

Lecture 16

Recall

def: A Markov chain is a sequence of RVs

X_0, X_1, X_2, \dots taking values in S (sample space) s.t.

$$P(X_{n+1} = j \mid X_0 = i_0, X_1 = i_1, \dots, X_n = i_n (= i))$$

$$= P(X_{n+1} = j \mid X_n = i) = P_{ij}$$

↖ Markov Property

for every $n \in \mathbb{N}$ & every sequence $i_0, i_1, \dots, i_n \in S$
for which $P(X_0 = i_0, \dots, X_n = i_n) > 0$.

Also,

$$P(X_0 = i_0, X_1 = i_1, \dots, X_n = i_n) = \alpha_{i_0} P_{i_0 i_1} \cdots P_{i_{n-1} i_n}$$

↑
 α_i 's initial distribution

↑
product of 1-step transition probabilities P_{ij} 's

Follows that

$$P(X_1 = j) = \sum_{i \in S} P(X_0 = i, X_1 = j)$$

$$= \sum_{i \in S} \alpha_i P_{ij}$$

* →

* Chain rule for conditional probabilities :

$$P(X_0 = i_0, X_1 = i_1, X_2 = i_2)$$

$$= P(X_0 = i_0) P(X_1 = i_1 | X_0 = i_0) P(X_2 = i_2 | X_0 = i_0, X_1 = i_1)$$

$$= \alpha_{i_0} P_{i_0 i_1} P_{i_1 i_2}$$

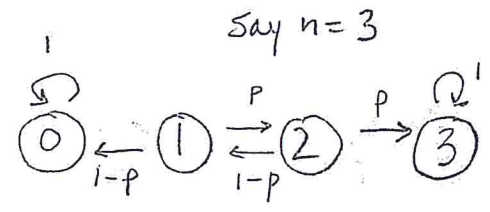
Lecture 16

Stat 706

3/27/18 (2)

Examples ± 1 each time step

① Simple Random Walk on a finite set:



Suppose $S = \{0, 1, \dots, n\}$

Fix $a \in S$ and let $\alpha_a = 1$ and $\alpha_i = 0$ for $i \neq a$ ($i \in S$).

Fix $p \in \mathbb{R}$ s.t. $0 < p < 1$ and let

$$\left. \begin{aligned} P_{i,i+1} &= p \\ P_{i,i-1} &= 1-p \end{aligned} \right\} \text{ for } 0 < i < n$$

$P_{00} = P_{nn} = 1$ \leftarrow absorbing states $0 \neq n$
 (once a particle enters an absorbing state, it cannot leave it)

In matrix form

$$P = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & \dots & n-1 & n \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ \vdots \\ n-1 \\ n \end{matrix} & \begin{bmatrix} 1 & 0 & & & & & 0 \\ 1-p & 0 & p & & & & \\ 0 & 1-p & 0 & p & & & \\ & & \ddots & \ddots & \ddots & & \\ & & & & & p & \\ & & & & & 1-p & 0 & p \\ 0 & & & & & 0 & 0 & 1 \end{bmatrix} \end{matrix}$$

This MC starts at $a \neq 0$ then at each step either
 - increases by 1 w/prob. p
 - decreases by 1 w/prob. $1-p$
 until reaching state 0 or n (absorbing states).

Simple - i.e. ± 1 each time step

② Unrestricted Random Walk - same setup as gambling game discussed last Lec.

Let $S = \mathbb{Z}$. Fix $a \in \mathbb{Z}$ & let $\alpha_a = 1$, $\alpha_i = 0$ for $i \neq a$.

Let $P_{i,i+1} = p$ and $P_{i,i-1} = 1-p$ $\forall i \in \mathbb{Z}$, $0 < p < 1$.

This MC has no absorbing states; the particle is free to move any where (in increments of ± 1).

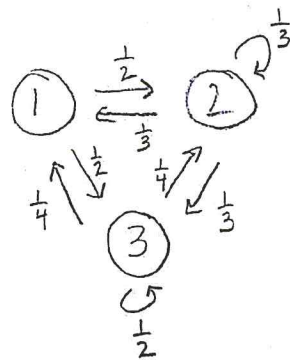
Random walk is symmetric if $p = \frac{1}{2}$.

e.g. $X_0 = 1, X_1 = 2, X_2 = 1, X_3 = 0, X_4 = -1, \dots$

③ MC on 3 points: $\{1, 2, 3\}$

$$S = \{1, 2, 3\}$$

$$P = \begin{matrix} & \begin{matrix} 1 & 2 & 3 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \end{matrix} & \begin{bmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{2} \end{bmatrix} \end{matrix}$$



check: sum of "out" arrows for each state is 1.

e.g. $X_0 = 2$

$X_1 = 3$

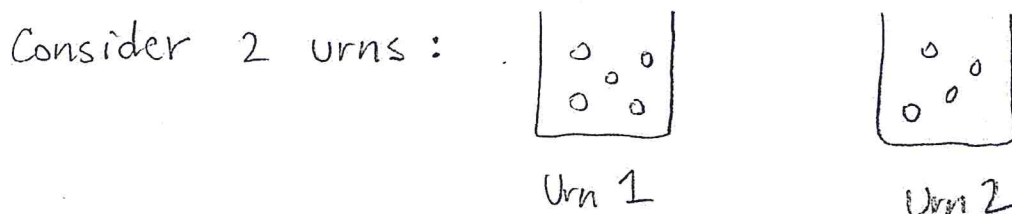
$X_2 = 1$

$X_3 = 3$

$X_4 = 3$

⋮

④ Ehrenfest's Urn



- Suppose there are d balls divided between the 2 urns.
- At each step, choose 1 ball uniformly at random (from all d balls) and switch it to the opposite urn.

Let $X_n = \#$ of balls in urn 1 at time n .

Then $S = \{1, 2, \dots, d\}$ with

$$\left. \begin{aligned} P_{i,i+1} &= \frac{d-i}{d} \\ P_{i,i-1} &= \frac{i}{d} \end{aligned} \right\} \begin{array}{l} \leftarrow \text{ie. increase \# in Urn 1 by 1 \# need to} \\ \text{pick a ball from Urn 2 \# switch to} \\ \text{Urn 1} \\ \text{for } 0 \leq i \leq d \end{array}$$

$$(P_{i,j} = 0 \text{ if } j \neq i \pm 1)$$

One might expect that, if d is large & MC is run for a long time, that there would most likely be $\approx \frac{d}{2}$ balls in Urn 1.

* we'll consider such d 's in a bit!

Existence Theorem

Thm 8.1.1: Given a non-empty countable set S and non-negative numbers $\{\alpha_i\}_{i \in S}$ and $\{p_{ij}\}_{i, j \in S}$ s.t.

$$\sum_{i \in S} \alpha_i = 1 \quad \text{and} \quad \sum_{j \in S} p_{ij} = 1 \quad \text{for each } i \in S, \quad \exists \text{ on some prob. space } (\Omega, \mathcal{F}, P)$$

a Markov chain X_0, X_1, X_2, \dots with initial probabilities α_i and transition probabilities p_{ij} .

Pf: See Billingsley or Rosenthal.

Let (Ω, \mathcal{F}, P) be Lebesgue measure on $[0, 1]$.

Careful partitioning of $[0, 1]$ $\hat{=}$ induction...

Transience, Recurrence, Irreducibility

Fundamental notions related to MCs.

For simplicity, assume $\alpha_i > 0 \quad \forall i \in S$.

Notation: $P_i(A)$ means $P(A \mid X_0 = i)$

$E_i(A)$ means expected value w.r.t. P_i

def: Let $f_{ij}^{(n)} = P_i(X_n = j, \text{ but } X_m \neq j \text{ for } 1 \leq m \leq n-1)$

for $i, j \in S$ and $n \in \mathbb{N}$. This is the probability, starting from i , that we first hit j at time n .