

Lecture 3

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MATH 285A - 4/9/07

Discrete Time Markov Chains, cont.

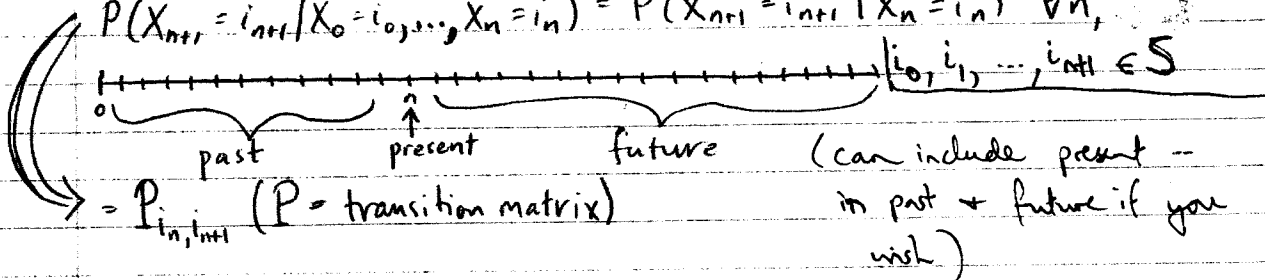
(Read: Classification of States; Hitting Times; Absorption Probabilities)

Section 1.2

Section 1.3

Defn: $\{X_n, n \geq 0\}$ is a Markov chain if:

$$P(X_{n+1} = i_{n+1} | X_0 = i_0, \dots, X_n = i_n) = P(X_{n+1} = i_{n+1} | X_n = i_n) \quad \forall n, i_0, i_1, \dots, i_{n+1} \in S$$

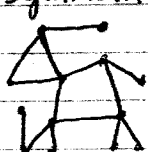


Markov property implies:

$$P(X_{n+m} = i_{n+m}, \dots, X_{n+1} = i_{n+1} | X_0 = i_0, \dots, X_n = i_n) = P(X_{n+m} = i_{n+m}, \dots, X_{n+1} = i_{n+1} | X_n = i_n) \\ \forall n \geq 0, m \geq 1, i_0, i_1, \dots, i_{n+m} \in S$$

Examples of Markov Chains

1. Symmetric random walk on a finite ~~path~~ graph



Graph = (V, E)
↑ vertices ↑ edges

degree of a vertex = # of edges attached to vertex

label vertices by $i = 1, 2, \dots, N$

$d(i)$ = degree of i (assume $d(i) \geq 1$ for all i)

$\lambda = (\frac{\quad}{N})$ - initial distribution

X_n = vertex that chain is at at time n (position at time n)

Fix $n \geq 0, i_0, i_1, \dots, i_{n+1} \in S = \{1, 2, \dots, N\}$

$$P(X_{n+1} = i_{n+1} | X_0 = i_0, \dots, X_n = i_n) = P(X_{n+1} = i_{n+1} | X_n = i_n),$$

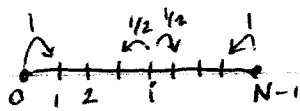
because given a state at time n , we go to neighbors with

prob. = $1/d(i)$. So:

$$P(X_{n+1} = i_{n+1} | X_n = i_n) = \begin{cases} 0 & \text{if } i_{n+1} \text{ is not a neighbor of } i_n \\ \frac{1}{d(i_n)} & \text{if } i_{n+1} \text{ is a neighbor of } i_n \end{cases}$$

Markov because the probability of moving from one node to another is path-independent, or memory less

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"reflecting random walk"

2. Branching Processes

Time $N = \{0, 1, 2, \dots\}$ n indexes generations

$X_n = \#$ of individuals in population at time n

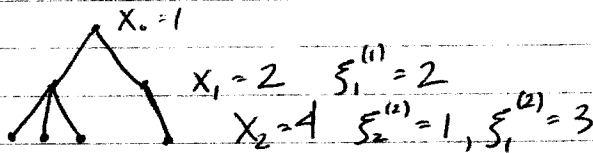
For each $n \geq 0$, $\{\xi_i^{(n+1)}\}_{i=1}^{\infty}$ are i.i.d random variables

taking values in non-negative integers and $P(\xi_i^{(n+1)} = i) = p_i, i = 0, 1, 2, \dots$
 $p_i \geq 0 \forall i, \sum_{i=0}^{\infty} p_i = 1$

$\{\xi_i^{(n+1)}\}_{i=1}^{\infty}$ are independent as n varies and independent of X_0

$$X_{n+1} = \sum_{i=1}^{X_n} \xi_i^{(n+1)}$$

EX. $X_0 = 1$



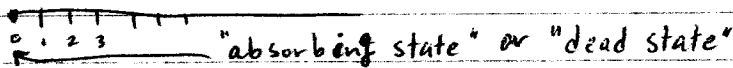
Check $\{X_n\}_{n=0}^{\infty}$ is Markov:

Fix $n \geq 0, i_0, i_1, \dots, i_{n+1} \in S = N = \{0, 1, 2, \dots\}$

$$P(X_{n+1} = i_{n+1} | X_0 = i_0, \dots, X_n = i_n) = P(\sum_{i=1}^{X_n} \xi_i^{(n+1)} = i_{n+1} | X_0 = i_0, \dots, X_n = i_n)$$

Recall that $\{\xi_i^{(n+1)}\}_{i=1}^{\infty}$ independent of $\{\xi_j^{(1)}\}_{j=1}^{\infty}, \{\xi_j^{(2)}\}_{j=1}^{\infty}, \dots, \{\xi_j^{(n)}\}_{j=1}^{\infty}$ & X_0

$$So P(\sum_{i=1}^{X_n} \xi_i^{(n+1)} = i_{n+1} | X_0 = i_0, \dots, X_n = i_n) = P(\sum_{i=1}^{X_n} \xi_i^{(n+1)} = i_{n+1}) = P(\sum_{i=1}^{X_n} \xi_i^{(n+1)} = i_{n+1} | X_n = i_n)$$



"absorbing state" or "dead state"

CLASSIFICATION OF STATES

We say state i leads to state j , written $i \rightarrow j$, if

$$P(X_n = j | X_0 = i) > 0 \text{ for some } n \geq 0 \quad (\text{equivalent to: } P(X_n = j \text{ for some } n \geq 0 | X_0 = i) > 0)$$

We say i and j communicate if $i \rightarrow j$ and $j \rightarrow i$, written $i \leftrightarrow j$

-communication is an equivalence relation, meaning it is:

(i) Reflexive ($i \leftrightarrow i$)

(ii) Symmetric ($i \leftrightarrow j \Rightarrow j \leftrightarrow i$)

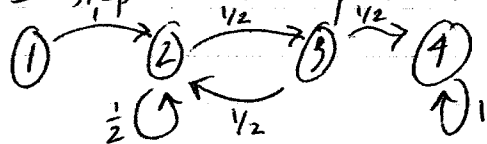
(iii) ~~transitive~~ Transitive ($i \leftrightarrow j, j \leftrightarrow k \Rightarrow i \leftrightarrow k$)

Therefore the state space can be partitioned into equivalence classes.

Each equivalence class contains states that communicate only with ~~those~~ states in that class.

Example:

1 step transition probabilities



Communicating classes: $\{1\}, \{2, 3\}, \{4\}$

Closed communicating class: A communicating class C s.t. if $i \in C + j \in S$ s.t. $i \rightarrow j$, then $j \in C$ ($\{4\}$, in the example)

EX.



$S = \mathbb{N}$, communicating classes are $\{0\}, \{1\}, \{2\}, \dots$ No closed communicating classes

If the state space is finite, there must be at least one closed communicating class.