

Continuous-time Markov Chain: Poisson Process



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- One important example of the CTMC is the Poisson process.
- A Poisson process $\{N(t)\}$ is a counting process representing the number of occurrences of an event up to time t (over time interval $(0, t]$).
- Used to model events that occur approximately at a certain rate, but at a completely random instants.
- Suppose you receive at an average 10 emails per day, but at random instants of time. The Poisson process may be good model to represent the number of emails in a time duration.
- Some simple examples are:
 - Number of alpha particles emitted by a radio-active substance.
 - Number of packets received at switching node of a communication network.
 - Number of earthquakes occurring during a month in an earth-quake prone zone.

Review of Poisson RVs

➤ A discrete random variable X is called a *Poisson random variable* with the

parameter $\mu > 0$ if $p_X(k) = \frac{e^{-\mu} \mu^k}{k!}$, $k = 0, 1, 2, \dots$

➤ X is denoted as $X \sim \text{Poi}(\mu)$

➤ EX and $\text{var}(X)$ given by

$$EX = \mu \text{ and } \text{var}(X) = \mu$$

➤ The MGF $M_X(s)$ is given by

$$M_X(s) = Ee^{sX} = e^{\mu(e^s - 1)}$$

➤ If $X_i \sim \text{Poi}(\mu_i)$, $i = 1, 2, \dots, n$, then

$$X_1 + X_2 + \dots + X_n \sim \text{Poi}(\mu_1 + \mu_2 + \dots + \mu_n)$$

Binomial RV

$$X \sim \text{Bi}(n, p) \quad \text{var}(X) = np(1-p)$$

when $n \rightarrow \infty$,
 $np \rightarrow \lambda$

Then $\lambda \sim \text{Poi}(\lambda)$
 $s(X_1 + X_2 + \dots + X_n)$

$$\begin{aligned} M_{X_1 + X_2 + \dots + X_n} &= Ee^{s(X_1 + X_2 + \dots + X_n)} \\ &= \prod_{i=1}^n Ee^{sX_i} = \prod_{i=1}^n e^{\mu_i(e^s - 1)} \\ &= e^{\sum_{i=1}^n \mu_i(e^s - 1)} = e^{(\mu_1 + \mu_2 + \dots + \mu_n)(e^s - 1)} \end{aligned}$$

$$\sum_{k=0}^{\infty} \frac{e^{-\mu} \mu^k}{k!} = e^{-\mu} \sum_{k=0}^{\infty} \frac{\mu^k}{k!} = e^{-\mu} e^{\mu} = 1$$

and independent

Poisson Process as a CTMC

- $\{N(t)\}$ is a Markov chain because of the independent increment property.
- $\{N(t)\}$ takes values from the infinite state space $V = \{0, 1, \dots\}$ and the probability $p_j(t) = P(N(t) = j)$ is given by

$$p_j(t) = e^{-\lambda t} \frac{(\lambda t)^j}{j!}, j \in V$$

Thus at any instant t , $\{N(t)\}$ is a Poisson RV.

Poisson process as a CTMC

Suppose the Poisson process has entered state i at time $t = 0$. It remains in same state until the next arrival with $T_i \sim \exp(\lambda)$. Once an arrival takes place, the state become $i+1$

Thus, for $j \neq i$, $P_{i,j} = \begin{cases} 1, & j = i+1 \\ 0 & \text{otherwise} \end{cases}$

. The transition rates are given by

$$q_{i,j} = \lambda P_{i,j} \quad \text{for } j \neq i$$

$$\Rightarrow q_{i,i+1} = \lambda, q_{i,i} = -\lambda, q_{i,j} = 0, j \neq i, i+1$$

Further, $N(0) = 0$ with probability 1

$$P(N(0) = 0) = 1$$

$$P_0(0) = 1 \text{ for } i=0, \\ P_i(0) = 0 \text{ for } i \neq 0.$$

Forward Kolmogorov Equation for Poisson Process $p_{ij}'(t) = \sum_k p_{ik}(t)q_{kj}$

$$p_{0,j}'(t) = \sum_k p_{0,k}(t)q_{kj} = -\lambda p_{0,j}(t) + \lambda p_{0,j-1}(t)$$

Since $p_0(0) = 1$ and $p_j(0) = 0, j \neq 0$, we have $p_j(t) = p_{0,j}(t)$. Therefore, in terms of the state probabilities,

$$p_j'(t) = -\lambda p_j(t) + \lambda p_{j-1}(t), j = 1, 2, \dots \quad (1)$$

For $j = 0$,

$$p_0'(t) = -\lambda p_0(t) \quad (2)$$

The solution of the differential equation (2) with $p_0(0) = 1$ and $p_j(0) = 0, j > 0$

Is given by $p_0(t) = e^{-\lambda t} \quad t \geq 0$

Handwritten notes in blue ink:

- Diagram showing transitions between states 0 and j.
- Equation: $p_0(0) = 1, p_j(0) = 0 \rightarrow [P]$
- Equation: $= [p(t) \phi(t) - \dots]$

For $j=1$

$$p_1'(t) = -\lambda p_1(t) + \lambda p_0(t)$$

Substituting $p_0(t) = e^{-\lambda t}$ $t \geq 0$, we get

$$p_1'(t) = -\lambda p_1(t) + \lambda e^{-\lambda t}$$

Solving the above linear differential equation with the initial condition $p_1(0) = 0$, we get

$$p_1(t) = \lambda t e^{-\lambda t} = \frac{(\lambda t)^1 e^{-\lambda t}}{1!} \quad t \geq 0$$

$j=1$, The formula is correct -

Thus $p_1(t)$ satisfies the formula. Now assuming $p_{j-1}(t) = \frac{(\lambda t)^{j-1} e^{-\lambda t}}{(j-1)!}$ $t \geq 0$, we can solve the

differential equation $p_j'(t) = -\lambda p_j(t) + \lambda \frac{(\lambda t)^{j-1} e^{-\lambda t}}{(j-1)!}$, we get

$$p_j(t) = \frac{(\lambda t)^j e^{-\lambda t}}{j!} \quad t \geq 0$$

$$p_j(t) = \frac{(\lambda t)^j e^{-\lambda t}}{j!} \quad t \geq 0$$

We can derive the same differential equations for the Poisson process using the following postulates:

Postulates of Poisson Process

- (i) $N(0)=0$ with probability 1.
- (ii) $N(t)$ is an *independent increment* process.
- (iii) $P(\{N(\Delta t) = 1\}) = \lambda\Delta t + o(\Delta t)$

where $o(\Delta t)$ implies any function such that $\lim_{\Delta t \rightarrow 0} \frac{o(\Delta t)}{\Delta t} = 0$.

- (iv) $P(\{N(\Delta t) \geq 2\}) = o(\Delta t)$

Remark

- The parameter λ is called the rate or intensity of the Poisson process. It can be shown that

$$P(N(t_2) - N(t_1) = j) = \frac{(\lambda(t_2 - t_1))^j e^{-\lambda(t_2 - t_1)}}{j!}$$

Thus, the probability of the increments depends on the length of the interval $t_2 - t_1$ and not on the absolute times t_2 and t_1 . The Poisson process is a process with *stationary increments*.

- The independent and stationary increment properties help us to compute the joint probability mass function of $N(t)$. For example,

$$\begin{aligned} p_{N(t), N(t_2)}(n_1, n_2) &= P(\{N(t_1) = n_1, N(t_2) = n_2\}) \\ &= P(\{N(t_1) = n_1\})P(\{N(t_2) = n_2\} | \{N(t_1) = n_1\}) \\ &= P(\{N(t_1) = n_1\})P(\{N(t_2) - N(t_1) = n_2 - n_1\} | \{N(t_1) = n_1\}) \\ &= P(\{N(t_1) = n_1\})P(\{N(t_2) - N(t_1) = n_2 - n_1\}) \\ &= \frac{(\lambda t_1)^{n_1} e^{-\lambda t_1}}{n_1!} \frac{(\lambda(t_2 - t_1))^{n_2 - n_1} e^{-\lambda(t_2 - t_1)}}{(n_2 - n_1)!} \end{aligned}$$

Mean, Variance and Autocorrelation function of $\{N(t)\}$

We have

$$p_j(t) = \frac{(\lambda t)^j e^{-\lambda t}}{j!} \quad t \geq 0$$

At any time $t > 0$, $N(t)$ is a Poisson random variable with the parameter λt .

Therefore, $EN(t) = \lambda t$ and $\text{var } N(t) = \lambda t$

Thus both the mean and variance of a Poisson process varies linearly with time.

We can use the independent increment property to find the autocovariance

We can show that

$$C_N(t_1, t_2) = \lambda \min(t_1, t_2)$$

$$C_N(t_1, t_2) = \text{Cov}(N(t_1), N(t_2))$$

$$= \text{Cov}(N(t_1),$$

$$N(t_2) - N(t_1) + N(t_1)) \neq \text{Cov}(N(t_1), N(t_1))$$

$$= \text{Cov}(N(t_1), N(t_2) - N(t_1)) + \text{Cov}(N(t_1), N(t_1))$$

$$\text{so } t_1 > t_2$$

$$C_N(t_1, t_2) = \lambda t_2$$

$$\therefore R_N(t_1, t_2) = C_N(t_1, t_2) + EN(t_1)EN(t_2)$$

$$= \lambda \min(t_1, t_2) + \lambda^2 t_1 t_2$$

Example A petrol pump serves on the average 30 cars per hour. Assuming the Poisson model, find the probability that during a period of 5 minutes (i) no car comes to the station, (ii) exactly 3 cars come to the station and (iii) more than 3 cars come to the station.

Average arrival = 30 cars/hr = $\frac{1}{2}$ car/min

Probability of no car in 5 minutes

$$(i) P\{N(5) = 0\} = e^{-\frac{1}{2} \times 5} = e^{-2.5} = 0.0821$$

$$(ii) P\{N(5) = 3\} = \frac{\left(\frac{1}{2} \times 5\right)^3}{3!} e^{-2.5} = 0.2138$$

(iii)

$$\begin{aligned} P(\{N(5) > 3\}) &= 1 - P(\{N(5) \leq 3\}) \\ &= 1 - P(\{N(5) = 0\}) - P(\{N(5) = 1\}) - P(\{N(5) = 2\}) - P(\{N(5) = 3\}) \\ &= 1 - 0.08 - 0.2052 - 0.2565 - 0.21 \\ &= 0.2424 \end{aligned}$$

To Summarise

- To characterize the transition probabilities dynamically, Kolmogorov backward and forward differential equations are used.
- Poisson process $\{N(t)\}$ is the well-known CTMC with

$$P_{i,j} = \begin{cases} 1, & j = i + 1 \\ 0 & \text{otherwise} \end{cases} \quad \text{and transition rates}$$

$$q_{i,i+1} = \lambda, \quad q_{i,i} = -\lambda, \quad q_{i,j} = 0, \quad j \neq i, i + 1$$

The state probabilities are given by

$$p_j(t) = e^{-\lambda t} \frac{(\lambda t)^j}{j!}, \quad j = 0, 1, \dots$$

- The independent increment property can be used to find the joint probability mass functions, autocovariance functions.