

#### BIJU PATNAIK UNIVERSITY OF TECHNOLOGY, ODISHA

#### Lecture Notes

#### On

#### **Markov Chain**

#### Part 1

Prepared by, Dr. Subhendu Kumar Rath, BPUT, Odisha.

# Markov Chain Part 1

Dr. Subhendu Kumar Rath Deputy Registrar, BPUT



- Stochastic Process
- Markov Chain

#### **Stochastic Process**

- A stochastic process is a indexed collection of random variables
   {X<sub>t</sub>} = { X<sub>0</sub>, X<sub>1</sub>, X<sub>2</sub>, ... } for describing the behavior of a system
   operating over some period of time.
- For example :

• 
$$X_0 = 3$$
,  $X_1 = 2$ ,  $X_2 = 1$ ,  $X_3 = 0$ ,  $X_4 = 3$ ,  $X_5 = 1$ 

## Stochastic Process (cont.)

- An inventory example:
- A camera store stocks a particular model camera.
- D<sub>t</sub> represents the demand for this camera during week t.
- D<sub>t</sub> has a Poisson distribution with a mean of 1.
- X<sub>t</sub> represents the number of cameras on hand at the end of week t. (X<sub>0</sub> = 3)
- If there are no cameras in stock on Saturday night, the store orders three cameras.
- { X<sub>t</sub> } is a stochastic process.

■ 
$$X_{t+1} = \max\{ 3 - D_{t+1}, 0 \}$$
 if  $X_t = 0$   
max{  $X_t - D_{t+1}, 0 \}$  if  $X_t \ge 0$ 

#### Markov Chain

- A stochastic process {X<sub>t</sub>} is a Markov chain if it has Markovian property.
- Markovian property:

• P{ 
$$X_{t+1} = j | X_0 = k_0, X_1 = k_1, ..., X_{t-1} = k_{t-1}, X_t = i$$
}  
= P{  $X_{t+1} = j | X_t = i$ }

• P{  $X_{t+1} = j | X_t = i$  } is called the transition probability.



- Stationary transition probability:
  - If ,for each i and j, P{ X<sub>t+1</sub> = j | X<sub>t</sub> = i } = P{ X<sub>1</sub> = j | X<sub>0</sub> = i }, for all t, then the transition probability are said to be stationary.

- Formulating the inventory example:
  - Transition matrix:

state 0 1 2 3  
0 
$$\rho_{00}$$
  $\rho_{01}$   $\rho_{02}$   $\rho_{03}$   
 $\mathbf{P} = 1 \rho_{10} \rho_{11} \rho_{12} \rho_{13}$   
2  $\rho_{20} \rho_{21} \rho_{22} \rho_{23}$   
3  $\rho_{30} \rho_{31} \rho_{32} \rho_{33}$ 

■ 
$$X_{t+1} = \max\{ 3 - D_{t+1}, 0 \}$$
 if  $X_t = 0$   
max{  $X_t - D_{t+1}, 0 \}$  if  $X_t \ge 1$ 

• 
$$p_{03} = P\{ D_{t+1} = 0 \} = 0.368$$

• 
$$p_{02} = P\{ D_{t+1} = 1 \} = 0.368$$

• 
$$p_{01} = P\{ D_{t+1} = 2 \} = 0.184$$

• 
$$p_{00} = P\{ D_{t+1} \ge 3 \} = 0.080$$

state 0 1 2 3

 $0 \quad 0.080 \ 0.184 \ 0.368 \ 0.368$ 

**P** =

- 2 0.264 0.368 0.368 0.000
- 3 0.080 0.184 0.368 0.368



• The state transition diagram:



n-step transition probability :

• 
$$p_{ij}^{(n)} = P\{ X_{t+n} = j | X_t = i \}$$

• n-step transition matrix :

• Chapman-Kolmogorove Equation :

$$p_{ij}^{(n)} = \sum_{k=0}^{M} p_{ik}^{(m)} p_{kj}^{(n-m)} \qquad \begin{array}{l} \text{for all } i = 0, 1, \dots, M, \\ j = 0, 1, \dots, M, \\ \text{and any } m = 1, 2, \dots, n-1, \\ n = m+1, m+2, \dots \end{array}$$

The special cases of m = 1 leads to :

$$p_{ij}^{(n)} = \sum_{k=0}^{M} p_{ik}^{(1)} p_{kj}^{(n-1)}$$
 for all i and j

 Thus the n-step transition probability can be obtained from onestep transition probability recursively.



- Conclusion :
  - $P^{(n)} = PP^{(n-1)} = PPP^{(n-2)} = \dots = P^n$
- n-step transition matrix for the inventory example :
- 2 3 state 0 1 2 3 state 0 1 0.080 0.184 0.368 0.368 0.289 0.286 0.261 0.164  $\cap$ 0  $P^{(4)} = 1$ 0.282 0.285 0.268 0.166 0.632 0.368 0.000 0.000 1  $\mathbf{P} =$ 2 0.264 0.368 0.368 0.000 0.284 0.283 0.263 0.171 2 3 0.080 0.184 0.368 0.368 3 0.289 0.286 0.261 0.164

What is the probability that the camera store will have three cameras on hand 4 weeks after the inventory system began ?

• 
$$P\{X_n = j\} = P\{X_0 = 0\}p_{0j}^{(n)} + P\{X_0 = 1\}p_{1j}^{(n)} + ... + P\{X_0 = M\}p_{Mj}^{(n)}$$

• P{ X<sub>4</sub> = 3 } = P{ X<sub>0</sub> = 0 } 
$$p_{03}^{(4)}$$
 + P{ X<sub>0</sub> = 1 }  $p_{13}^{(4)}$   
+ P{ X<sub>0</sub> = 2 }  $p_{23}^{(4)}$  + P{ X<sub>0</sub> = 3 }  $p_{33}^{(4)}$   
= (1)  $p_{33}^{(4)}$  = 0.164



- Long-Run Properties of Markov Chain
  - Steady-State Probability

2 state 0 1 2 3 state 0 1 3 0.080 0.184 0.368 0.368 0.286 0.285 0.264 0.166 0 Ω 0.632 0.368 0.000 0.000 0.286 0.285 0.264 0.166  $P^{(8)} = 1$ 1  $\mathbf{P} =$ 2 0.264 0.368 0.368 0.000 0.286 0.285 0.264 0.166 2 3 0.080 0.184 0.368 0.368 3 0.286 0.285 0.264 0.166

- The steady-state probability implies that there is a limiting probability that the system will be in each state j after a large number of transitions, and that this probability is independent of the initial state.
- Not all Markov chains have this property.

state 0 1		1	2	3
0	$\pi_0$	$\pi_1$	$\pi_2$	$\pi_3$
1	$\pi_0$	$\pi_1$	$\pi_2$	$\pi_3$
2	$\pi_0$	$\pi_1$	$\pi_2$	$\pi_3$
3	$\pi_0$	$\pi_1$	$\pi_2$	$\pi_3$

• Steady-State Equations :

$$\pi_{j}=\sum_{i=0}^{M}\pi_{i}p_{ij}$$
 for i = 0, 1, ..., M 
$$\sum_{j=0}^{M}\pi_{j}=1$$

■ , which consists of M+2 equations in M+1 unknowns.

• The inventory example :

$$\bullet \quad \pi_0 = \pi_0 p_{00} + \pi_1 p_{10} + \pi_2 p_{20} + \pi_3 p_{30} ,$$

$$\pi_1 = \pi_0 p_{01} + \pi_1 p_{11} + \pi_2 p_{21} + \pi_3 p_{31} ,$$

$$\pi_2 = \pi_0 p_{02} + \pi_1 p_{12} + \pi_2 p_{22} + \pi_3 p_{32}$$

$$\pi_3 = \pi_0 p_{03} + \pi_1 p_{13} + \pi_2 p_{23} + \pi_3 p_{33} ,$$

$$\bullet \quad \mathbf{1} = \pi_0 + \pi_1 + \pi_2 + \pi_3.$$

$$\begin{aligned} \pi_0 &= 0.080\pi_0 + 0.632\pi_1 + 0.264\pi_2 + 0.080\pi_3 , \\ \pi_1 &= 0.184\pi_0 + 0.368\pi_1 + 0.368\pi_2 + 0.184\pi_3 , \\ \pi_2 &= 0.368\pi_0 + + 0.368\pi_2 + 0.368\pi_3 , \\ \pi_3 &= 0.368\pi_0 + + 0.368\pi_3 , \\ 1 &= \pi_0 + \pi_1 + \pi_2 + \pi_3. \end{aligned}$$

• 
$$\pi_0 = 0.286$$
,  $\pi_1 = 0.285$ ,  $\pi_2 = 0.263$ ,  $\pi_3 = 0.166$ 

# Reference

 Hillier and Lieberman, "Introduction to Operations Research", seventh edition, McGraw Hill

# THANK YOU

