

Chap. 3: Continuous Time Markov Chains (Ross Chap 6)

We now consider a class of stochastic processes that contains the Poisson Process, but is also an analog of the discrete time M-C, in continuous time

I. Introduction

As a continuous-time analog of the Chap 1, the following Markovian property characterizes the process

Recall: In discrete time, the Markov property states that

$$\begin{aligned} P(X_{n+1} = j \mid (X_n, X_{n-1}, \dots) = (i_n, i_{n-1}, \dots)) \\ = P(X_{n+1} = j \mid X_n = i_n) \end{aligned}$$

Def: Let $\{X(t), t \geq 0\}$ be a collection of r.v.'s $X(t)$, each taking values in $\{0, 1, 2, \dots\}$ (discrete state space). $\{X(t), t \geq 0\}$ is

a continuous-time Markov chain if

$$P(X(s+t) = j \mid X(s) = i, X(u) = x(u) \text{ for } 0 \leq u \leq s)$$

$$= P(X(s+t)=j \mid X(s)=i) \quad (2)$$

$$\forall s, t \geq 0, \forall \text{ states } i, j \quad \forall x(v) \quad (0 \leq v < s)$$

assume

Remark: We will always have stationarity of the process, i.e.,

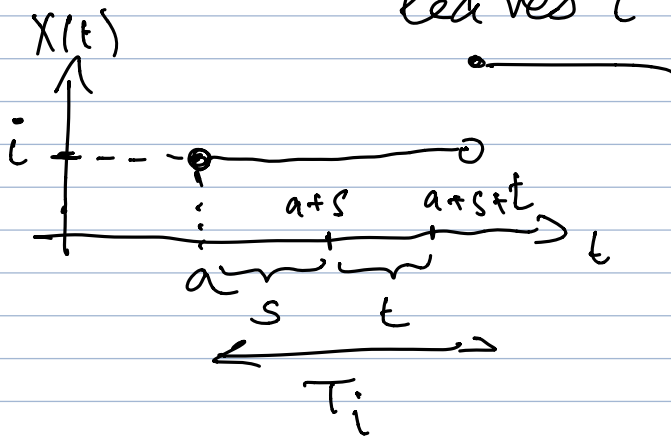
$P(X(s+t)=j \mid X(s)=i)$ is independent of s ,

so the process is a **homogeneous CTMC**

- This has the following key consequence on interarrival times:

Suppose that the MC is in a state i at time a , and let

T_i = additional time until the MC leaves i



Then $P(T_i > s+t \mid T_i > s)$

$$= P(X(r)=i \quad \forall r \in [a+s, a+s+t] \mid X(v)=i \quad \forall v \in [a, a+s])$$

$$= P(X(r) = i \forall r \in [a+s, a+s+t] \mid X(a+s) = i) \quad (3)$$

↑
Markov property

$$= P(X(a+s+u) = i \forall u \in [0, t] \mid X(a+s) = i)$$

$$= P(X(u) = i \forall u \in [0, t] \mid X(0) = i)$$

$$\stackrel{\uparrow}{\text{stationarity}} = P(T_i > t)$$

$$\Rightarrow \boxed{P(T_i > s+t \mid T_i > s) = P(T_i > t)}$$

$$\Rightarrow \underline{T_i \text{ has no-memory property (chap. 2)}}$$

$$\Rightarrow \boxed{T_i \sim \text{Exp}(\nu_i)} \text{ for some } \nu_i > 0$$

- In addition, T_i must be independent of the next state that the chain jumps to (otherwise, the Markov property would be violated, as the waiting time in a state would affect the next jump outcome)

Conclusion: We can fully describe a CTMC by

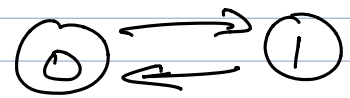
- $T_i \sim \text{Exp}(\nu_i), \nu_i > 0$ (characterizes the sojourn time in a state)

- P_{ij} = transition probability from i to j which satisfy $P_{ii} = 0$ & $\sum_j P_{ij} = 1$

Rule: This characterization provides a way to simulate the MC (\rightarrow next ~~note~~ week's notebook)

Example (6.11 txt book): 2-state CTMC

state = 0 working machine
1 broken —



Assume: $\left\{ \begin{array}{l} \text{time to breakdown} \sim \text{Exp}(\lambda) \\ \text{repair} \sim \text{Exp}(\mu) \end{array} \right.$

$$\rightarrow \left\{ \begin{array}{ll} \lambda_0 = \lambda & P_{01} = 1 \\ \mu_1 = \mu & P_{10} = 1 \end{array} \right.$$

Birth and Death Processes

We consider $X(t)$ = Population size at time t , where

- birth (arrival) occurs at a rate λ_n when pop. size is n
- death (departure) ————— μ_n —————

Given $\lambda_0, \lambda_1, \dots$; μ_0, μ_1, \dots , with $\mu_0 = 0$,

this defines a CTMC $0 \rightleftharpoons 1 \rightleftharpoons 2 \dots$,

where

$$\begin{cases} V_0 = \lambda_0 \\ V_n = \lambda_n + \mu_n \\ (n \geq 0) \end{cases}$$

← We need to consider for a given population size the time that it takes for either a birth or a death event to occur. (5)

$$\begin{cases} p_{01} = 1 \\ p_{n,n+1} = P(\text{birth time} < \text{death time}) = \frac{\lambda_n}{\lambda_n + \mu_n} \\ p_{n,n-1} = P(\text{birth time} > \text{death time}) = \frac{\mu_n}{\lambda_n + \mu_n} \end{cases} \quad \begin{aligned} &T_n = \min(\text{Exp}(\lambda_n), \text{Exp}(\mu_n)) \\ &\sim \text{Exp}(\lambda_n + \mu_n) \end{aligned}$$

chap. 2

ex: (cf. Ross)

6.2: Poisson process: $\mu_n = 0$, $\lambda_n = \lambda \forall n \geq 0$

6.3: Yule process: $\mu_n = 0$, $\lambda_n = n\lambda \forall n \geq 0$

6.4: Linear growth with immigration: $\mu_n = n\mu$, $\lambda_n = n\lambda + \theta \forall n \geq 0$

immigration rate

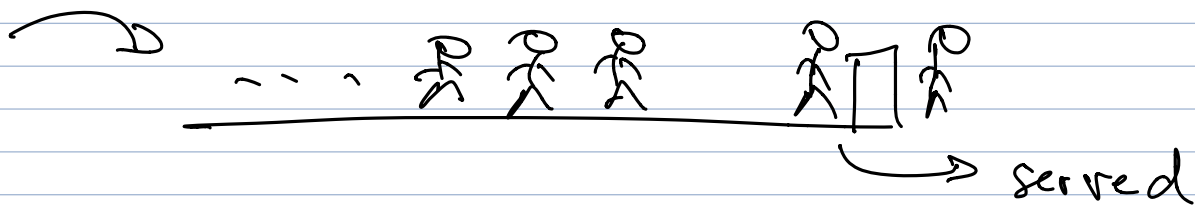
6.5: M/M/1 queue (queueing theory)

Markov arrivals Markov arrivals # server

→ A single server receives customers as a λ -Poisson process, and service times are

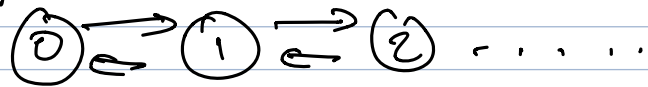
arrival independent $\text{Exp}(\mu)$ r.v.'s.

(6)



$X(t)$ = # customers in the system
(waiting to be served) at time t

it is a
B-D process



$$\rightarrow \lambda_n = \lambda \quad \mu_n = \mu$$

6.6. $M/M/s$ queue (s servers)

$$\lambda_n = \lambda, \quad \mu_n = \begin{cases} n\mu & 1 \leq n \leq s \\ s\mu & \text{else} \end{cases}$$

II. Transition probabilities & Kolmogorov eqs.

Goal: Study

$$\begin{aligned} P_{ij}(t) &= P(X(s+t)=j \mid X(s)=i) \\ &= P(X(t)=j \mid X(0)=i) \end{aligned}$$

↑
(stationarity)

Remark: $P_{ij}(t)$ is the continuous-time analog of $P_{ij}^{(n)}$ studied in discrete time.

Similarly, it satisfies the Chapman-Kolmogorov ^⑦

eq.

Prop (C-K-eq.) $\forall s, t \geq 0$

$$P_{ij}(s+t) = \sum_k P_{ik}(s) P_{kj}(t)$$