

### 3. Discrete Time Markov Chain

#### Discrete Time Markov Chain

Let  $\{X_n, n \geq 0\}$  be a stochastic process taking values in a state space  $S$  that has  $N$  states. such a stochastic process is a Markov processes if it satisfies a following property :

$$P(X_{n+1} = k_{n+1} | X_n = k_n, X_{n-1} = k_{n-1}, \dots, X_1 = k_1) = P(X_{n+1} = k_{n+1} | X_n = k_n)$$

For a markov process, the *future state* only depends on the *present state* and not on the *past states*.

If the state space of a Markov process is discrete, it's called a **Markov Chain**.

To understand the behaviour of this process, we will need to calculate probabilities like,

$$P[X_0 = i_0, X_1 = i_1, \dots, X_n = i_n]$$

..(1)

∴  $P(A, B) = P(A) \cdot P(B|A)$ , this can be computed by multiplying conditional probabilities as follows.

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

$$P(X_n = i_n | X_{n-1} = i_{n-1}, X_{n-2} = i_{n-2}, \dots, X_0 = i_0)$$

..(2)

From the markovian property,

$$= P(X_0 = i_0) \cdot P(X_1 = i_1 | X_0 = i_0) \cdot P(X_2 = i_2 | X_1 = i_1) \dots P(X_n = i_n | X_{n-1} = i_{n-1})$$

..(3)

## State Transition Probabilities

For a discrete time Markov Chain  $\{X_n : n = 1, 2, \dots\}$  with discrete state space  $S = \{0, 1, 2, \dots\}$  where this set may be finite or infinite, if  $X_n = i$  then the Markov Chain is said to be in state  $i$  at time  $n$  (or the  $n^{\text{th}}$  step)

### One Step Transition Probability

A discrete time Markov Chain  $\{X_n : n = 1, 2, \dots\}$  is characterized by

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

Where  $P[X_{n+1} = j | X_n = i]$  is called one step transition probability

If  $P[X_{n+1} = j | X_n = i]$  is independent of  $n$  then the Markov Chain is said to possess stationary transition probabilities and the process is referred to as a homogeneous Markov Chain. Otherwise the process is called a non-homogeneous Markov Chain.

### Transition Probability Matrix

The matrix called the **state transition matrix (t.p.m)** or **transition probability matrix** is usually denoted by  $P$ .

Let  $\{X_n : n = 1, 2, \dots\}$  be a homogeneous Markov Chain with a discrete finite state space  $S = \{0, 1, 2, \dots, m\}$  then

$$p_{ij} = P[X_{n+1} = j | X_n = i] \quad i \geq 0, j \geq 0$$

regardless of the value of  $n$ .

A t.p.m of  $\{X_n\}$  is defined by

$$P = [p_{ij}] = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ p_{31} & p_{32} & \cdots & p_{3m} \\ \vdots & \ddots & & \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix}$$

Where

$$p_{ij} \geq 0$$

and

$$\sum_{j=1}^m p_{ij} = 1, \quad i = 1, 2, \dots, m$$

### State Transition Diagram

A Markov Chain is usually shown by a state transition diagram. Consider a Markov Chain with three possible states  $S = \{1, 2, 3\}$  and the following transition probabilities

$$P = \begin{bmatrix} \frac{1}{4} & \frac{1}{2} & \frac{1}{4} \\ \frac{1}{3} & 0 & \frac{2}{3} \\ \frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix}$$

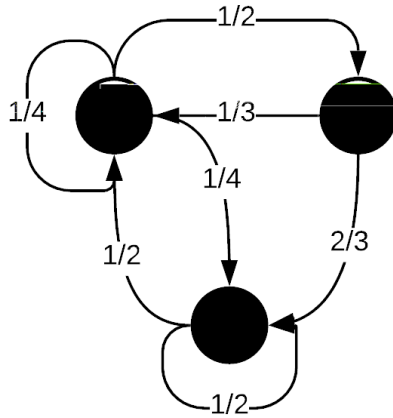
Which satisfies the two criterias, i.e.

$$p_{ij} \geq 0$$

and

$$\sum_{j=1}^3 p_{ij} = 1, \quad i = 1, 2, 3$$

The figure below shows the state transition diagram for this Markov Chain



### $n$ -step Transition Probability

Consider a Markov Chain  $\{X_n : n = 0, 1, 2, \dots\}$  if  $X_0 = i$  then  $X_1 = j$  with probability  $p_{ij}$  is the probability of going from state  $i$  to state  $j$  in one step.

Now suppose we're interested in finding the probability of going from state  $i$  to state  $j$  in two steps, i.e.

$$p_{ij}^{(2)} = P(X_2 = j | X_0 = i)$$

$$p_{ij}^{(2)} = P(X_{n+2} = j | X_n = i)$$

We can find the probability by applying the law of total probability  $X_1$  can take one of the possible values of  $S$

$$\begin{aligned} p_{ij}^{(2)} &= P(X_2 = j | X_0 = i) \\ &= \sum_{k \in S} P(X_2 = j | X_1 = k, X_0 = i) \cdot P(X_1 = k | X_0 = i) \end{aligned}$$

[by law of total probability]

$$= \sum_{k \in S} P(X_2 = j | X_1 = k) \cdot P(X_1 = k | X_0 = i)$$

[by markovian property]

$$\begin{aligned} &= \sum_{k \in S} p_{kj} \cdot p_{ik} \\ &= \sum_{k \in S} p_{ik} \cdot p_{kj} \end{aligned}$$

$$\therefore p_{ij}^{(2)} = P(X_2 = j | X_0 = i) = \sum_{k \in S} p_{ik} \cdot p_{kj}$$

Which means that in order to get to state  $j$  from  $i$ , we need to pass through some intermediate state  $k$ .

$$i \longrightarrow k \longrightarrow j$$

### **$n$ -step Transition Probability Matrix**

We can define the **two-step transition matrix** as

$$P^{(2)} = \begin{bmatrix} p_{11}^{(2)} & p_{12}^{(2)} & \cdots & p_{1m}^{(2)} \\ p_{21}^{(2)} & p_{22}^{(2)} & \cdots & p_{2m}^{(2)} \\ p_{31}^{(2)} & p_{32}^{(2)} & \cdots & p_{3m}^{(2)} \\ \vdots & \ddots & & \\ p_{m1}^{(2)} & p_{m2}^{(2)} & \cdots & p_{mm}^{(2)} \end{bmatrix}$$

We conclude that two-step transition matrix can be obtained by squaring the state transition matrix.

$$P^{(2)} = P \cdot P = P^2$$

Similarly,

$$P^{(3)} = P \cdot P^2 = P \cdot P^{(2)}$$

Generally we can define the  $n$ -step transition probability  $p_{ij}^{(n)}$  as

$$p_{ij}^{(n)} = P(X_n = j | X_0 = i), \quad i = 0, 1, 2, \dots$$

In order to get from state  $i$  to state  $j$ , we need to pass through  $n-1$  intermediate states  $k_1, k_2, \dots, k_{n-1}$

$$i \longrightarrow k_1 \longrightarrow k_2 \longrightarrow \dots \longrightarrow k_{n-1} \longrightarrow j$$

The  **$n$ -step transition matrix** is defined as follows

$$P^{(n)} = \begin{bmatrix} p_{11}^{(n)} & p_{12}^{(n)} & \dots & p_{1r}^{(n)} \\ p_{21}^{(n)} & p_{22}^{(n)} & \dots & p_{2r}^{(n)} \\ p_{31}^{(n)} & p_{32}^{(n)} & \dots & p_{3r}^{(n)} \\ \vdots & \ddots & & \\ p_{r1}^{(n)} & p_{r2}^{(n)} & \dots & p_{rr}^{(n)} \end{bmatrix}$$

$$P^{(n)} = P^n$$

Let  $m$  and  $n$  be two positive integers and assume  $X_0 = i$ . In order to get to state  $j$  in  $(m+n)$  steps, the chain will be at some intermediate state  $k$  after  $m$  steps.

To obtain

$$\begin{aligned} p_{ij}^{(m+n)} &= P[X_{n+m} = j | X_0 = i] \\ &= \sum_{k \in S} p_{ik}^{(n)} \cdot p_{kj}^{(m)} \end{aligned}$$

This equation is called the **Chapman–Kolmogorov Equation**

### Probability distribution of $X_n, n \geq 0$

Consider a Markov Chain  $\{X_n : n = 0, 1, 2, \dots\}$ . Suppose we know the probability distribution of  $X_0$ .

Define the row vector  $\pi^{(0)}$  as

$$\pi^{(0)} = [ \quad P(X_0 = 1) \quad P(X_0 = 2) \quad \dots \quad P(X_0 = r) \quad ]$$

Now, we can obtain the probability distribution of  $X_1, X_2, \dots$

Using the law of total probability, for any  $j \in S$ , we can write

$$\begin{aligned} P(X_1 = j) &= \sum_{k=1}^r P(X_1 = j | X_0 = k) \cdot P(X_0 = k) \\ &= \sum_{k=1}^r p_{kj} \cdot P(X_0 = k) \end{aligned}$$

$$\pi^{(n)} = [ \quad P(X_n = 1) \quad P(X_n = 2) \quad \dots \quad P(X_n = r) \quad ]$$

Given the state transition matrix  $P$ , we can rewrite the above results in the form of matrix multiplication

$$\begin{aligned} \pi^{(1)} &= \pi^{(0)} \cdot P \\ \pi^{(2)} &= \pi^{(1)} \cdot P \\ &\vdots \\ \pi^{(n)} &= \pi^{(n-1)} \cdot P \end{aligned}$$

or

$$\pi^{(n)} = \pi^{(0)} \cdot P^n$$