

Lecture 3: Aug 25, 2016

Lecturer: Prof: Nayyar <>

Scribe: Saket Choudhary

3.1 Stochastic Processes

For each t , $X(t)$ is a random variable

T = range of time

If T is countable we have discrete time stochastic process. If T is interval we have continuous time stochastic process.

Example: Suppose we are tossing a fair coin infinitely many times.

$\Omega = \{\text{Any infinite string of H and T}\}$

Like *HHHTHTHHHTHT..*

Look at range of time interval $T = [1, \infty)$

For $1 \leq t \leq M$

$$X(t)(\omega) = \begin{cases} 1 & \text{if the first toss is head} \\ -1 & \text{otherwise} \end{cases}$$

For $n \leq t \leq M$

$$X(t)(\omega) = \begin{cases} 1 & \text{if the } n^{\text{th}} \text{ toss is head} \\ -1 & \text{otherwise} \end{cases}$$

E.g. $X(t)(HTHHTTT) = 1$ $X(t)(THHTTHHT) = -1$

So we defined collection of random variables $\{X(t), 1 \leq t < \infty\}$ In a stochastic process, each $X(t)$ is random variable

Fix an ω and look at $X(t)(\omega)$ as a function of time.

Consider $X(t)(\omega)$ for *HHTHHH...*

$$X(t)(\omega) = \begin{cases} 1 \end{cases}$$

IF we change ω we get a different sample path. So sample path is a realization of the stochastic process. If we fix time we get a random variable

For $n = 1, 2, 3, \dots$

$$Y_n = \begin{cases} 1 & \text{if } n^{\text{th}} \text{ toss is heads} \\ 0 & \text{otherwise} \end{cases}$$

Assume coin tosses are independent and $P(\text{heads}) = p; P(\text{tails}) = q; p + q = 1$

$$\begin{aligned} P(Y_n = 1) &= P(n^{\text{th}} \text{ toss is heads}) \\ &= p \\ P(Y_n = 0) &= q \end{aligned}$$

$\{Y_n\}_{n=1,2,3}$ are independent and identically distributed random variables.

3.2 Bernoulli Process

$$P(Y_1 = 1, Y_2 = 0, Y_3 = 1) = P(Y_1 = 1)P(Y_2 = 0)P(Y_3 = 1) = pqp$$

$$P(Y_1 + Y_2 + Y_3 = 1) = 3pq^2$$

$$\text{Generalization: } P(\sum Y_i = k) = n \binom{n-1}{k} p^k q^{n-k}$$

3.3 Convergence of Random Variables

Suppose a_1, a_2, \dots, a_n is sequence of real numbers and $\lim_{n \rightarrow \infty} a_n = b$ i.e. $\{a_n\}_{n \geq 1}$ converges to b
 a_n converges to b if for every $\epsilon > 0$ there exists a natural number N_ϵ such that $|a_n - b| < \epsilon$ if $n > N_\epsilon$

Almost sure convergence

Convergence with probability 1.

$\{X_n\}_{n=1,2,3}$ are all defined on (Ω, \mathcal{F}, P)

for any $\omega \in \Omega$, $X_1(\omega), X_2(\omega), X_3(\omega) \dots$ Is the sequence of real numbers $\{X_n(\omega)\}$ converging to number $Y(\omega)$

Look at collection $\{\omega \in \Omega : \{X_n(\omega)\} \text{converges to } Y(\omega)\}$

If $P(\{\omega \in \Omega : \lim_{n \rightarrow \infty} X_n(\omega) = Y(\omega)\}) = 1$ then we say that r.v $\{X_n\}_{n \geq 1}$ converge to random variable Y almost surely.

Example: $\Omega = (0, 1)$

$$X_1(\omega) = 1 \forall \omega \in \Omega \quad X_2(\omega) = \begin{cases} 2 & \text{if } 0 < \omega \leq 0.5 \\ 0 & \text{if } 0.5 < \omega < 1 \end{cases}$$

$$X_n(\omega) = \begin{cases} n & 0 < \omega \leq 1/n \\ 0 & \text{otherwise} \end{cases}$$

Pick an arbitrary $\omega = 1/3$

$$X_1(\omega)X_2(\omega) \dots X_n(\omega) = 123000 \dots$$

$$Y(1/3) = 0$$

$$\lim_{n \rightarrow \infty} X(1/3) = Y(1/3)$$

For all $\omega \in (0, 1)$, $\lim_{n \rightarrow \infty} X_n(\omega) = Y(\omega)$

So $P(\{\omega : \lim_n X_n(\omega) = Y(\omega)\}) = 1$ so $X(w)$ converges almost surely

3.3.1 Strong Law of large numbers

$\{X_n\}_n$ are iid. $E[X_n] = \mu < \infty$ and $E[|X_n|] < \infty$

$$S_n = X_1 + X_2 + \dots + X_n$$

Then $\frac{S_n}{n}$ converges almost surely to μ

$$P(\{\omega : \lim_n \frac{S_n(\omega)}{n} = \mu\}) = 1$$

3.3.2 Convergence in probability

We say that $X_n(\omega)$ converges to Y then $P(|X_n - Y_n| > \epsilon) > \epsilon$ converges to 0

Weak law of large numbers

$\{X_n\}$ are iid with $E[X_n] = \mu$, $E[|X_n|] < \infty$

$S_n = \sum X_i$ then $\frac{S_n}{n}$ converges to μ in probability.

Check if $\lim_{n \rightarrow \infty} P(|\frac{S_n}{n} - \mu| > \epsilon) = 0$ $E[\frac{S_n}{n}] = \mu$ and $Var(\frac{S_n}{n}) = \frac{\sigma^2}{n}$

$$0 \leq P(|S_n/n - \mu| > \epsilon) \leq E[(S_n/n - \mu)^2] / \epsilon^2 = \frac{\sigma^2}{n\epsilon^2}$$

Thus, $\lim_{n \rightarrow \infty} P(|S_n/n - \mu| > \epsilon) = 0$

So S_n/n converges to μ in probability.

Thus, almost sure convergence \implies convergence in probability but converse is not true.

Convergence in distribution

$\{X_n\}_{n \geq 1}$ We look at cdfs $F_{X_n}(x)$ and we want to check if $\lim_{n \rightarrow \infty} F_{X_n}(x) = F_Y(x)$

for all x where F_Y is continuous

Example: $Y \sim \mathcal{N}(0, 1)$ and $X_n = (-1)^n Y$ Does X_n converge to Y in distribution

$$F_{X_1}(x) = F_{-Y}(x) = P(-Y \leq x) = P(Y \geq -x) = P(Y \leq x) = F_Y(x)$$

$$F_{X(2)}(x) = P(Y \leq x) = F_Y(x)$$

Example: Central limit theorem

$\{X_n\}_{n \geq 1}$ are iid random variable with $E[X_n] = \mu$ and $Var[X_n] = \sigma^2$

$$Z_n = \frac{\sum_{i=1}^n X_i - n\mu}{\sigma\sqrt{n}}$$

$$Z_1 = \frac{X_1 - \mu}{\sigma}$$

$$Z_2 = \frac{X_1 + X_2 - 2\mu}{\sigma\sqrt{2}}$$

CLT: $\{Z_n\}_{n \geq 1}$ converges to Y where $Y \sim \mathcal{N}(0, 1)$

$$\lim_{n \rightarrow \infty} P(Z_n \leq x) = F_Y(x)$$

Almost sure convergence \implies Convergence in probability \implies Convergence in distribution

Convergence in mean square

$\{X_n\}$ converge to Y in mean square of $\lim_{n \rightarrow \infty} E[(X_n - Y)^2] = 0$

Example: IID X_n and $S_n = \sum X_i$

then $\lim_{n \rightarrow \infty} E[(\frac{S_n}{n} - \mu)^2] = 0$

i.e. $\lim_{n \rightarrow \infty} \frac{\sigma^2}{n} = 0$

3.4 How to remember