

29/6/2015

9 am

Prof. Gopal Basak

Probability Theory - Lecture 1

Let Ω be the sample space and $\mathcal{A}$ be the power set of Ω

Then probability is a set function s.t.
 $P: \mathcal{A} \rightarrow \mathbb{R}^+$ satisfying

(i) $P(\emptyset) = 0$ $P(\Omega) = 1$

(ii) $A \subseteq B \Rightarrow P(A) \leq P(B)$ where $A, B \in \mathcal{A}$

(iii) For $\{A_n\}_{n \geq 1} \in \mathcal{A}$
 $P(\cup A_n) = \sum_{n \geq 1} P(A_n)$ whenever $\{A_n\}$ are disjoint.

Q.1. Verify that the quadruplet $\{a, b, c, d\}$ satisfy the probability condition where

$$\begin{aligned} \Omega &= \{HH, HT, TH, TT\} \\ \mathcal{A} &= \{ \{HH\}, \{HT\}, \{TH\}, \{TT\}, \dots \} \end{aligned}$$

$\downarrow$
 $a \geq 0$

$\downarrow$
 $b \geq 0$

$\downarrow$
 $c \geq 0$

$\downarrow$
 $d \geq 0$

s.t. $a+b+c+d = 1$.

Independence

If $(\Omega, \mathcal{A}, P)$ is a probability space,
 For $A, B \in \mathcal{A}$, A & B are independent if
 $P(A \cap B) = P(A) P(B)$.

The assignment

$$a = pq$$

$$b = p(1-q)$$

$$c = (1-p)q$$

$$d = (1-p)(1-q)$$

is a generalised way of assignment of probabilities in 2 coin toss case.

where $p =$ Probability of first coin being head
 $q =$ " " " second " "

σ -field

Let Ω be the whole set
Then a collection of subsets $\mathcal{A}$ is called

a σ -field if

(i) $\emptyset, \Omega \in \mathcal{A}$

(ii) $A \in \mathcal{A} \Rightarrow A^c \in \mathcal{A}$

(iii) $\{A_n\}_{n=1}^{\infty} \in \mathcal{A}$ then $\bigcup_{n=1}^{\infty} A_n \in \mathcal{A}$ & $\bigcap_{n=1}^{\infty} A_n \in \mathcal{A}$

eg. 1. $\{\emptyset, \Omega\}$

2. $\{\emptyset, A, A^c, \Omega\}$.

3. If A & B are given, then partition them into disjoint sets $\{A \setminus B, B \setminus A, A \cap B, (A \cup B)^c\}$ and then use this partition.

Q.2. Let $\{A_1, \dots, A_k\}$ be the partition of Ω . Then find the σ -field generated by $\{A_1, \dots, A_k\}$.

Defn: Let C be a collection of subsets of Ω . Then σ -field generated by C means $\bigcap_{A \in C} A$ and is denoted by $\sigma(C)$.

Q.3. σ -field is either finite or uncountable.

Properties

(a) Let A_1 & A_2 be two σ -fields. Then $A_1 \cap A_2$ is a σ -field but $A_1 \cup A_2$ need not be.

(b) Let $\{A_n\}$ be the sequence of σ -fields s.t. $A_n \subseteq A_{n+1} \forall n \geq 1$. Then $\bigcup_{n \geq 1} A_n$ need not be a σ -field even though countable unions are σ -fields.

eg. $A_n = \sigma\left(\left(0, \frac{1}{2^n}\right], \left(\frac{1}{2^n}, \frac{2}{2^n}\right], \dots, \left(\frac{2^n-1}{2^n}, 1\right]\right)$

then $\{1\} \notin A_i$ for any $i \therefore \{1\} \notin \bigcup_{n \geq 1} A_n$
 But $\{1\} = \bigcap_{n \geq 1} \left(\frac{2^n-1}{2^n}, 1\right]$

and hence should belong to $\bigcup_{n \geq 1} A_n$ if $\bigcup_{n \geq 1} A_n$ is a σ -field.

Altm: A is an atom if for any $B \in \mathcal{A}$ & $B \subseteq A$
 then $B = A$ or $B = \emptyset$.

eg. $\Omega = \{1, 2, \dots\}$
 $\mathcal{A}_n = \sigma(\{1\}, \{2\}, \dots, \{n\})$

Then set of odd nos. $\notin \bigcup_{n \in \mathbb{N}} \mathcal{A}_n$

& hence $\bigcup_{n \in \mathbb{N}} \mathcal{A}_n$ is not a σ -field.

Borel σ -field

It is the σ -field generated by open sets

Consider $\mathcal{A} = \sigma(\{[a, b] : a, b \text{ rationals}\})$.

Atoms are all singletons.

Let $\mathcal{A}_\mathbb{Q} = \sigma$ -field generated by singletons in $\mathbb{R}$
 $= \{\text{all countable \& co-countable subsets in } \mathbb{R}\}$.

eg. (i) $P([a, b]) = b - a$

(ii) $P([a, b]) = \int_a^b f(x) dx$

for any $f \geq 0$ & $\int_a^b f(x) dx < \infty$
 for any $a, b \in \mathbb{R}$

These are examples where measure at a point is 0 but measure in an interval is non-zero.

For probability, $\int_a^b f(x) dx = 1$.

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2 p.m

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Probability Theory - Lecture 2

Q.5. $\mathcal{C} = \{A_1, A_2, \dots\}$

Then $\sigma(\mathcal{C})$ contains an atom which is given by $\{\bigcap_{i \geq 1} D_i : D_i = A_i \text{ or } A_i^c\}$.

Consider $\mathcal{C} = \{\text{finite disjoint union of } (a_i, b_i], a_i, b_i \in \mathbb{R}\}$

Then $P(\bigcup_i (a_i, b_i]) = \sum_i \int_{a_i}^{b_i} f(x) dx$.

Then $\mathcal{C}$ is a field, i.e.

- (i) $\emptyset, \Omega \in \mathcal{C}$
- (ii) $A \in \mathcal{C} \Rightarrow A^c \in \mathcal{C}$
- (iii) $A, B \in \mathcal{C} \Rightarrow A \cap B \in \mathcal{C}$
 $\& A \cup B \in \mathcal{C}$

(the only point of difference with σ -field being the non-existence of countable union in field).

$F(b) \rightarrow 1$ as $b \rightarrow \infty$

$\& F(a) \rightarrow 0$ as $a \rightarrow -\infty$

i.e. $\forall \epsilon > 0, \exists a, b \in \mathbb{R}$ s.t.
 $1 - F(b) < \epsilon$
 $\& F(a) < \epsilon$

Step 1: First we need to show that P is countably additive on $\mathcal{C}$.

Step 2: Extend P to monotone limits of $\mathcal{C}$, say

$$\mathcal{G} = \left\{ A : A = \lim A_n \text{ whenever } A_n \uparrow A \text{ or } A_n \downarrow A \text{ for } \{A_n\} \in \mathcal{C} \right\}.$$

Step 3: $P^*(A) = \inf \left\{ P\left(\bigcup_{i=1}^{\infty} A_i\right) : \bigcup_{i=1}^{\infty} A_i \supseteq A \text{ and } \bigcup_{i=1}^{\infty} A_i \in \mathcal{G} \right\}.$

(i) P^* is countably subadditive.
(i.e. P^* of union $\leq$ sum of P^*).

(ii) $P^*|_{\mathcal{C}} = P$
or
 $\mathcal{G}$

(iii) $P^*(A \cup A^c) = P^*(A) + P^*(A^c) \stackrel{?}{=} 1$

Q6. Show that if $\mathcal{M}$ is a monotone class containing $\mathcal{G}$, then $\sigma(\mathcal{G}) \subseteq \mathcal{M}$.

Step 4: Consider $\mathcal{F} = \{ A \subseteq \Omega : P^*(A) + P^*(A^c) = 1 \}.$

Show that $\mathcal{F}$ is a field.

Step 5 : p^* is finite additive on $\mathcal{Y}$.

Step 6 : p^* is countably additive on $\mathcal{F}$

Step 7 : $\mathfrak{F}$ is a σ -field and hence $\sigma(\mathcal{E}) \subseteq \mathfrak{F}$.

Step 8 : $|S| > |R| \quad |S(0)| = |R|$

If $A \in \mathcal{F}$ & $P^*(A) = 0$ then $B \in \mathcal{F}$ for any $B \subseteq A$ & $P^*(B) = 0$

$$|g| \geq |R| \quad \& \quad |\sigma(B)| = |R|$$

$\therefore |Z| = 2^{|R|}$ ($\because$ there is nothing in between $|R|$ & $2^{|R|}$)

[illegible]

We keep doing this till ~~β~~ where ~~β~~ α
 α being the first uncountable ordinal)

Then $\bigcap_{\beta \in \mathcal{A}} \mathcal{O}(\mathcal{C}_\beta) = \mathcal{O}(\mathcal{C})$ is the smallest $\sim$ -field.

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Probability Theory - Lecture 3

$$P(A) = \int_A dP = \int_{\Omega} 1_A dP$$

$$\text{If } f = \sum_{i=1}^n c_i 1_{A_i} = \begin{cases} c_i & \text{if } x \in A_i \end{cases}$$

Then, $\int_{\Omega} f dP = \int_{\Omega} \sum_{i=1}^n c_i 1_{A_i} dP$

$$= \sum_{i=1}^n c_i \int_{\Omega} 1_{A_i} dP$$

$$= \sum c_i P(A_i)$$

Measurable functions

Let $(\Omega, \mathcal{F}, P)$ be a probability space.

$$\text{If } f: \Omega \rightarrow \mathbb{R}$$

$$\text{If } f^{-1}(B) \in \mathcal{F} \quad \forall B \in \mathcal{B}(\mathbb{R})$$

Then f is called a measurable function

But showing for every Borel set is difficult

$\therefore$ Consider $\mathcal{C} = \{B \in \mathcal{B}(\mathbb{R}) : f^{-1}(B) \in \mathcal{F}\}$
and show that $\mathcal{C}$ is a σ -field.

$$\emptyset, \Omega \in \mathcal{C}$$

$$A \in \mathcal{C} \Rightarrow f^{-1}(A^c) = [f^{-1}(A)]^c \in \mathcal{F} \Rightarrow A^c \in \mathcal{C}$$

$$f^{-1}\left(\bigcup_n A_n\right) = \bigcup_n f^{-1}(A_n) \in \mathcal{F}$$

$$\Rightarrow \bigcup_n A_n \in \mathcal{G}$$

$$f^{-1}\left(\bigcap_n A_n\right) = \bigcap_n f^{-1}(A_n) \in \mathcal{F}$$

$$\Rightarrow \bigcap_n A_n \in \mathcal{G}$$

$\therefore \mathcal{G}$ is a σ -field.

But $\mathcal{G} \subseteq \mathcal{B}(\mathbb{R})$

$$\text{Also } \{(-\infty, x] : x \in \mathbb{R}\} \subseteq \mathcal{G}$$

$$\therefore \sigma\{(-\infty, x] : x \in \mathbb{R}\} \subseteq \sigma(\mathcal{G}) = \mathcal{G}$$

$$\Rightarrow \mathcal{B}(\mathbb{R}) = \mathcal{G}$$

$\therefore$ Checking for measurability reduces to checking if $f^{-1}(-\infty, x] \in \mathcal{F} \quad \forall x \in \mathbb{R}$.

Let f be a measurable function, $f \geq 0$.

Define $\int_{\Omega} f dP = \sup \left\{ \int_{\Omega} s dP : 0 \leq s \leq f, s \text{ being a simple function} \right\}$

Defn: Simple functions are those that take finitely many values on partitions of Ω .

$$Q. \int_{\Omega} (f+g) dP = \int_{\Omega} f dP + \int_{\Omega} g dP \quad \text{wherever they are defined.}$$

$$\int_{\Omega} c f dP = c \int_{\Omega} f dP$$

Case 1: Let $f \geq 0$ be a measurable function & bounded.

Define

$$f_n = \begin{cases} \frac{k-1}{2^n} & , \frac{k-1}{2^n} \leq f(x) < \frac{k}{2^n} \\ n & , f(x) \geq n \end{cases}$$

$$\therefore \int_{\Omega} f_n dP = \sum_{k=1}^{n2^n} \frac{k-1}{2^n} P\left(f^{-1}\left[\frac{k-1}{2^n}, \frac{k}{2^n}\right]\right) + n P(f^{-1}[n, \infty)).$$

Then $f_n \uparrow$ in n
 & $f - f_n \leq \frac{1}{2^n} \rightarrow 0$ for large enough n
 $n > \sup |f(x)|$

Case 2 : Let f be a measurable function & f need not be bounded.

Let $f_M = f \wedge M$ where $M \geq 0$ is a constant.

For each n ,
 $|f_M - f| \rightarrow 0$ as $M \rightarrow \infty$

$$\therefore \int f_n dP \rightarrow \int f dP$$

Monotone Convergence Theorem

Q. Let $f_n \geq 0$ be measurable functions.
 Show that (i) f is measurable.
 (ii) $\limsup f_n$ & $\liminf f_n$ are measurable.
 (iii) Limit (if exists) is measurable.

Let $f_n \geq 0$ be measurable function & $f_n \uparrow f$. Then

$$\int f dP = \lim_{n \rightarrow \infty} \int f_n dP$$

Case 3 : For f measurable,
 take $f = f^+ - f^-$

$$f^+ = (f \vee 0)$$

$$f^- = (-f \vee 0)$$

Now $\int f dP = \int f^+ dP - \int f^- dP$ whenever at least one of the integrals in RHS is finite.

Fatou's Lemma

If $f_n \geq 0$ are measurable

$$\text{Then } \liminf \int f_n dP \geq \int (\liminf f_n) dP$$

$$\lim_{n \rightarrow \infty} \int f_n = \sup_{n \geq 1} \left(\inf_{k \geq n} \int f_k \right)$$

Note: $f_k \leq f_n \quad \forall n \geq k$
 $\therefore \int f_k dP \leq \int f_n dP \quad \forall n \geq k$

Now, $\lim_{k \rightarrow \infty} \int f_k dP = \int \left(\lim_{k \rightarrow \infty} f_k \right) dP$
 $= \int \left(\lim_{k \rightarrow \infty} \inf_{n \geq k} f_n \right) dP$

$$\therefore \int f_k dP \leq \inf_{n \geq k} \int f_n dP$$

$$\Rightarrow \lim_{k \rightarrow \infty} \int f_k dP \leq \lim_{k \rightarrow \infty} \inf_{n \geq k} \int f_n dP$$

$$\Rightarrow \int \left(\lim_{k \rightarrow \infty} \inf_{n \geq k} f_n \right) dP \leq \lim_{k \rightarrow \infty} \int \inf_{n \geq k} f_n dP$$

Dominated Convergence Theorem

If $|f_n| \leq g$ & $f_n \rightarrow f$ all measurable
 & g is integrable (i.e. $\int |g| dP < \infty$)
 Then

(i) $\int f_n dP \rightarrow \int f dP$

(ii) $\int |f_n - f| dP \rightarrow 0$

Expectations

Let $(\Omega, \mathcal{F}, P)$ be a probability space

Define a random variable $X: \Omega \rightarrow \mathbb{R}$

Then $E[X] = \int_{\Omega} X dP$

& $E[X^2] = \int_{\Omega} X^2 dP$ whenever they exist

Consider $(P \circ X^{-1})((-\infty, x])$

$$= P(X^{-1}(-\infty, x])$$

$$= P(\omega: X(\omega) \leq x)$$

$$= P(X \leq x) = F(x)$$

This $F(x)$ is called the distribution function.

Properties of distribution function

(i) F is right continuous

(ii) F is non-decreasing

(iii) $F(x) \rightarrow 1$ as $x \rightarrow \infty$

& $F(x) \rightarrow 0$ as $x \rightarrow -\infty$

$$\begin{aligned} \int_{\Omega} X(\omega) dP &= \int_{\mathbb{R}} x d(P \circ X^{-1})((-\infty, x]) \\ &= \int_{\mathbb{R}} x dF(x). \end{aligned}$$

Bounded Variation

A function $f : \mathbb{R} \rightarrow \mathbb{R}$ is said to have BV property on $[a, b]$ if

$$\sup_{\{t_i\}} \sum_{i=1}^n |f(t_i) - f(t_{i-1})| < \infty$$

$a = t_0 < t_1 < \dots < t_n = b$

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Probability Theory - Lecture 4Absolutely continuous functions

$$\forall \varepsilon > 0, \exists \delta > 0 \text{ s.t. } \sum_{j=1}^n (t_j - t_{j-1}) < \delta$$

$$\Rightarrow \sum_{j=1}^n |f(t_j) - f(t_{j-1})| < \varepsilon$$

where $t_0 < t_1 < \dots < t_n$ Absolutely Continuous functions $\Rightarrow$ Bounded variation.

Q. Check whether $|V|$ is absolutely continuous or not.

Q. Check where $f(x) = \begin{cases} \sqrt{|x|} \sin \frac{1}{x} & x \neq 0 \\ 0 & x = 0 \end{cases}$ is absolutely continuous on $(-\frac{\pi}{2}, \frac{\pi}{2})$.

Conditional ExpectationLet $(\Omega, \mathcal{F}, P)$ be the probability space. $\mathcal{G}$ is a σ -field s.t. $\mathcal{G} \subseteq \mathcal{F}$

Consider $\min_{f \text{ is } \mathcal{G}\text{-measurable}} E[X - f]^2$ s.t. $E[f] = E[X]$

Then arg min $f = E[X|g]$

where

$$\int_A E(X|g) dP = \int_A X dP \quad \forall A \in \mathcal{G}$$

Proof: $E[X - E(X|g)]^2 = E[X - f + f - E(X|g)]^2$
 $= E[X - f]^2 + E[f - E(X|g)]^2$
 $+ 2E[(X - f)(f - E(X|g))]$

$$E[(X - f)(f - E(X|g))] = E[E[(X - f)(f - E(X|g)) | g]]$$

Since f $\mathcal{G}$ -measurable & $h \in \mathcal{G}$ measurable $\Rightarrow$
 $E[fh|g] = f E[h|g]$

$\therefore$ We get

$$E[(X - f)(f - E(X|g))] = E[(f - E(X|g)) E[(X - f)|g]]$$

$$= E[f - E(X|g)]^2$$

$$\therefore E[X - E(X|g)]^2 = E[X - f]^2 - E[f - E(X|g)]^2$$

$$\leq E[X - f]^2$$

$$\text{let } \mathcal{G} = \{\emptyset, \Omega\}$$

Then $E(X|\mathcal{G}) = E(X)$ a.s.

& only measurable functions of $\mathcal{G}$ are constants.

$$\begin{aligned} c P(\Omega) &= \int_{\Omega} c dP = \int_{\Omega} E(X|\mathcal{G}) dP \\ &= \int_{\Omega} X dP \\ &= E[X] \end{aligned}$$

$$\therefore c = E[X].$$

$$\text{let } X = 1_A$$

$$\int_{\Omega} E(X|\mathcal{G}) dP = \int_{\Omega} X dP$$

$$\text{let } \mathcal{G} = \{\emptyset, B, B^c, \Omega\}$$

$$f = \begin{cases} c_1 & \text{on } B \\ c_2 & \text{on } B^c \end{cases}$$

$$\text{let } X = 1_A$$

$$\int_B E(X|\mathcal{G}) dP = \int_B X dP = \int_B 1_A dP = \int_B 1_A 1_B dP = \int 1_{A \cap B} dP$$

$$\begin{aligned} \int_B (c_1 1_B + c_2 1_{B^c}) dP &= c_1 P(B \cap B) + c_2 P(B \cap B^c) \\ &= c_1 P(B) = P(A \cap B) \end{aligned}$$

$$\Rightarrow c_1 P(B) = P(A \cap B)$$

$$\Rightarrow c_i = P(A|B)$$

$$\therefore E(X|g) = \begin{cases} P(A|B) & \text{for } \omega \in B \\ P(A|B^c) & \text{for } \omega \in B^c \end{cases}$$

In general, if $g = \sigma(\{B_n\})$ where $\{B_n\}$ are partitions of Ω .

Then $f(\omega) = c_n$ on $\omega \in B_n$ are the only measurable functions.

Now, if X is a simple function,

$$X = \sum_i a_i 1_{A_i}$$

$$\Rightarrow E[X|g] = \sum a_i E[1_{A_i}|g]$$

$$= \sum a_i P(A_i | B_n) \text{ for } \omega \in B_n. \\ \text{a.s.}$$

$$\begin{aligned} \Rightarrow E[X|B_n] &= \frac{\sum a_i \int_{B_n} 1_{A_i} dP}{P(B_n)} \\ &= \frac{\int_{B_n} X dP}{P(B_n)} \end{aligned}$$

For non-negative X , take over simple functions
 For general X , write $X = X^+ - X^-$

Martingales

Let $\{X_n\}_{n \geq 0}$ be a sequence of random variables on $(\Omega, \mathcal{F}, P)$ satisfying

$$(i) \ E(|X_n|) < \infty \quad \forall n$$

$$(ii) \ E(X_{n+1} | X_0, \dots, X_n) = X_n$$

Then $\{X_n\}$ is called a martingale

Filtrations

$$\mathcal{F}_1 = \sigma(X_1) \subseteq \mathcal{F}$$

$$\mathcal{F}_2 = \sigma(X_1, X_2) = \sigma(X_1^{-1}(B_1) \cap X_2^{-1}(B_2) : B_1, B_2 \in \mathcal{B}(\mathbb{R}))$$

Then choosing $B_2 = \Omega$ gives elements sets from $\sigma(X_1)$

& choosing $B_1 = \Omega$ gives from $\sigma(X_2)$

$$\therefore \mathcal{F}_1 \subseteq \mathcal{F}_2 \subseteq \mathcal{F}_3 \subseteq \dots$$

Q. Show that if $S_n = X_0 + \dots + X_n$, $P(X_i = 1) = p$ & $P(X_i = -1) = 1-p$
 Then $\{S_n\}$ is a martingale w.r.t $\mathcal{F}_n = \sigma(X_0, \dots, X_n)$
 when $p = q = \frac{1}{2}$.

Q. $W_n = S_n^2 - n$

Then $\{W_n\}$ is a martingale w.r.t $\{\mathcal{F}_n\}$

Q. $Z_n = \left(\frac{q}{p}\right)^{S_n} \quad p \neq q$

Then Z_n is a martingale w.r.t $\{\mathcal{F}_n\}$

Q. $Y_n = S_n - n(p-q)$ is a martingale w.r.t $\{\mathcal{F}_n\}$.

Q. $H_n = \exp\left\{S_n - \frac{n\sigma^2}{2}\right\}$ where $X_i \sim N(0, \sigma^2)$.

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Probability Theory - Lecture 5

$E(X|G)$ is the best (mean square deviation sense) estimator of X given the info of G .

$\{X_n\}_{n \geq 0}$ is a martingale w.r.t $\{\mathcal{F}_n\}$, a filtration if it satisfies (i) $E|X_n| < \infty \quad \forall n$
(ii) $E(X_{n+1} | \mathcal{F}_n) = X_n$

Here, $\{\mathcal{F}_n\}$ is an increasing sequence of σ -fields
& X_n is measurable w.r.t $\mathcal{F}_n$
 $\therefore X_0$ measurable w.r.t $\mathcal{F}_0$
 X_1 " " $\mathcal{F}_1$
 $\vdots$ " " $\mathcal{F}_k$
 X_k " " $\mathcal{F}_k$

But $\mathcal{F}_0 \subseteq \mathcal{F}_1 \subseteq \dots \subseteq \mathcal{F}_k \subseteq \dots$

$\therefore X_0$ measurable w.r.t $\mathcal{F}_0, \mathcal{F}_1, \dots, \mathcal{F}_k$

eg. $\{S_n\}$ is a simple random walk

$$P(X_i = +1) = p, \quad \text{and}$$

$$P(X_i = -1) = 1-p.$$

$$S_n = X_0 + \dots + X_n$$

~~(1) (2) (3)~~

where $X_0 = c$

$$(i) E|S_n| \leq E|X_0| + \dots + E|X_n| \\ = c + n < \infty \quad \text{for each } n.$$

$$(i) E(S_{n+1} | X_0, \dots, X_n) = E(S_n + X_{n+1} | \mathcal{F}_n).$$

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

$\bullet$ $S_n + 0$ (in first part, S_n is measurable w.r.t $\mathcal{F}_n$. So it comes out of expectation & X_{n+1} . In second part X_{n+1} is independent of $\mathcal{F}_n$.)

$$\therefore E(X_{n+1} | \mathcal{F}_n) = E(X_{n+1}) = 0.$$

$$= S_n.$$

eg. $Z_n = \left(\frac{q}{p}\right)^{S_n}$

$$(i) E|Z_n| = E\left(\frac{q}{p}\right)^{X_0 + \dots + X_n}$$

$$= \left(\frac{q}{p}\right)^c E\left(\frac{q}{p}\right)^{X_1} \dots E\left(\frac{q}{p}\right)^{X_n}$$

Now $E\left(\frac{q}{p}\right)^{X_1} = \left(\frac{q}{p}\right)^1 p + \left(\frac{q}{p}\right)^{-1} q$

$$= q + p$$

$$\therefore E|Z_n| = \left(\frac{q}{p}\right)^c$$

$$(ii) E(Z_{n+1} | \mathcal{F}_n) = E\left[\left(\frac{q}{p}\right)^{S_{n+1}} | \mathcal{F}_n\right].$$

$$\begin{aligned}
&= E \left[\left(\frac{q}{p} \right)^{S_n + X_{n+1}} \mid \mathcal{F}_n \right] \\
&= E \left[\left(\frac{q}{p} \right)^{S_n} \left(\frac{q}{p} \right)^{X_{n+1}} \mid \mathcal{F}_n \right] \\
&= \left(\frac{q}{p} \right)^{S_n} E \left[\left(\frac{q}{p} \right)^{X_{n+1}} \mid \mathcal{F}_n \right] \\
&= \left(\frac{q}{p} \right)^{S_n} E \left[\left(\frac{q}{p} \right)^{X_{n+1}} \right] \\
&= \left(\frac{q}{p} \right)^{S_n} \\
&= Z_n
\end{aligned}$$

Gambler's Ruin

Start with Rs 20

$$P(\text{win}) = p$$

$$P(\text{lose}) = 1-p$$

$X_i = \pm 1$ in the i^{th} game

We want to know if we reach Rs 100 before reaching Rs 0.

ie if τ is a stop time, then we want to find

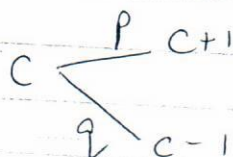
$$\phi(20) = P_{20}(\tau_{100} < \tau_0).$$

τ is a stopping time if $\tau: \Omega \rightarrow \{0, 1, \dots, \infty\}$ satisfying $\{\tau \leq n\} \in \mathcal{F}_n$.

Generalising this,

$$\phi(c) = P_c(\tau_b < \tau_a) \quad a < c < b.$$

~~$\phi(c)$~~



$$\Rightarrow \phi(c) = p \phi(c+1) + q \phi(c-1)$$

$$\Rightarrow p[\phi(c+1) - \phi(c)] = q[\phi(c) - \phi(c-1)]$$

We solve this difference equation using boundary conditions

$$\phi(a) = 0$$

$$\phi(b) = 1.$$

Doob Optional Stopping time

Let $\{Y_n\}$ be a martingale w.r.t $\{\mathcal{F}_n\}$ & τ be a stopping time w.r.t $\{\mathcal{F}_n\}$.

Then $E[Y_\tau] = E[Y_0]$ or

$$E[Y_\tau | \mathcal{F}_0] = Y_0$$

provided

(i) $P(\tau < \infty) = 1$

(ii) $E|Y_\tau| < \infty$

(iii) $E(Y_m | \tau > m) \rightarrow 0$ as $m \rightarrow \infty$

Consider $E(Y_{n+1} | \mathcal{F}_n) = Y_n$

$$\Rightarrow E[E(Y_{n+1} | \mathcal{F}_n) | \mathcal{F}_{n-1}] = E(Y_n | \mathcal{F}_{n-1})$$

$$\Rightarrow E[Y_{n+1} | \mathcal{F}_{n-1}] = Y_{n-1}$$

$$E[Y_{n+1} | \mathcal{F}_0] = Y_0$$

Q. Show that hypothesis of Doob's OST holds for Gambler's ruin.

$$\text{If } p = q = \frac{1}{2}, \text{ use } X_n = S_n$$

$$\tau = \tau_a \wedge \tau_b$$

$$\begin{aligned} \text{Then } c = E_c(S_\tau) &= a P_c(\tau_a < \tau_b) + b P_c(\tau_b < \tau_a) \\ &= a(1 - P_c(\tau_b < \tau_a)) + b P_c(\tau_b < \tau_a) \\ &= (b-a) P_c(\tau_b < \tau_a) + a \end{aligned}$$

$$\Rightarrow P_c(\tau_b < \tau_a) = \frac{c-a}{b-a}$$

$$\text{If } p \neq q, \text{ we use } Y_n = Z_n = \left(\frac{q}{p}\right)^{S_n}$$

$$E_c(Z_\tau) = \left(\frac{q}{p}\right)^c$$

$$\Rightarrow \left(\frac{q}{p}\right)^a P_c(\tau_a < \tau_b) + \left(\frac{q}{p}\right)^b P_c(\tau_b < \tau_a) = \left(\frac{q}{p}\right)^c$$

$$\Rightarrow P_c(\tau_b < \tau_a) = \frac{\left(\frac{q}{p}\right)^c - \left(\frac{q}{p}\right)^a}{\left(\frac{q}{p}\right)^b - \left(\frac{q}{p}\right)^a}$$

If $E[Y_{n+1} | \mathcal{F}_n] \geq Y_n$
 $\{Y_n\}$ is called submartingale

If $E[Y_{n+1} | \mathcal{F}_n] \leq Y_n$
 $\{Y_n\}$ is called supermartingale

Properties

1. If $\{Y_n\}$ is a martingale w.r.t $\{\mathcal{F}_n\}$ & ϕ is a convex function, then $\{\phi(Y_n)\}$ is a submartingale w.r.t $\{\mathcal{F}_n\}$ provided $\phi(Y_n)$ is properly defined & $E|\phi(Y_n)| < \infty$.

Similarly
 Concave functions give supermartingale.

2. Let $\{Y_n\}$ be a martingale w.r.t $\{\mathcal{F}_n\}$ & $\{A_n\}$ be a predictable sequence, i.e. A_n is measurable w.r.t $\mathcal{F}_{n-1}$.

Define $X_n = Y_n - Y_{n-1}$ (called martingale difference sequence)

Then $Z_n = \sum_{k=1}^n A_k X_k$ is a martingale w.r.t $\{\mathcal{F}_n\}$

provided $E[A_k] < \infty$.

→ This can be considered as a discrete space integration where X_k denotes the difference.

Doob - Meyer Decomposition

Let $\{H_n\}$ be a submartingale w.r.t $\{\mathcal{F}_n\}$. Then $\exists \{A_n\}$ an increasing predictable, integrable sequence s.t.

$H_n - A_n = M_n$ is a martingale

i.e. $H_n = M_n + A_n$ and the decomposition is unique with $A_0 = 0$

$(A_n = \sum_{k=1}^n (E(H_k | \mathcal{F}_{k-1}) - H_{k-1}))$ works)

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Submartingale convergence theorem

Let $\{Y_n\}$ be a submartingale w.r.t $\{\mathcal{F}_n\}$ &

$$\sup_n E(|Y_n|) < \infty$$

Then $\exists Y_\infty$ s.t. $Y_n \rightarrow Y_\infty$ as $n \rightarrow \infty$ q.s.
s.t. $E(|Y_\infty|) < \infty$.

If $E[Y_n] \rightarrow E[Y_\infty]$, then $E|Y_n - Y_\infty| \rightarrow 0$.

If $\{Y_n\}$ is a martingale itself then
 $Y_n = E(Y_\infty | \mathcal{F}_n)$ q.s.

1/7/2015

2 p.m

Prof. Gopel Ba

Probability Theory - Lecture 6

Markov Processes

$\{X_n\}_{n \in \mathbb{N}}$ is a discrete time process
 $\{X_t\}_{t \in T}$ is a continuous time process.

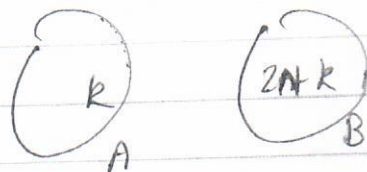
A stochastic process $\{X_n\}_{n \geq 0}$ is called a Markov chain if

$$P(X_{n+1} = x_{n+1} \mid X_0 = x_0, \dots, X_n = x_n) = P(X_{n+1} = x_{n+1} \mid X_n = x_n) \\ \forall x_0, \dots, x_0, x_{n+1} \\ \text{whenever } P(X_0 = x_0, \dots, X_n = x_n) > 0.$$

Transition is homogeneous if
$$P(X_{n+1} = y \mid X_n = x) = P(X_1 = y \mid X_0 = x) \quad \forall n$$

eg. Let S be the state space of a Markov chain and it is finite.

$$S = \{0, 1, \dots, 2N\}$$



Let $X_n = N_A$ of molecules in A at time n.

~~If a molecule~~ The experiment is to randomly pick a molecule. If it is in A, then transfer it to B. If it is in B, then transfer it to A.

$$\therefore P(X_{n+1} = y | X_n = x) = \begin{cases} \frac{2N - x}{2N} & , y = x+1 \\ \frac{x}{2N} & , y = x-1 \\ 0 & , \text{otherwise.} \end{cases}$$

If π is the equilibrium distribution of this transition matrix & then the k -step transition matrix is P^k

Then $\frac{1}{n+1} \sum_{k=0}^n P^k \longrightarrow \begin{bmatrix} \leftarrow \pi \rightarrow \\ \leftarrow \pi \rightarrow \\ \vdots \\ \leftarrow \pi \rightarrow \end{bmatrix}$

$$\& \pi P = \pi$$

$$\Rightarrow \pi_j = \sum_i \pi_i P_{ij}$$

π is that distribution that makes X_i -distribution the same $\forall i$ if π is X_0 -distribution.

$$\begin{aligned} P(X_1 = j) &= \sum_i P(X_1 = j, X_0 = i) \\ &= \sum_i P(X_0 = i) P(X_1 = j | X_0 = i) \\ &= \sum_i \pi_i P_{ij} \\ &= \pi_j \end{aligned}$$

Hence π is also called stationary / invariant distribution

Theorem : Let $\{X_n\}$ be an irreducible Markov Chain on a finite state space with period 1.

Then $p_{ij}^{(n)} \rightarrow \pi_j$ as $n \rightarrow \infty$

Period : $d(i) = \gcd \{n : p_{ii}^{(n)} > 0\}$.

If $i \leftrightarrow j$, then $d(i) = d(j)$. Thus for an irreducible Markov chain, there is only one period.

The reason why we took average in the previous example was that the Markov chain had period 2.
 $\therefore p_{ii}^{(n)}$ does not converge.

But the average will always converge.

For a simple random walk,

$$\sum_{n=0}^{\infty} p_{00}^{(n)} = \infty$$

$$\text{iff } p = q = \frac{1}{2}$$

Called recurrent

$$< \infty$$

$$\text{iff } p \neq q$$

Called transient,

In an irreducible chain, all classes have similar properties.

Let $E_i(\tau_i)$ be the expected time to come to state i starting from i .

If $E_i(\tau_i) < \infty \rightarrow$ positive recurrent
 $= \infty \rightarrow$ null recurrent.

In a random walk with $p=q = \frac{1}{2}$

$$\sum_{n=0}^m P_{00}(2n) = \sum_{n=0}^m \binom{2n}{n} p^n q^n$$

By Sterling approx

$$= \sum_{n=0}^m \binom{2n}{n} \left(\frac{1}{2}\right)^{2n} \approx \sum_{n=0}^m \frac{1}{\sqrt{\pi n}} = \infty$$

In the continuous^{state} sense, then $\{X_n\}$ is called irreducible if $\forall (x, y)$ in $S \times S$, $\exists n$ s.t.
 $p^n(x, y) > 0$ where $p(x, y)$ is the density (note: not probability).

$$p^2(x, y) = \int_S p(x, z) p(z, y) dz.$$

In continuous time, Markov property is

$$P(X_t \in U \mid X_{\tau_1} \in U_{\tau_1}, \dots, X_{\tau_k} \in U_{\tau_k}, \tau_1 < \tau_2 < \dots < \tau_k) \\
= P(X_t \in U \mid X_{\tau_k} \in U_{\tau_k})$$

whenever $P(X_{\tau_i} \in U_{\tau_i}, i=1, \dots, k) > 0$
 $\forall \tau_1 < \dots < \tau_k, k \geq 1$

$\therefore$ If X_s is measurable w.r.t $\mathcal{F}_s$,
then $E(f(X_t) \mid \mathcal{F}_s) \text{ s.t. } s < t$

Markov property. $= E(f(X_t) \mid \sigma(X_s))$. if $\{X_s\}$ follows

where $\mathcal{F}_s = \sigma(X_u : 0 \leq u \leq s)$.

Brownian Motion
 $\{B_t\}_{t \geq 0}$ is a Brownian Motion if

(i) $t \rightarrow B_t$ is continuous.
 $B_0 = x$ (or $B_0 = 0$) with P_x probability 1.

(ii) $(B_t - B_s) | \mathcal{F}_s, 0 \leq s < t$ is independent of $\mathcal{F}_s$
i.e. the increments are independent.

(iii) $B_t - B_s \sim N(\mu(t-s), \sigma^2(t-s))$.

For $\mu=0$ & $\sigma=1$, $\{B_t\}$ is called
Standard Brownian motion.