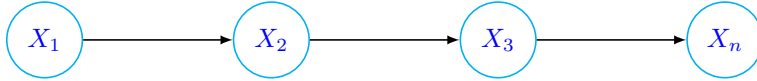


# HGEN 48600/STAT 35450: Lecture 5

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*Note: These lecture notes are still rough, and have only have been mildly proofread.*

## Discrete Markov Chain



### Time homogeneous markov chain:

$P(X_{n+1} = j | X_n = i) = P(X_2 = j | X_1 = i) = P_{ij}$ , for all  $n$ .

Time homogeneous markov chains have properties that make them easier to analyze.

### Discrete Markov Chain Examples:

#### Random walk :

Given a current state  $X_i = k$ ,  $X_{i+1}$  is either  $k + 1$  or  $k - 1$  with equal probability.

In terms of transition matrix,

$P_{i,i-1} = \frac{1}{2}$ .  $P_{i,i+1} = \frac{1}{2}$ .  $P_{i,i} = 0$ , and otherwise 0.

(More in Ross example 4.18)

#### Jukes Cantor Model

Given a current state of a single site, it has probability  $\mu$  of substitution, with the same probability of mutating into one in other three states.

$$M = \begin{matrix} & \begin{matrix} A & C & T & G \end{matrix} \\ \begin{matrix} A \\ C \\ T \\ G \end{matrix} & \begin{pmatrix} 1-\mu & \mu/3 & \mu/3 & \mu/3 \\ \mu/3 & 1-\mu & \mu/3 & \mu/3 \\ \mu/3 & \mu/3 & 1-\mu & \mu/3 \\ \mu/3 & \mu/3 & \mu/3 & 1-\mu \end{pmatrix} \end{matrix}$$

#### Wright-Fisher Model

We have  $N$  diploid individuals, and there's no overlap between generations.

$X_i$ : number of copies of allele A.

$X_i \sim \text{Binom}(2N, \frac{X_{i-1}}{2N})$

$$P = \begin{bmatrix} & & & \\ & & & \\ & & & \\ & & & \end{bmatrix} \in R^{2N \times 2N}$$

Each row of  $P$  is a binomial distribution.  $P_{ij} = \binom{2N}{j} (\frac{i}{2N})^j (1 - \frac{i}{2N})^{2N-j}$

## Useful formula

Chapman-Kolmogorov:

Let  $P_{ij}^{(n)} = P(X_{n+k} = j, X_k = i)$ .

$P^{(n+m)} = p^{(n)}p^{(m)}$ , e.g.  $P^{(2)} = p^{(1)}p^{(1)}$ .

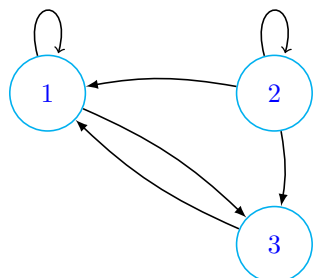
$P(X_1 = j) = \sum_i P(X_0 = i)P(X_1 = j|X_0 = i)$ , where  $P(X_0 = i)$  is initiated from  $\pi_0$ .

e.g.  $\pi_1^T = \pi_0^T P$ ,  $\pi_{10}^T = \pi_0^T P^{10}$ .

Forward Kolmogorov:

$\pi^n = \pi^{(n-1)}P$

## Classification of states



$$P = \begin{bmatrix} .8 & 0 & .2 \\ .2 & .2 & .6 \\ .2 & 0 & .8 \end{bmatrix}$$

$f_i$  = the probability of reentering at state i given we start at state i.

$f_i = P(T_i < \infty | X_0 = i)$ , where  $T_i = \{\min n > 0 : X_n = i\}$ .

$f_i = 1 \rightarrow$  state i is recurrent.

$f_i < 1 \rightarrow$  state i is transient.

Remark: with the markov property, when recurrence happens, it re-initialize the chain. Hence the process will reenter the recurrent states infinite times.

Also let  $N_j = \min\{n > 0 : X_n = j\}$ , and  $m_j = E[N_j | X_0 = j]$ . The chain is **positively recurrent** if  $m_j < \infty$ , and otherwise **null recurrent**.

## Ergodic Chain

- irreducible: single class of states (Within a class, states communicate with each other)
- all states are aperiodic (periodic: chain can return to the state only periodically. It is also a class property)
- all states are recurrent

An ergodic chain with finite state space has a single stationary distribution.

## Global Balance Equation

$$\pi^T = \pi^T P$$

Also recall the R vignette.  $P^{(n)}$  with  $n \rightarrow \infty$  would have a stationary distribution in every row.

## Aside: matrix power

Suppose  $P$  is diagonalizable, we perform EVD and let  $P = V\Lambda V^{-1}$ , where the columns of  $V$  are right eigenvectors of  $P$ , and rows of  $V^{-1}$  are left eigenvectors of  $P$ . Then  $P^n = V\Lambda^n V^{-1}$ .

EVD is useful for finding stationary states for markov chain.  $\pi$ , the stationary state could be found normalizing the left eigenvector associated with eigen value 1. (Or it can be obtained from  $\pi P = \pi$  s.t.  $\sum_i \pi = 1$ )

Note that in **R** the `eigen` command computes right eigenvectors, one can inverse  $V$  to obtain left eigenvectors.

## Time Reversible Markov Chain

$$Q_{ij} = P(X_m = j | X_{m+1} = i) = \frac{P(X_m=j, X_{m+1}=i)}{P(X_{m+1}=i)} = \frac{P(X_{m+1}=i | X_m=j)P(X_m=j)}{P(X_{m+1}=i)} = \frac{\pi_j P_{ji}}{\pi_i}.$$

When  $Q_{ij} = P_{ij}$ , or  $\pi_i P_{ij} = \pi_j P_{ji}$  we say its time reversible.

In plain text, it says for all states  $i$  and  $j$ , the rate at which the process goes from  $i$  to  $j$  is equal to the rate at which it goes from  $j$  to  $i$ .

## Reference

1. Discrete-Time Markov Chains, five-minute stats
2. Ch4, Ross