

process occurs at time S_n , where

$$S_n \equiv X_1 + X_2 + \cdots + X_n.$$

The resultant counting process $\{N(t), t \geq 0\}$ will be Poisson with rate λ .

2.3 CONDITIONAL DISTRIBUTION OF THE ARRIVAL TIMES

Suppose we are told that exactly one event of a Poisson process has taken place by time t , and we are asked to determine the distribution of the time at which the event occurred. Since a Poisson process possesses stationary and independent increments, it seems reasonable that each interval in $[0, t]$ of equal length should have the same probability of containing the event. In other words, the time of the event should be uniformly distributed over $[0, t]$. This is easily checked since, for $s \leq t$,

$$\begin{aligned} P\{X_1 < s | N(t) = 1\} &= \frac{P\{X_1 < s, N(t) = 1\}}{P\{N(t) = 1\}} \\ &= \frac{P\{1 \text{ event in } [0, s], 0 \text{ events in } [s, t]\}}{P\{N(t) = 1\}} \\ &= \frac{P\{1 \text{ event in } [0, s]\}P\{0 \text{ events in } [s, t]\}}{P\{N(t) = 1\}} \\ &= \frac{\lambda s e^{-\lambda s} e^{-\lambda(t-s)}}{\lambda t e^{-\lambda t}} \\ &= \frac{s}{t}. \end{aligned}$$

This result may be generalized, but before doing so we need to introduce the concept of order statistics

Let Y_1, Y_2, \dots, Y_n be n random variables. We say that $Y_{(1)}, Y_{(2)}, \dots, Y_{(n)}$ are the order statistics corresponding to Y_1, Y_2, \dots, Y_n if $Y_{(k)}$ is the k th smallest value among Y_1, \dots, Y_n , $k = 1, 2, \dots, n$. If the Y_i 's are independent identically distributed continuous random variables with probability density f , then the joint density of the order statistics $Y_{(1)}, Y_{(2)}, \dots, Y_{(n)}$ is given by

$$f(y_1, y_2, \dots, y_n) = n! \prod_{i=1}^n f(y_i), \quad y_1 < y_2 < \cdots < y_n.$$

The above follows since (i) $(Y_{(1)}, Y_{(2)}, \dots, Y_{(n)})$ will equal (y_1, y_2, \dots, y_n) if (Y_1, Y_2, \dots, Y_n) is equal to any of the $n!$ permutations of (y_1, y_2, \dots, y_n) ,

and (ii) the probability density that (Y_1, Y_2, \dots, Y_n) is equal to $y_{i_1}, y_{i_2}, \dots, y_{i_n}$ is $f(y_{i_1})f(y_{i_2}) \cdots f(y_{i_n}) = \prod_1^n f(y_i)$ when $(y_{i_1}, y_{i_2}, \dots, y_{i_n})$ is a permutation of (y_1, y_2, \dots, y_n) .

If the $Y_i, i = 1, \dots, n$, are uniformly distributed over $(0, t)$, then it follows from the above that the joint density function of the order statistics $Y_{(1)}, Y_{(2)}, \dots, Y_{(n)}$ is

$$f(y_1, y_2, \dots, y_n) = \frac{n!}{t^n}, \quad 0 < y_1 < y_2 < \dots < y_n < t.$$

We are now ready for the following useful theorem.

THEOREM 2.3.1

Given that $N(t) = n$, the n arrival times S_1, \dots, S_n have the same distribution as the order statistics corresponding to n independent random variables uniformly distributed on the interval $(0, t)$.

Proof We shall compute the conditional density function of S_1, \dots, S_n given that $N(t) = n$. So let $0 < t_1 < t_2 < \dots < t_{n+1} = t$ and let h_i be small enough so that $t_i + h_i < t_{i+1}, i = 1, \dots, n$. Now,

$$\begin{aligned} &P\{t_i \leq S_i \leq t_i + h_i, i = 1, 2, \dots, n | N(t) = n\} \\ &= \frac{P\{\text{exactly 1 event in } [t_i, t_i + h_i], i = 1, \dots, n, \text{ no events elsewhere in } [0, t]\}}{P\{N(t) = n\}} \\ &= \frac{\lambda h_1 e^{-\lambda h_1} \cdots \lambda h_n e^{-\lambda h_n} e^{-\lambda(t-h_1-h_2-\dots-h_n)}}{e^{-\lambda t} (\lambda t)^n / n!} \\ &= \frac{n!}{t^n} h_1 \cdot h_2 \cdots h_n \end{aligned}$$

Hence,

$$\frac{P\{t_i \leq S_i \leq t_i + h_i, i = 1, 2, \dots, n | N(t) = n\}}{h_1 \cdot h_2 \cdots h_n} = \frac{n!}{t^n},$$

and by letting the $h_i \rightarrow 0$, we obtain that the conditional density of S_1, \dots, S_n given that $N(t) = n$ is

$$f(t_1, \dots, t_n) = \frac{n!}{t^n}, \quad 0 < t_1 < \dots < t_n,$$

which completes the proof

Remark Intuitively, we usually say that under the condition that n events have occurred in $(0, t)$, the times S_1, \dots, S_n at which events occur, considered as unordered random variables, are distributed independently and uniformly in the interval $(0, t)$

EXAMPLE 2.3(A) Suppose that travelers arrive at a train depot in accordance with a Poisson process with rate λ . If the train departs at time t , let us compute the expected sum of the waiting times of travelers arriving in $(0, t)$. That is, we want $E[\sum_{i=1}^{N(t)} (t - S_i)]$, where S_i is the arrival time of the i th traveler. Conditioning on $N(t)$ yields

$$\begin{aligned} E \left[\sum_{i=1}^{N(t)} (t - S_i) | N(t) = n \right] &= E \left[\sum_{i=1}^n (t - S_i) | N(t) = n \right] \\ &= nt - E \left[\sum_{i=1}^n S_i | N(t) = n \right] \end{aligned}$$

Now if we let U_1, \dots, U_n denote a set of n independent uniform $(0, t)$ random variables, then

$$\begin{aligned} E \left[\sum_{i=1}^n S_i | N(t) = n \right] &= E \left[\sum_{i=1}^n U_{(i)} \right] \quad (\text{by Theorem 2.3.1}) \\ &= E \left[\sum_{i=1}^n U_i \right] \quad \left(\text{since } \sum_{i=1}^n U_{(i)} = \sum_{i=1}^n U_i \right) \\ &= \frac{nt}{2}. \end{aligned}$$

Hence,

$$E \left[\sum_{i=1}^{N(t)} (t - S_i) | N(t) = n \right] = nt - \frac{nt}{2} = \frac{nt}{2}$$

and

$$E \left[\sum_{i=1}^{N(t)} (t - S_i) \right] = \frac{t}{2} E[N(t)] = \frac{\lambda t^2}{2}.$$

As an important application of Theorem 2.3.1 suppose that each event of a Poisson process with rate λ is classified as being either a type-I or type-II event, and suppose that the probability of an event being classified as type-I depends on the time at which it occurs. Specifically, suppose that if an event occurs at time s , then, independently of all else, it is classified as being a type-I event with probability $P(s)$ and a type-II event with probability $1 - P(s)$. By using Theorem 2.3.1 we can prove the following proposition.

PROPOSITION 2.3.2

If $N_i(t)$ represents the number of type- i events that occur by time t , $i = 1, 2$, then $N_1(t)$ and $N_2(t)$ are independent Poisson random variables having respective means λtp and $\lambda t(1 - p)$, where

$$p = \frac{1}{t} \int_0^t P(s) ds$$

Proof We compute the joint distribution of $N_1(t)$ and $N_2(t)$ by conditioning on $N(t)$

$$\begin{aligned} P\{N_1(t) = n, N_2(t) = m\} &= \sum_{k=0}^{\infty} P\{N_1(t) = n, N_2(t) = m | N(t) = k\} P\{N(t) = k\} \\ &= P\{N_1(t) = n, N_2(t) = m | N(t) = n + m\} P\{N(t) = n + m\} \end{aligned}$$

Now consider an arbitrary event that occurred in the interval $[0, t]$. If it had occurred at time s , then the probability that it would be a type-I event would be $P(s)$. Hence, since by Theorem 2.3.1 this event will have occurred at some time uniformly distributed on $(0, t)$, it follows that the probability that it will be a type-I event is

$$p = \frac{1}{t} \int_0^t P(s) ds$$

independently of the other events. Hence, $P\{N_1(t) = n, N_2(t) = m | N(t) = n + m\}$ will just equal the probability of n successes and m failures in $n + m$ independent trials when p is the probability of success on each trial. That is,

$$P\{N_1(t) = n, N_2(t) = m | N(t) = n + m\} = \binom{n + m}{n} p^n (1 - p)^m$$

Consequently,

$$\begin{aligned} P\{N_1(t) = n, N_2(t) = m\} &= \frac{(n + m)!}{n! m!} p^n (1 - p)^m e^{-\lambda t} \frac{(\lambda t)^{n+m}}{(n + m)!} \\ &= e^{-\lambda p t} \frac{(\lambda p t)^n}{n!} e^{-\lambda t(1-p)} \frac{(\lambda t(1-p))^m}{m!}, \end{aligned}$$

which completes the proof

The importance of the above proposition is illustrated by the following example