T \leq k$ & pick \mathcal{F}_k)

Hint \mathcal{F}_T - σ -alg

Lemma 1) If S, T - stopping times s.t. $P(S < \infty) = P(T < \infty) = 1$,
& $S \leq T$ a.s., then $\mathcal{F}_S \subseteq \mathcal{F}_T$.

$$2) E[Y | \mathcal{F}_T] \mathbb{1}_{T \leq n} = E[Y | \mathcal{F}_n] \mathbb{1}_{T \leq n} \quad \forall Y \in L^1(P), n \geq 1.$$

$$\begin{aligned} \text{Pf 1) If } A \in \mathcal{F}_S, \text{ then } A \cap \{T = n\} &= \bigcup_{k=0}^{\infty} (A \cap \{S = k\}) \cap \{T = n\} \\ &= \bigcup_{k=0}^n (A \cap \{S = k\}) \cap \{T = n\} \in \mathcal{F}_n \quad \text{since } S \leq T \end{aligned}$$

$$\Rightarrow A \in \mathcal{F}_T$$

skip 2)

Prop If S, T stopping times, $\mathcal{F}_{S \wedge T} = \mathcal{F}_S \cap \mathcal{F}_T$

$$\mathcal{F}_{S \wedge T} \subset \mathcal{F}_S \cap \mathcal{F}_T \quad \text{from 1)}$$

$$\text{If } A \in \mathcal{F}_S \cap \mathcal{F}_T \quad A \cap \{S \wedge T > n\} = A \cap (\{S > n, T > n\})$$

$$= (A \cap \{S > n\}) \cup (A \cap \{T > n\})$$

$\in \mathcal{F}_n \qquad \qquad \in \mathcal{F}_n$

$$\Rightarrow A \in \mathcal{F}_{S \wedge T}$$

Rem: The whole point of \mathcal{F}_T is to find a σ algebra st $X_T := X_{T(\omega)}$ is meas. wrt to it. One option is to consider $\mathcal{G}(T)$, but if $T = \infty$, then $\mathcal{G}(T)$ is trivial.

Prob Let (Y_n) be \mathcal{F}_n adapted and let T be a stopping time.

Then Y_T is well defined on $\{T < \infty\}$ and is meas. wrt \mathcal{F}_T .

$$\text{Pf: } \{Y_T \in B\} \cap \{T = n\} = \{Y_n \in B\} \cap \{T = n\}$$

$\in \mathcal{F}_n$ $\in \mathcal{F}_n$

Thm: (Optional Stopping, easy) Let $(X_n)_{n \in \mathbb{Z}}$ be a martingale (or super)

let T be a stopping time, then $(X_{n \wedge T})$ is a martingale (or super)

a) If $T \leq K$ a.s. $E[X_T] = E[X_0]$

b) If $|X_n| \leq K$ a.s., and $T < \infty$ a.s., $E[X_T] = E[X_0]$

Pf: Let $H_n = 1_{\{T \geq n\}}$ \mathcal{F}_{n-1} meas.

$$\begin{aligned} X_{n \wedge T} &= \sum_{i=1}^{n \wedge T} X_i - X_{i-1} + X_0 = X_0 + \sum_{i=1}^n 1_{\{i \leq T\}} (X_i - X_{i-1}) \\ &= X_0 + (H \bullet X)_n \end{aligned}$$

for a) $\lim_{n \rightarrow \infty} E[X_{n \wedge T}] = E[X_{K \wedge T}] = E[X_0]$

b) $\lim_{n \rightarrow \infty} E[X_{n \wedge T}] \stackrel{\text{bdd}}{=} E[X_T] = E[X_0]$

Optional Stopping Theorem

Consider a fair game. E.g. X_1, X_2, \dots indep, $E X_i = 0 \forall i$;
 $S_n = X_1 + \dots + X_n$.

$ES_n = 0$, so if playing for n steps your expected winnings are 0.

What if you devise some strategy for when you stop instead of stopping after n steps? You have to stop at a stopping time (can't use info from the future).

Can you come up w/ a strategy T s.t. $ES_T > 0$?

No (Saw w/ random walks, $ES_n = EX_1 = 0 \forall$ stopping time n)

Thm: (Doob's optional stopping thm).

Suppose S, T are a.s. \leq stopping times s.t. $S \leq T$ a.s.

If X is a subm, then $E[X_T | \mathcal{F}_S] \geq X_S$ a.s.

$$\begin{array}{ccc} \text{Super-} & & \leq \\ \text{martingale} & & = \end{array}$$

pf: let $K \in \mathcal{N}$ be s.t. $S \leq T \leq K$ a.s. (K -cont)

X -subm.

Write $X_n = d_1 + d_2 + \dots + d_n$ (i.e. $d_k = X_k - X_{k-1}$, $\forall k \in \mathcal{N}$ w/ $X_0 = 0$).

X -subm. $\Rightarrow E[d_j | \mathcal{F}_{j-1}] \geq 0$ a.s. $\forall j$

$$X_T = \sum_{j=1}^K d_j \mathbb{1}_{j \leq T} \quad \text{d.t.t.o for } X_S.$$

$$\text{E.T.S } E[X_T - X_S; A] \geq 0 \quad \forall A \subseteq \mathcal{F}_S.$$

$$\begin{aligned} E[X_T - X_S; A] &= \sum_{j=1}^K E[d_j \mathbb{1}_{S < j \leq T}; A] \\ &= \sum_{j=1}^K E[d_j \mathbb{1}_{\{S < j \leq T\} \cap A}] \end{aligned}$$

$$= \sum_{j=1}^k \mathbb{E} [\mathbb{E} [d_j \mathbb{1}_{\{S \leq T \leq T \cap A\}} | \mathcal{F}_{j-1}]]$$

$\underbrace{\{S \leq T \leq T \cap A\}}_{\in \mathcal{F}_j} \cap \underbrace{\{T \leq T \cap A\}}_{\in \mathcal{F}_{j-1}}$

$$= \sum_{j=1}^k \mathbb{E} [\mathbb{E} [d_j | \mathcal{F}_{j-1}] \mathbb{1}_{\{S \leq T \leq T \cap A\}}] \geq 0. \quad \triangle$$

Cor: If T is a stopping time wrt \mathcal{F} & X subm, then
 so is $\{X_{T \wedge n}\}_{n=1}^{\infty}$ wrt $\{\mathcal{F}_{T \wedge n}\}_{n=1}^{\infty}$. supermartingale

~~Pf:~~ apply prev thm w/ $T = T \wedge n$ & $S = T \wedge n$ △

Read Section 8.4 to see how to obtain
 the Random walk results from earlier wa martingale
 theory. Especially Thm 8.34.

St. Petersburg paradox

Recall $\Omega = \{-1, +1\}^{\mathbb{Z}_+}$, $P = \mu^{\otimes \mathbb{Z}_+}$ (product meas.)

let $Y_n(\omega) = \omega_n$ represent the outcome of the game.

If it's fair $E[Y_n(\omega)] = 0$.

let H_0 be initial bet, $H_n = 2H_{n-1}$ (double)

let $T = \inf \{n : Y_n = 1\}$ (quits)

Net winnings after n games is $(H \bullet S)_n$.

We care about $(H \bullet S)_T = W_T$

$$W_T = \sum_{i=0}^{T-1} H_i Y_i + H_T Y_T \quad \text{on } T < \infty$$

$$= -H_0 \sum_{i=1}^{T-1} 2^i + H_0 2^T$$

$$= H_0 \left[-\left(\frac{2^T - 1}{2 - 1} \right) + 2^T \right] = H_0$$

If $P(T < \infty) = 1$ we have ensured $E[W_T] = H_0$

$$\neq E[W_0] = E[Y_0 H_0] = 0$$

Gambler's ruin

Consider the previous example, but now, let $H_n = 1$. Let $S_0 = k$ represent your initial fortune, and if $S_n = M$, then you bankrupt Mr. House.

$$\text{let } T = \inf \{n : S_n = 0 \text{ or } M\}$$

let $A = \{S_T = 0\}$ this is \mathcal{F}_T meas.

$S_n - k$ is a martingale. $|S_{n \wedge T} - k| \leq k + M$, so stopping theorem gives

$$E[S_T - k] = E[S_0 - k] = 0$$

$$\Rightarrow -k P(S_T = 0) + M (1 - P(S_T = 0)) = 0$$

$$\Rightarrow P(S_T = 0) = \frac{M - k}{M}$$

$$\text{Need to show } P(S_T = 0) + P(S_T = M) = 1$$

But this is equivalent to showing $P(T < \infty) = 1$ (which was needed for the stopping theorem anyway)

$$\begin{aligned} \text{How to show? } P(0 < S_n < M) &= P\left(0 < \frac{S_n}{\sqrt{n}} < \frac{M}{\sqrt{n}}\right) \\ &\leq P\left(0 \leq \frac{S_n}{\sqrt{n}} \leq \epsilon\right) \rightarrow \int_0^\epsilon \frac{e^{-\frac{x^2}{2}}}{\sqrt{2\pi}} dx \leq C\epsilon \end{aligned}$$

But

$$P(T = +\infty) = P\left(\bigcap_n \{0 < S_n < M\}\right) \leq P(0 < S_n < M)$$

Ballot theorem

Given A receives α votes & B receives β , what's the chance that A always strictly leads B in the counting process?

This can be proved in two different ways.

- 1) Using the reflection principle
- 2) Using "backward" martingales.

1)

Assume all vote counting sequences are equally likely.

$n = \alpha + \beta$. Let

$$X_i \in \begin{cases} +1 & \text{if vote for A} \\ -1 & \text{if vote for B} \end{cases}$$

X_i represents the i^{th} vote.

$$\text{let } S_k = \sum_{i=1}^k X_i$$

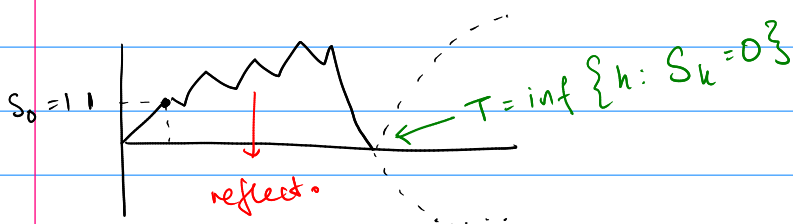
Find sequences $\vec{X}_n = (X_1, \dots, X_n)$ st $S_k > 0 \quad \forall k=1, \dots, n$.

$(S_k)_{k=1}^n$ is clearly a SRW. we need $\alpha > \beta$

$$\# \{ \vec{X}_n : S_0 = 0, S_k > 0 \quad \forall k, S_n = \alpha - \beta \}$$

$$= \# \{ \vec{X}_n : S_1 = 1, S_k > 0 \quad k=2, \dots, n, S_n = \alpha - \beta \}$$

$$= \# \{ \vec{X}_{n-1} \in \{\pm 1\}^{n-1} : S_0 = 1, S_k > 0, k=1, \dots, n-1, S_{n-1} = \alpha - \beta \}$$



Consider the set

$$\{\vec{X}_{n-1} : S_0 = 1, S_{n-1} = \alpha - \beta\} \quad \text{If } T \leq n, \text{ that is, the trajectory}$$

hits the y -axis then the trajectory is not good; i.e.,

$$\vec{X}_{n-1} \notin \{\vec{X}_{n-1} \in \{\pm 1\}^{n-1} : S_0 = 1, S_k > 0, k = 1, \dots, n-1, S_{n-1} = \alpha - \beta\}$$

But for trajectories in this set, we can replace the initial part of the trajectory with each (X_1, \dots, X_T) replaced by $(-X_1, \dots, -X_T)$

Then it is easy to see that the reflected trajectory starts at $S_0 = -1$ and ends up at $S_{n-1} = \alpha - \beta$. In fact

$$\# \{\vec{X}_{n-1} : S_0 = 1, S_{n-1} = \alpha - \beta\} = \# \{\vec{X}_{n-1} : S_0 = -1, S_{n-1} = \alpha - \beta\}$$

In $n-1$ steps of ± 1 , we have to end up at $\alpha - \beta + 1$

$$\# \{\text{Up steps}\} - \# \{\text{down steps}\} = \alpha - \beta + 1$$

$$a - (n-1-a) = \alpha - \beta + 1 \Rightarrow 2a = n-1 + \alpha - \beta + 1$$

$$a = \frac{\alpha + \beta + \alpha - \beta}{2} = \alpha.$$

$$S_0 \quad \# \{\vec{X}_{n-1} : S_0 = -1, S_{n-1} = \alpha - \beta\} = \binom{n-1}{\alpha}$$

$$\# \{\vec{X}_{n-1} : S_0 = 1, S_{n-1} = \alpha - \beta\} = \binom{n-1}{\alpha-1}$$

↑ one up step is already taken

$$\# \{\vec{X}_{n-1} : S_0 = 1, S_{n-1} = \alpha - \beta, T > n\} = \# \{\vec{X}_{n-1} : S_0 = 1, S_{n-1} = \alpha - \beta\}$$

$$- \# \{\vec{X}_{n-1} : S_0 = 1, S_{n-1} = \alpha - \beta, T \leq n\}$$

$$= \binom{n-1}{\alpha-1} - \binom{n-1}{\alpha} = \frac{(n-1)!}{(\alpha-1)! \beta!} - \frac{(n-1)!}{\alpha! (\beta-1)!}$$

$$= \frac{(n-1)!}{(\alpha-1)! (\beta-1)!} \left[\frac{\alpha - \beta}{\alpha \beta} \right] = \frac{(n-1)!}{\alpha! \beta!} (\alpha - \beta)$$

$$\# \{ \vec{X}_n, S_0 = 0, S_n = \alpha - \beta \} = \binom{n}{\alpha} = \frac{n!}{\alpha! \beta!}$$

Taking the ratio gives $\frac{\alpha - \beta}{\alpha + \beta}$.

2)

Backward Martingales

$$\text{Suppose } S_n = \frac{1}{n} \sum_{i=1}^n X_i \quad \mathcal{F}_n = \sigma(S_n, S_{n+1}, \dots)$$

Then S_n is \mathcal{F}_n measurable. Let $\tilde{S}_n = \frac{S_n}{n}$

$$E[\tilde{S}_n | \mathcal{F}_{n+1}] = E\left[\frac{S_{n+1} - X_n}{n} \mid \mathcal{F}_{n+1}\right] = \frac{S_{n+1}}{n} - E\left[\frac{X_n}{n} \mid \mathcal{F}_{n+1}\right] \quad \text{--- } \star 1$$

$$E[X_i | \mathcal{F}_{n+1}] = E[X_j | \mathcal{F}_{n+1}] \quad i, j \leq n+1 \text{ by symmetry.}$$

$$\Rightarrow \sum_{i=1}^{n+1} E[X_i | \mathcal{F}_{n+1}] = S_{n+1} \Rightarrow E[X_n | \mathcal{F}_{n+1}] = \frac{S_{n+1}}{n+1}$$

$$\star 1 = \frac{S_{n+1}}{n} - \frac{S_{n+1}}{n+1} = \tilde{S}_{n+1}$$

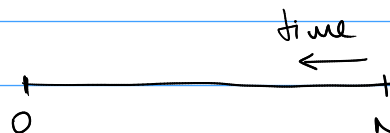
Thus \tilde{S}_n is a backwards martingale satisfying

$$E[\tilde{S}_n | \mathcal{F}_{n+1}] = \tilde{S}_{n+1}$$

The stopping Theorem applies to backward martingales.

Let N be some fixed horizon, and let $0 \leq T \leq N$ be st

$\{T \geq k\}$ is \mathcal{F}_k measurable.



As before $T \vee k$ is a stopping time,

$$E[\tilde{S}_T] = \lim_{k \downarrow 0} E[\tilde{S}_{T \vee k}] = \tilde{E}[S_N]$$

Remark: There is no centering here to worry about in \tilde{S}_n

Let us apply this to Ballots.

Let $X_i \in \{0, 2\}$, where 2 represents a vote for B & 0 for A.

$$\begin{aligned} \bar{X}_i &= -(X_i - 1) \in \{-1, 1\} & \{ \bar{S}_0 = 0, \bar{S}_k > 0, k=1, \dots, N, \bar{S}_N = \alpha - \beta \} \\ &= \{ S_0 = 0, -(S_k - k) > 0, k=1, \dots, N, S_N = (N - k - \beta) \} & \alpha + \beta - \alpha + \beta = 2\beta \\ &= \{ S_0 = 0, k > S_k, k=1, \dots, N, S_N = 2\beta \} \\ &= G \end{aligned}$$

Let $T = \sup \{0 \leq k \leq N : S_k \geq k\}$ and $T = 1$ if it doesn't happen.

$$\tilde{S}_T = 1 \text{ on } G^c. \quad S_{T+1} < T+1 \quad \text{Then}$$

$S_T \leq S_{T+1} \leq T$ since S_{j+1} is integer valued and $X_i \geq 0$.

$$\Rightarrow S_T = T \Rightarrow \hat{S}_T = 1.$$

On G , $T=1$, and $S_1 < 1$ (since G happens)

$$\Rightarrow S_1 = 0 \text{ (since } X_i \in \{0, 2\} \text{)}$$

Therefore $S_T = 0$ on G .

Then $\hat{S}_T = 1_G$

$$E[1_G] = E[\hat{S}_T] = E[\tilde{S}_N] = \frac{S_N}{N} = \frac{\alpha - \beta}{\alpha + \beta}$$

Crazy, huh? A more general version appears in Durrett.

Thm: (Doob's Maximal inequality)

If X -subm, then $\forall \lambda > 0, \forall n \geq 1$

$$1) \quad \textcircled{*} \quad \lambda P\left(\max_{1 \leq j \leq n} X_j \geq \lambda\right) \leq E[X_n; \max_{1 \leq j \leq n} X_j \geq \lambda] \leq E[X_n^+]$$

$$2) \quad \lambda P\left(\min_{1 \leq j \leq n} X_j \leq -\lambda\right) \leq E[X_n^+] - E[X_1]$$

Pf:) Let $T = \inf\{j; X_j \geq \lambda\}$. T is a stopping time
 $\{T \leq n\} = \{\max_{1 \leq j \leq n} X_j \geq \lambda\}$.

$$\begin{aligned} \text{LHS of } \textcircled{*} &= \lambda P(T \leq n) = \sum_{j=1}^n \lambda P(T=j) \\ &\leq \sum_{j=1}^n E[X_j; T=j] \end{aligned}$$

$$\begin{aligned} X\text{-subm} &\Rightarrow E[X_j; T \geq j] \leq E[E[X_n | \mathcal{F}_j]; T \geq j] \\ \{T \geq j\} &\subseteq \mathcal{F}_j \Rightarrow = E[X_n; T \geq j] \end{aligned}$$

$$\text{So LHS of } \textcircled{*} \leq \sum_{j=1}^n E[X_n; T \geq j] = E[X_n; T \leq n] \leq E[X_n^+]$$

2) $\tau := \inf\{1 \leq i \leq n : X_i \leq -\lambda\}$. - stopping time.
 (inf $\emptyset = \infty$)

$$\text{so } \left\{ \min_{1 \leq i \leq n} X_i \leq -\lambda \right\} = \{\tau \leq n\}.$$

On $\tau \leq n$ have $X_\tau \leq -\lambda$ so

$$\left. \begin{aligned} E[X_\tau; \tau \leq n] &\leq -\lambda P(\tau \leq n) \\ \text{also } E[X_n; \tau > n] &\leq E[X_n^+] \end{aligned} \right\}$$

add \nearrow $E[X_{\tau \wedge n}] \leq -\lambda P(\tau \leq n) + E[X_n^+]$

$1 \leq \tau \wedge n$ a.s. \Rightarrow by Optional stopping

$$X_1 \leq E[X_{\tau \wedge n}; \mathcal{F}_1]$$

$$E X_1 \leq E \text{---} = E X_{\tau \wedge n}$$



~~Proof~~
Thm 1. Martingale c.v. thm

let X be a subm. Suppose

or i) X is bdd in $L^1(P)$

or ii) $X \leq 0$ a.s.

Then lim X_n exists a.s. & is finite a.s.

Pf 1 Like LCM, let do L^2 case, ~~then use truncation~~

non-neg, L^2 -bdd case

Let's show X_n is Cauchy, so cv on L^2 .

$X \geq 0$, L^2 -bdd, so

$$\begin{aligned} \|X_{n+k} - X_n\|_2^2 &= \|X_{n+k}\|_2^2 + \|X_n\|_2^2 - 2E[X_{n+k} X_n] \\ &\quad - 2E[E(X_{n+k} | \mathcal{F}_n) X_n] \\ &\leq \|X_{n+k}\|_2^2 - \|X_n\|_2^2 \end{aligned}$$

X^2 subm $\Rightarrow \|X_n\|_2 \nearrow \sup_n \|X_n\|_2 < \infty$ since L^2 bdd.

$\Rightarrow \{X_n\}_{n=1}^\infty$ Cauchy since in $L^2 \Rightarrow$ cv on L^2 .

let $X_\infty = L^2$ limit of X_n

To show $X_n \rightarrow X_\infty$ a.s., use Borel-Cantelli

Need $\sum_{k=1}^{\infty} P(|X_\infty - X_{n_k}| > \varepsilon) < \infty$. Might not have it. Work up a subseq. 1st.

Find n_k s.t. $\|X_\infty - X_{n_k}\|_2 \leq 2^{-k}$.

Then $\sum_{k=1}^{\infty} P(|X_\infty - X_{n_k}| > \varepsilon) \leq \frac{1}{\varepsilon^2} \sum_{k=1}^{\infty} 4^{-k} < \infty$ so $X_{n_k} \rightarrow X_\infty$ a.s.

let's show X_j w/ $n_k \leq j \leq n_{k+1}$ are close to X_{n_k} .
Consider $\max_{n_k \leq j \leq n_{k+1}} |X_j - X_{n_k}|$.

Use Doob's max'l chg. Apply to $X_j - X_{n_k} = X_{n_k+l} - X_{n_k}$
 $\{X_{n_k+l} - X_{n_k}\}_{l=0}^{\infty}$ is a martingale \Rightarrow by Doob's chg.
(combine both parts)

$$P\left(\max_{n_k \leq j \leq n_{k+1}} |X_j - X_{n_k}| > \varepsilon\right) \leq \frac{2}{\varepsilon} E|X_{n_{k+1}} - X_{n_k}| = \frac{2}{\varepsilon} E0$$

$$\leq \frac{2}{\varepsilon} \|X_{n_{k+1}} - X_{n_k}\|_2 \leq \frac{2}{\varepsilon} (\|X_{n_{k+1}} - X_\infty\|_2 + \|X_\infty - X_{n_k}\|_2) \\ \leq \frac{2}{\varepsilon} (2^{-k} + 2^{-k-1}) = \frac{3}{\varepsilon} 2^{-k}$$

Since this is summable we have by Borel-Cantelli

$$\max_{n_k \leq j \leq n_{k+1}} |X_j - X_{n_k}| \xrightarrow[k \rightarrow \infty]{} 0 \text{ a.s.}$$

Combined w/ $X_{n_k} \rightarrow X_\infty$ a.s. get $X_n \rightarrow X_\infty$ a.s.

$X_\infty \in L^2(P) \Rightarrow X_\infty$ is a.s. finite

non-positive case

If $X_n \leq 0$ subm, $\Rightarrow e^{X_n}$ is non-neg subm \Rightarrow by prev.

(case $e^{X_n} \rightarrow e^{X_\infty}$ a.s. w/ e^{X_∞} finite a.s.)

non-neg L^1 -bd case

$X_n \geq 0$, subm, $L^1(P)$ \Rightarrow by Krockenberg decomp.

$X_n = Y_n - Z_n$, Y_n - martingale, Z_n - non-neg superm.

From pt of Krickeberg $Y_n \geq 0$.

both Y_n, Z_n - L^1 -bdd

$-Y_n$ - nonpos. subm \Rightarrow by prev. step $-Y_n$ cr as. to as. finite limit.

$-Z_n$ - $\frac{1}{n}$ $\frac{1}{n}$

L^1 -bdd case

$X_n = Y_n - Z_n$ Y L^1 -bdd m, Z - non-neg L^1 -bdd

as in prev. case Z_n cr as. to as. finite limit. super-

$Y_n = Y_n^+ - Y_n^-$, Y_n^+, Y_n^- - non-neg L^1 -bdd subm \Rightarrow
by prev. done. △

Suggest reading applications of martingales
e.g. pf of Kolmogorov's 0-1 law
Lévy's Borel-Cantelli

Khintchine's law of iterated logarithms

$\{X_i\}_{i=1}^{\infty}$ iid $S_n = X_1 + \dots + X_n$

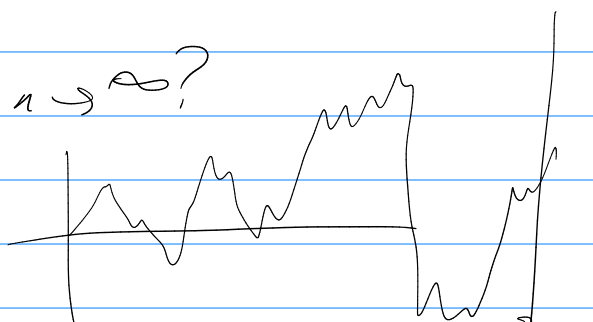
mean μ

var σ^2

How does S_n behave as $n \rightarrow \infty$?

$\frac{S_n}{n}$ a.s. $\rightarrow \mu$

$\frac{S_n - n\mu}{\sqrt{n}} \Rightarrow N(0,1)$.



So typically S_n is of order \sqrt{n}
away from the mean

(Q) How large does it get?

slow far away
down - normal

Khintchine's Law of the iterated logarithm

$\limsup_{n \rightarrow \infty} \frac{S_n}{\sqrt{2n \ln \ln n}} = 1$ a.s. (for liminf get -1)

pf on book.

Another big application - Stock market
 Option pricing
 Black-Scholes

Rademacher's thm I - any interval $\subseteq \mathbb{R}$

Defn: A fun $f: I \rightarrow \mathbb{R}$ is Lipschitz $\iff \exists \text{ const } A > 0$
 $\text{s.t. } \forall x, y \in I$
 $|f(x) - f(y)| \leq A|x - y|$

The optimal A is called the Lipschitz const of f .
 (and hence for f' .

Lipschitz \Rightarrow Cts.

diff'ble w/ cts derivative on cpt set \Rightarrow Lipschitz

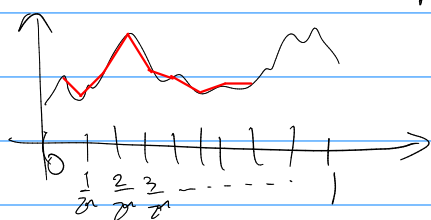
converse

In pf: if f has deriv, $f' = g$, and g int'l, then can write $f(x) - f(0) = \int_0^x g(t) dt$. Let's try to write f as such integral. If g is cts, then FundThmCalc tells us f diff'le. We won't have g diff'le, but only int'l. Lebesgue differentiation thm gives that integrals of L^1 functions are almost everywhere differentiable. What's a good candidate for g ? Take approximation of g by finite difference quotients.

Thm (Rademacher)

$\text{If } f: I \rightarrow \mathbb{R} \text{ is Lipschitz where } I \text{ is an interval, then } f \text{ is diff'le almost everywhere.}$

pf: Let $I = [0, 1]$, P - the Leb m're on $(0, 1]$, $B([0, 1])$
 P - prob m're



Divide $[0, 1]$ into 2^n parts & consider the slopes on each:

$$\frac{f((j+1)2^{-n}) - f(j2^{-n})}{(j+1)2^{-n} - j2^{-n}} \quad j \in \{0, 1, \dots, 2^n-1\}$$

Let $F_n^0 = \{ [j2^{-n}, (j+1)2^{-n}] , j \in \{0, \dots, 2^n-1\} \}$ - dyadic intervals
 $F_n = \sigma(F_n^0)$

$F = \{F_n\}_{n=1}^{\infty}$ - dyadic filtration

Given $Q \in F_n^0$, let $l(Q)$ be the left endpt
 $r(Q)$ - right -

Define $X_n(\omega) = \sum_{Q \in F_n^0} \frac{f(r(Q)) - f(l(Q))}{r(Q) - l(Q)} \mathbb{1}_Q(\omega) \quad \forall \omega \in [0, 1]$

Remark: notice that $\forall \omega \in [0, 1]$ exactly one summand is nonzero.

Remark 2: Given $w \in (0,1]$, $\{X_n(w)\}_n$ is a seq of difference quotients approximating what would be $f'(w)$.

Claim: X is a martingale wrt \mathcal{F} .

Pf: nts $E[X_n | \mathcal{F}_{n-1}] = X_{n-1}$.

Write X_n in terms of \mathcal{F}_{n-1}^0

$$X_n = \sum_{J \in \mathcal{F}_{n-1}^0} \sum_{\substack{Q \in \mathcal{F}_n^0 \\ Q \subseteq J}} \frac{f(r(Q)) - f(l(Q))}{2^{-n}} \mathbb{1}_Q(w)$$

For $Q \in \mathcal{J}$ as before sum $E[\mathbb{1}_Q | \mathcal{F}_{n-1}] = \frac{1}{2} \mathbb{1}_J$

so

$$E[X_n | \mathcal{F}_{n-1}] = \frac{1}{2} \sum_{J \in \mathcal{F}_{n-1}^0} \sum_{\substack{Q \in \mathcal{F}_n^0 \\ Q \subseteq J}} \frac{f(r(Q)) - f(l(Q))}{2^{-n}} \mathbb{1}_J(w) = X_{n-1}.$$

So X - Martingale wrt \mathcal{F} .

X -bdd \Rightarrow by w.e. thm \exists RV X_∞ st.

$X_n \rightarrow X_\infty$ almost surely & in $L^1(P)$ Δ claim

Claim: $f(x) - f(0) = \int_0^x X_\infty(w) dw \quad \forall x \in (0,1]$.

Pf: Given $x \in (0,1]$, $\exists!$ $J \in \mathcal{F}_n^0$ st. $x \in J$.

$$\text{Then } |f(x) - f(r(J))| \leq \underbrace{A|x - r(J)|}_{\text{Lipschitz const of } f} \leq \frac{A}{2^n} \quad (1)$$

$$f(r(J)) - f(0) = \sum_{\substack{L \in \mathcal{F}_n^0 \\ L \subseteq J}} (f(r(L)) - f(l(L)))$$

$$= \sum_{\substack{L \in \mathcal{F}_n^0 \\ L \subseteq J}} \int_L X_n(w) dw = \int_0^{r(J)} X_n(w) dw$$

Now $\left| \int_0^{r(J)} X_n(w) dw - \int_0^x X_n(w) dw \right| \leq \int_x^{x+2^{-n}} |X_n(w)| dw \xrightarrow[\text{by DCT}]{n \rightarrow \infty} 0 \quad (3)$

so combining (1), (2), (3) get $\lim_{n \rightarrow \infty} f(x) - f(0) - \int_0^x X_n(w) dw = 0$.

Now $\left| \int_0^x X_n(u) - X_\infty(u) du \right| \leq \int_0^x |X_n(u) - X_\infty(u)| du \leq \int_0^1 |X_n(u) - X_\infty(u)| du \rightarrow 0$
 so $f(x) - f(0) = \int_0^x X_\infty(u) du \quad \forall x \in (0, 1] \quad \triangle \text{check.}$

If X_∞ were a.s., could use the fundamental thm of calc to say f is diffble everywhere w/ $f' = X_\infty$.

Only know $X_\infty \in L^1(P)$.

Generalization of FTC, Lebesgue's differentiation thm (see pg in section 8.4) says

if $\int_0^1 |X_\infty(u)| du < \infty$, then $\lim_{\delta \downarrow 0} \frac{1}{\delta} \int_x^{x+\delta} X_\infty(y) dy = X_\infty(x)$ almost every $x \in (0, 1]$

i.e. $\frac{f(x+\delta) - f(x)}{\delta} \rightarrow X_\infty(x) \quad \text{---} \quad \triangle$

Random patterns

Let X_1, X_2, \dots be i.i.d $P(X_i = 1) = p \in (0, 1)$.
 $P(X_i = 0) = q = 1 - p$.

X_1, X_2, X_3, \dots - random slice of \mathbb{N} a.s.

Q: How long do you need to wait for the 1st 0?

$N = \inf\{k: X_1, \dots, X_k \text{ contains a } 0\}$.

$EN = ?$

More generally, for any deterministic pattern.

e.g. $P = 011001$

$N_P := \inf\{k: X_1, \dots, X_k \text{ contains the pattern } P\}$

$EN_P = ?$

Easy to check $N_P < \infty$ a.s. $\forall P$.

i.e. \forall pattern appears a.s.

E.g. $P(N_0 = j) = p^{j-1}q$ so $EN_0 = \sum_{j=1}^{\infty} j p^{j-1} q = \frac{1}{q}$

Hard to replicate even for N_{01} .

$$\text{Let } Y_n = \frac{1}{q} \mathbb{1}_{\{X_n=0\}} + \frac{1}{2} \mathbb{1}_{\{X_n=2\}} = \frac{\# \text{ Os up to } n}{q}$$

$$F_n := \sigma(X_1, \dots, X_n).$$

$$E[Y_{n+1} | F_n] = Y_n + \frac{1}{q} P(X_{n+1}=0 | F_n) = Y_n + \frac{1}{q}$$

so $\{Y_n - n/q\}_{n \geq 1}$ - mean zero martingale

\Rightarrow by the optional stopping theorem

$$E[Y_{N_{nn}} - N_{nn}/q] = 0.$$

$$\text{so } E Y_{N_{nn}} = E N_{nn} / q$$

$N \leq \infty$ a.s. & $N_{nn} \rightarrow N$ increasing

so can apply MCT, $n \rightarrow \infty$ get $E Y_N = E N / q$.

$$Y_N = \frac{1}{q} \text{ a.s. so } E N = \frac{1}{q}$$

This generalizes.

$$\text{E.g. } E N_{\frac{010}{T}} = ? \quad Z_n = \frac{1}{qpq} \mathbb{1}_{(X_{n-1}, X_n, X_{n+1})=T} + \frac{1}{qpq} \mathbb{1}_{(X_{n-1}, X_n, X_{n+1})=T} + \frac{1}{qpq} \mathbb{1}_{(X_{n-1}, X_n, X_{n+1})=T} \\ + \frac{1}{qp} \mathbb{1}_{(X_{n-1}, X_n)=(0,1)} + \frac{1}{q} \mathbb{1}_{X_n=0}.$$

$$E[Z_{n+1} - Z_n | F_n] = E \left[\frac{1}{qpq} \mathbb{1}_{(X_{n-1}, X_n, X_{n+1})=(0,1,0)} + \frac{1}{qpq} \mathbb{1}_{(X_{n-1}, X_n, X_{n+1})=(0,1,1)} + \frac{1}{qpq} \mathbb{1}_{(X_{n-1}, X_n, X_{n+1})=(1,0,1)} + \frac{1}{qp} \mathbb{1}_{(X_{n-1}, X_n)=(0,1)} + \frac{1}{q} \mathbb{1}_{X_n=0} \right. \\ \left. - \frac{1}{qp} \mathbb{1}_{(X_{n-1}, X_n)=(0,1)} - \frac{1}{q} \mathbb{1}_{X_n=0} \middle| F_n \right]$$

$$= \frac{1}{qpq} \mathbb{1}_{(X_{n-1}, X_n)=(0,1)} \underbrace{E[\mathbb{1}_{X_{n+1}=0} | F_n]}_{P(X_{n+1}=0)=q} \\ + \frac{1}{qp} \mathbb{1}_{X_n=0} \underbrace{E[\mathbb{1}_{X_{n+1}=1} | F_n]}_{P(X_{n+1}=1)=p} \\ + \frac{1}{q} \underbrace{E[\mathbb{1}_{X_{n+1}=0} | F_n]}_{P(X_{n+1}=0)=q} - \frac{1}{qp} \mathbb{1}_{(X_{n-1}, X_n)=(0,1)} - \frac{1}{q} \mathbb{1}_{X_n=0} \\ = 0.$$

so $\{Z_n - n/q\}$ - martingale of mean 0.

$$\Rightarrow E N_{010} = E Z_N = \frac{1}{2pq} + \frac{1}{q}$$

$$\text{Similarly } E N_{001} = \frac{1}{2qp} : W_n = \sum_{i=3}^n \frac{1}{2qp} \mathbb{1}_{(X_{i-2}, X_{i-1}, i) = 001} + \frac{1}{2q} \mathbb{1}_{(X_{n-1}, X_n = 00)} + \frac{1}{q} \mathbb{1}_{X_n = 0}$$

Which pattern comes first, 010 or 011?

$$P(010 \text{ before } 001) = ?$$

$Z_n - W_n$ - mean 0 martingale

Let $T = \inf\{k : X_1, \dots, X_k \text{ contains } 010 \text{ or } 011\}$.

Optional stopping of MCT $E[Z_T - W_T] = 0$.

$$Z_T - W_T = \begin{cases} \frac{1}{2pq} + \frac{1}{qp} + \frac{1}{q} - \frac{1}{q} & \text{if } 010 \text{ comes first} \\ -\left(\frac{1}{2qp} + \frac{1}{2q} + \frac{1}{q} - \frac{1}{q}\right) & \text{if } 001 \text{ comes first} \end{cases}$$

$$\text{So } E[Z_T - W_T] = \underbrace{P(010 \text{ is } A)}_S \cdot \left(\frac{1}{2pq} + \frac{1}{qp}\right) - \underbrace{P(011 \text{ is } A)}_{1-S} \left(\frac{1}{2qp} + \frac{1}{q}\right) = 0$$

$$P(010 \text{ before } 011) = S = \frac{\frac{1}{2pq} + \frac{1}{qp}}{\frac{1}{2pq} + \frac{1}{qp} + \frac{1}{2qp} + \frac{1}{qp}} = \frac{\frac{1}{p} + \frac{1}{q}}{\frac{1}{p} + \frac{1}{q} + \frac{1}{p} + \frac{1}{q}} = \frac{q+p^2}{q+p^2+p+pq} = \frac{p^2-p+1}{p^2-p+1}$$