

Continuous Markov Chain (CMC) 4.1 Definitions & Examples

Def of CMC:

In discrete time, we formulate Markov property as:

$$P(X_{n+1}=j | X_n=i, X_{n-1}=x_{n-1}, \dots, X_0=x_0) = P(X_{n+1}=j | X_n=i)$$

But in continuous time, defining all X_r for $r \leq s$ can be challenging.

So instead, we say that $X_t, t \geq 0$ is a Markov Chain if for any $0 \leq s_0 < s_1 < \dots < s_n < s$ and possible states $i_0, \dots, i_n, i, j$, we have

$$P(X_{t+s}=j | X_s=i, X_{s_n}=i_n, \dots, X_{s_0}=i_0) = P(X_t=j | X_0=i)$$

In a word, given the present state, the rest of the past is irrelevant for predicting the future.

i.e., prob of going from i at times to j at time $s+t$, only depends on t .

Example. Let $N(t), t \geq 0$ be PP with rate λ and let Y_n be a discrete MC with transition probability $u(i, j)$. Then $X_t = Y_{N(t)}$ is a CMC.

In words, X_t takes one jump according to $u(i, j)$ at each arrival time of $N(t)$. X_t transit when pp has a new point at a time t .

This is a valid CMC, since in PP point's arrival time is independent, and X_t transite $u(i, j)$ are independent, and independent of time t .

We therefore define: $P_t(i, j) = P(X_t=j | X_0=i)$

In the PP example above $P_t(i, j) = \sum_{n=0}^{\infty} e^{-\lambda t} \frac{(\lambda t)^n}{n!} u^n(i, j)$

In time span t , the prob that X transit n times $\leftarrow \frac{(\lambda t)^n}{n!}$ prob that $i \rightarrow \dots \rightarrow j$ with path of length n

Theorem: Chapman - Kolmogorov Equation

$$\sum_k p_s(i, k) p_t(k, j) = p_{s+t}(i, j) \quad \text{Intuitively: Yes!}$$

Pf: $P(X_{s+t}=j | X_0=i) = \sum_k P(X_{s+t}=j, X_s=k | X_0=i)$

$$= \sum_k P(X_{s+t}=j | X_s=k, X_0=i) P(X_s=k | X_0=i) = \sum_k P_t(k, j) p_s(i, k)$$

From Chapman - Kolmogorov, we can know that: if we know the transition probability within $[0, t_0]$, then we will know the transition probability for any t . Because we can iteratively apply this equation.

We will soon justify: $q_{ij}(t) = \lim_{h \rightarrow 0} \frac{P_h(i, j)}{h}$ for $j \neq i$

If this limit exists, we will call $q_{ij}(t)$ the jump rate from i to j .

Back to the example of PP. Consider the prob of at least 2 jumps at time h :

$$P = 1 - (e^{-\lambda h} + \lambda h e^{-\lambda h}) = 1 - (1 + \lambda h) \left(1 - \lambda h + \frac{(\lambda h)^2}{2!} + \dots\right)$$

$$= \frac{(\lambda h)^2}{2!} + \dots = o(h), \text{ so if divided by } h \text{ and } h \rightarrow 0, \text{ they } \rightarrow 0$$

$$\therefore q_{ij}(t) = \lim_{h \rightarrow 0} \frac{P_h(i, j)}{h} = \lim_{h \rightarrow 0} \frac{e^{-\lambda h}}{h} \cdot u^0(i, j) + \frac{\lambda h e^{-\lambda h}}{h} \cdot u^1(i, j)$$

$$= \lambda u(i, j)$$

Now we may ask: Given the rates, how do we construct chain?

Let $\lambda_i = \sum_{j \neq i} q_{ij}(t)$ be the rate at which X_t leave i . If $\lambda_i = \infty$, then the procedure will want to leave i immediately. So we always suppose each state i has $\lambda_i < \infty$. If $\lambda_i = 0$, then X_t will never leave i . When $\lambda_i > 0$, we get:

$$r_{ij}(t) = q_{ij}(t) / \lambda_i \text{ for } j \neq i, \lambda_i = \sum_{j \neq i} q_{ij}(t)$$

is the probability that chain goes to j when it leaves i .

Formal Construction. Suppose $\lambda_i > 0$ for all i . If there are absorbing states, then when chain hits one, it stays forever. Let Y_n be a Markov chain with transition probability $r_{ij}(t)$. The discrete-time chain Y_n , gives the road map that the continuous-time process will follow. To determine how long will the process should stay in each state let $\tau_1, \tau_2, \dots$ be independent exponentials with rate 1, and:

At time 0: state Y_0 stays for $t_1 = \tau_0 / \lambda(Y_0)$ time

At time t_1 : jump to Y_1 and stay for $t_2 = \tau_1 / \lambda(Y_1)$ time

$\therefore$ { jump to Y_{n+1} at time: $T_{n+1} = t_1 + \dots + t_{n+1}$

If $T_0 = 0$, then for $n \geq 0$, $X(t) = Y_n$ for $T_n \leq t < T_{n+1}$

Wrap up: λ_i : the rate of leaving $i \Rightarrow \text{time} \propto \frac{1}{\lambda_i}$

τ_i : determine the time of staying

Y_i : record state transition

4.2 Computing the transition probability

$P_t(i, j) = P(X_t = j | X_0 = i)$. How to compute prob P_t from the jump rates q_h ?

$$P_{t+h}(i, j) - P_t(i, j) = \left[\sum_k P_h(i, k) P_t(k, j) \right] - P_t(i, j)$$

$$= \left[\sum_{k \neq i} P_h(i, k) P_t(k, j) \right] + [P_h(i, i) - 1] P_t(i, j)$$

Goal: Divide each side by h and $h \rightarrow 0$ to compute

$$P'_t(i, j) = \lim_{h \rightarrow 0} \frac{P_{t+h}(i, j) - P_t(i, j)}{h}$$

By the def of the jump rates: $q_h(i, j) = \lim_{h \rightarrow 0} \frac{P_h(i, j)}{h}$ for $i \neq j$

$$\text{So: } \lim_{h \rightarrow 0} \frac{1}{h} \sum_{k \neq i} P_h(i, k) P_t(k, j) = \sum_{k \neq i} q_h(i, k) P_t(k, j)$$

Also: $1 - P_h(i, i) = \sum_{k \neq i} P_h(i, k)$, so:

$$\lim_{h \rightarrow 0} \frac{P_h(i, i) - 1}{h} = - \lim_{h \rightarrow 0} \sum_{k \neq i} \frac{P_h(i, k)}{h} = - \sum_{k \neq i} q_h(i, k) = -\lambda_i$$

$$\therefore P'_t(i, j) = \sum_{k \neq i} q_h(i, k) P_t(k, j) - \lambda_i P_t(i, j)$$

To neaten up, we introduce: $Q(i, j) = \begin{cases} q_h(i, j) & \text{if } j \neq i \\ -\lambda_i & \text{if } j = i \end{cases}$

So $P'_t = Q P_t$

This is called Kolmogorov's backward equation. Inspired:

$$e^{Qt} = \sum_{n=0}^{\infty} Q^n \cdot \frac{t^n}{n!}, \text{ and } \frac{d}{dt} e^{Qt} = Q e^{Qt}$$

Now, revisit: $P_{t+h}(i, j) - P_t(i, j) = \left[\sum_k P_t(i, k) P_h(k, j) \right] - P_t(i, j)$

$$= \left[\sum_{k \neq j} P_t(i, k) P_h(k, j) \right] + [P_h(j, j) - 1] P_t(i, j)$$

Equation:

--- We have $P'_t = P_t Q = Q P_t$, this is called Kol Forward

4.3 Limiting Behavior

Markov chain X_t is irreducible if for any two states i and j , it is possible to get from i to j in finite number of jumps.

Lemma: If X_t is irreducible and $t > 0$, then $p_t(i, j) > 0$ for all i, j .

In CMT, π is said to be a stationary distribution if $\pi p_t = \pi$ for all $t > 0$. But p_t can be hard to compute. So:

$$Q(i, j) = \begin{cases} q(i, j), & j \neq i \\ -\lambda_i, & j = i. \end{cases}$$

where $\lambda_i = \sum_{j \neq i} q(i, j)$ is the total rate of transitions out of i .

Lemma: π is a stationary distribution iff $\pi Q = 0$

Theorem: If a CMT X_t is irreducible and has a π , then:

$$\lim_{t \rightarrow \infty} p_t(i, j) = \pi(j).$$

Detailed balance condition: We can formulate:

$$\pi(k) q(k, j) = \pi(j) q(j, k) \quad \text{for all } j \neq k$$

And: Theorem: If $\pi(k) q(k, j) = \pi(j) q(j, k)$ holds, then π is a stationary distribution.

Important topic: Birth and Death Process

Suppose that $S = \{0, 1, \dots, N\}$ with $N \leq \infty$, and: $q(n, n+1) = \lambda_n, n > 0$

So here: λ_n represents the birthrate when there are n individuals in the system, and μ_n denotes the death rate. **Formulation**

If the birth and death chain is irreducible, and we can divide to write the detailed balance condition as:

$$\pi(n) = \frac{\lambda_{n-1}}{\mu_n} \pi(n-1)$$

$$\text{i.e., } \pi(n) = \frac{\lambda_{n-1} \cdot \lambda_{n-2} \cdots \lambda_0}{\mu_n \cdot \mu_{n-1} \cdots \mu_1} \pi(0)$$