

# STK2130 – Chapter 5.4.1

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# The non-homogeneous Poisson Process

## Definition

A counting process  $\{N(t) : t \geq 0\}$  is said to be a *non-homogeneous Poisson process* with intensity function  $\lambda(t)$ ,  $t \geq 0$ , if:

- (i)  $N(0) = 0$
- (ii)  $\{N(t), t \geq 0\}$  has independent increments.
- (iii)  $P(N(t+h) - N(t) = 1) = \lambda(t)h + o(h)$
- (iv)  $P(N(t+h) - N(t) \geq 2) = o(h)$

We also introduce the *mean value function*  $m(t)$  defined by:

$$m(t) = \int_0^t \lambda(u) du$$

# The non-homogeneous Poisson Process (cont.)

## Lemma (5.3)

If  $\{N(t) : t \geq 0\}$  is a non-homogeneous Poisson process with intensity function  $\lambda(t)$ , then:

$$P(N(t) = 0) = e^{-m(t)}, \quad t \geq 0.$$

## Corollary

If  $\{N(t) : t \geq 0\}$  is a non-homogeneous Poisson process with intensity function  $\lambda(t)$ , and let  $T_1$  be the time of the first event. Then we have:

$$P(T_1 > t) = P(N(t) = 0) = e^{-m(t)}, \quad t \geq 0.$$

Moreover, the density of  $T_1$  is given by:

$$f_{T_1}(t) = \lambda(t)e^{-m(t)}, \quad t \geq 0.$$

## The non-homogeneous Poisson Process (cont.)

If  $\{N(t) : t \geq 0\}$  is a non-homogeneous Poisson process, and  $s > 0$ , we define:

$$N_s(t) = N(s + t) - N(s).$$

### Lemma (5.4)

*If  $\{N(t) : t \geq 0\}$  is a non-homogeneous Poisson process with intensity function  $\lambda(t)$ , then  $\{N_s(t) : t \geq 0\}$  is a non-homogeneous Poisson process with intensity function  $\lambda_s(t) = \lambda(s + t)$ ,  $t \geq 0$ .*

NOTE:

$$N_s(t - s) = N(t - s + s) - N(s) = N(t) - N(s)$$

## The non-homogeneous Poisson Process (cont.)

The mean value function of  $\{N_s(t) : t \geq 0\}$  is given by:

$$\begin{aligned}m_s(t) &= \int_0^t \lambda_s(u) du \\&= \int_0^t \lambda(s+u) du \quad \text{Subst.: } v = s+u, dv = du. \\&= \int_s^{s+t} \lambda(v) dv \\&= m(s+t) - m(s)\end{aligned}$$

NOTE:

$$m_s(t-s) = m(t-s+s) - m(s) = m(t) - m(s) = \int_s^t \lambda(u) du$$

# The non-homogeneous Poisson Process (cont.)

## Theorem (5.3)

If  $\{N(t) : t \geq 0\}$  is a non-homogeneous Poisson process with intensity function  $\lambda(t)$ , then:

$$P(N(t) = n) = \frac{(m(t))^n}{n!} e^{-m(t)}, \quad t \geq 0, \quad n = 0, 1, 2, \dots$$

PROOF: Induction with respect to  $n$ . By Lemma 5.3 the theorem holds for  $n = 0$ .

We then assume that we have shown that:

$$P(N(t) = n) = \frac{(m(t))^n}{n!} e^{-m(t)}, \quad t \geq 0,$$

and consider the probability  $P(N(t) = n + 1)$ .

## The non-homogeneous Poisson Process (cont.)

In order to calculate this probability we condition on  $T_1$ , noting that if  $s > t$ , then obviously  $P(N(t) = n + 1 | T_1 = s) = 0$ .

$$\begin{aligned}P(N(t) = n + 1) &= \int_0^t P(N(t) = n + 1 | T_1 = s) f_{T_1}(s) ds \\&= \int_0^t P(N(t) = n + 1 | T_1 = s) \lambda(s) e^{-m(s)} ds \\&= \int_0^t P(N(t) - N(s) = n | T_1 = s) \lambda(s) e^{-m(s)} ds \\&= \int_0^t P(N(t) - N(s) = n) \lambda(s) e^{-m(s)} ds \quad (\text{Indep. incr.}) \\&= \int_0^t P(N_s(t - s) = n) \lambda(s) e^{-m(s)} ds\end{aligned}$$

## The non-homogeneous Poisson Process (cont.)

By Lemma 5.4 and the induction hypothesis it follows that:

$$\begin{aligned}P(N_s(t-s) = n) &= \frac{(m_s(t-s))^n}{n!} e^{-m_s(t-s)} \\ &= \frac{(m(t) - m(s))^n}{n!} e^{-(m(t)-m(s))}\end{aligned}$$

By inserting this into the integral we get:

$$\begin{aligned}P(N(t) = n+1) &= \int_0^t P(N_s(t-s) = n) \lambda(s) e^{-m(s)} ds \\ &= \int_0^t \frac{(m(t) - m(s))^n}{n!} e^{-(m(t)-m(s))} \lambda(s) e^{-m(s)} ds\end{aligned}$$



## The non-homogeneous Poisson Process (cont.)

Simplifying the integrand yields:

$$\begin{aligned}P(N(t) = n + 1) &= \int_0^t \frac{(m(t) - m(s))^n}{n!} e^{-(m(t)-m(s))} \lambda(s) e^{-m(s)} ds \\ &= \frac{e^{-m(t)}}{n!} \int_0^t (m(t) - m(s))^n \lambda(s) ds\end{aligned}$$

Substitute:  $u = m(t) - m(s) = \int_s^t \lambda(v) dv$  and  $du = -\lambda(s) ds$ , and get:

$$\begin{aligned}P(N(t) = n + 1) &= -\frac{e^{-m(t)}}{n!} \int_{m(t)}^0 u^n du = \frac{e^{-m(t)}}{n!} \int_0^{m(t)} u^n du \\ &= \frac{e^{-m(t)}}{n!} \cdot \frac{(m(t))^{n+1}}{n+1} = \frac{(m(t))^{n+1}}{(n+1)!} e^{-m(t)}\end{aligned}$$

which completes the induction proof ■

## The non-homogeneous Poisson Process (cont.)

### REMARK

We recall that  $\{N_s(t) : t \geq 0\}$  is a non-homogeneous Poisson Process with mean function:

$$m_s(t) = m(s+t) - m(s) = \int_0^{s+t} \lambda(u) du - \int_0^s \lambda(u) du = \int_s^{s+t} \lambda(u) du$$

By Theorem 5.3 this implies that  $N_s(t) = N(s+t) - N(s) \sim Po(m_s(t))$ , and:

$$E[N_s(t)] = m_s(t) = \int_s^{s+t} \lambda(u) du.$$

Moreover,  $N_s(t-s) = N(t) - N(s) \sim Po(m_s(t-s)) = Po(m(t) - m(s))$ , and:

$$E[N_s(t-s)] = m_s(t-s) = m(t) - m(s) = \int_s^t \lambda(u) du$$

## Example 5.24

Hot dog stand, opens at 08 A.M., closes at 05 P.M.

- 08 A.M. — 11 A.M.: Steadily increasing intensity from 5 to 20
- 11 A.M. — 01 P.M.: Constant intensity of 20
- 01 P.M. — 05 P.M.: Steadily decreasing intensity from 20 to 12

By letting  $t = 0$  represent 8 a.m. the **customer arrival intensity function**, denoted  $\lambda(t)$ , can be expressed as:

$$\lambda(t) = \begin{cases} 5 + 5t & 0 \leq t \leq 3 \\ 20 & 3 \leq t \leq 5 \\ 20 - 2(t - 5) & 5 \leq t \leq 9 \end{cases}$$

Hence, we have:

$$\lambda(0) = 5 + 5 \cdot 0 = 5, \quad \lambda(3) = 5 + 5 \cdot 3 = 20,$$

$$\lambda(5) = 20 - 2 \cdot (5 - 5) = 20, \quad \lambda(9) = 20 - 2 \cdot (9 - 5) = 12.$$

## Example 5.24 (cont.)

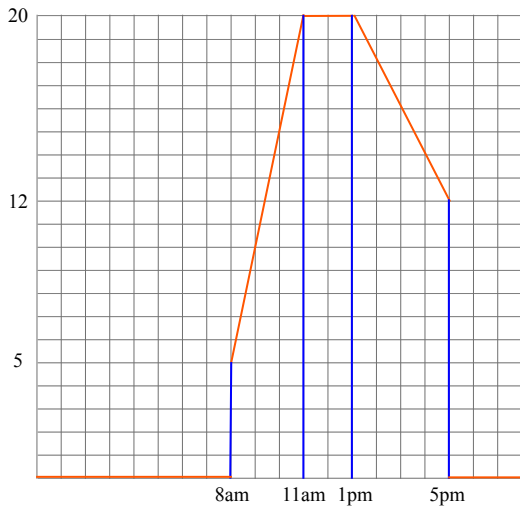


Figure: Customer arrival intensity function

## Example 5.24 (cont.)

For  $0 \leq s \leq t$  we let:

$N(t)$  = Number of arrivals at the hot dog stand in  $[0, t]$

$N(s, t)$  = Number of arrivals at the hot dog stand in  $[s, t] = N(t) - N(s)$ .

By Theorem 5.3  $N(t) \sim Po(m(t))$  and  $N(s, t) \sim Po(m(t) - m(s))$ , where:

$$m(t) = \int_0^t \lambda(u) du, \quad 0 \leq t$$

$$m(t) - m(s) = \int_s^t \lambda(u) du, \quad 0 \leq s \leq t$$

## Example 5.24 (cont.)

**Ex. A.** What is the expected number of arrivals between 8:30 A.M. and 9:30 A.M.? What is the probability that no customers arrive in this period?

SOLUTION: 8:30 A.M. and 9:30 A.M. correspond to respectively  $s = \frac{1}{2}$  and  $t = \frac{3}{2}$ . From this we get that:

$$\begin{aligned} E[N(\frac{1}{2}, \frac{3}{2})] &= m(\frac{3}{2}) - m(\frac{1}{2}) = \int_{1/2}^{3/2} \lambda(u) du = \int_{1/2}^{3/2} (5 + 5u) du \\ &= \left| \frac{(3/2)}{(1/2)} (5t + \frac{5}{2}t^2) \right| \\ &= (\frac{15}{2} + \frac{45}{8}) - (\frac{5}{2} + \frac{5}{8}) = \frac{105}{8} - \frac{25}{8} = 10. \end{aligned}$$

Moreover, we have:

$$P(N(\frac{1}{2}, \frac{3}{2}) = 0) = e^{-(m(t)-m(s))} = e^{-10} \approx 0.000045$$

## Example 5.24 (cont.)

**Ex. B.** What is the expected number of arrivals between 1:00 P.M. and 3:00 P.M? What is the probability that at least two customers arrive in this period?

SOLUTION: 1:00 P.M. and 3:00 P.M correspond to respectively  $s = 5$  and  $t = 7$ . From this we get that:

$$\begin{aligned} E[N(5, 7)] &= m(7) - m(5) = \int_5^7 \lambda(u) du = \int_5^7 (20 - 2(u - 5)) du \\ &= \int_5^7 (20 - 2u + 10) du = \Big|_5^7 (20t - t^2 + 10t) \\ &= (140 - 49 + 70) - (100 - 25 + 50) \\ &= 161 - 125 = 36. \end{aligned}$$

## Example 5.24 (cont.)

Moreover, we have:

$$\begin{aligned}P(N(5, 7) \geq 2) &= 1 - P(N(5, 7) \leq 1) \\&= 1 - [P(N(5, 7) = 0) + P(N(5, 7) = 1)] \\&= 1 - \left[ e^{-(m(7)-m(5))} + \frac{(m(7) - m(5))^1}{1!} e^{-(m(7)-m(5))} \right] \\&= 1 - \left[ 1 + \frac{36}{1} \right] \cdot e^{-36} \\&= 1 - 37 \cdot e^{-36} \approx 1\end{aligned}$$



# Time sampling a homogeneous Poisson Process

We recall the following result (slightly modified):

## Theorem (5.2)

We consider a Poisson process  $\{N(t) : t \geq 0\}$ , and assume that  $N(t) - N(s) = n$ , where  $s < t$ . Then the arrival times  $S_1 < S_2 < \dots < S_n$  in  $(s, t]$  has the following joint density:

$$f(s_1, s_2, \dots, s_n | N(t) - N(s) = n) = \frac{n!}{(t - s)^n}, \quad s < s_1 < s_2 < \dots < s_n < t.$$

The preceding result is often stated as follows:

## Corollary (5.2)

Given that  $n$  events have occurred in the interval  $(s, t]$ , the times at which the events occur, considered as unordered random variables, are distributed *independently* and *uniformly* in the interval  $(s, t]$ .

## Time sampling a Poisson Process (cont.)

Let  $\{N(t) : t \geq 0\}$  be a **homogeneous** Poisson Process with rate  $\lambda$  where each event can be classified as either a Type 1 event or a Type 2 event.

If an event occurs at time  $t$ , then the probability that it is of type 1 is  $p_1(t)$ , and the probability that it is of type 2 is  $p_2(t) = 1 - p_1(t)$ .

We assume that the event type at time  $t$  is **independent** of the history of the Poisson process up to time  $t$ , and introduce:

$$N_i(t) = \text{The number of events of type } i \text{ in } [0, t] \quad t \geq 0, \quad i = 1, 2.$$

NOTE:  $N(t) = N_1(t) + N_2(t)$ . Moreover, it can be shown that for  $s < t$ :

$$(N_i(t) - N_i(s) | N(t) - N(s) = n) \sim \text{Bin}(n, \bar{p}_i(s, t)), \quad i = 1, 2,$$

where:

$$\bar{p}_i(s, t) = \frac{1}{t-s} \int_s^t p_i(u) du, \quad i = 1, 2.$$

## Time sampling a Poisson Process (cont.)

In order to explain this, we recall that conditional on the event that  $N(t) - N(s) = n$ , the  $n$  arrival times in the interval  $(s, t]$  are independent and uniformly distributed.

Given that the arrival time of an event is  $u$ , the probability that this event is of type  $i$  is  $p_i(u)$ . Hence, the unconditional probability that the event is of type  $i$  is:

$$P(\text{Type } i \text{ event}) = \int_s^t p_i(u) \frac{1}{t-s} du = \bar{p}_i(s, t).$$

Since all event types are classified independent of the Poisson process, we have a series of  $n$  binomial experiments with the same probability of success.

Hence, we have:

$$(N_i(t) - N_i(s) | N(t) - N(s) = n) \sim \text{Bin}(n, \bar{p}_i(s, t)), \quad i = 1, 2 \quad \blacksquare$$

## Time sampling a Poisson Process (cont.)

We will now show that:

- $\{N_i(t) : t \geq 0\}$  is a **non-homogeneous** Poisson Process with intensity function  $\lambda p_i(t)$ ,  $i = 1, 2$ .
- $\{N_1(t) : t \geq 0\}$  and  $\{N_2(t) : t \geq 0\}$  are **independent** of each other.

In order to show the first claim, we verify that  $\{N_i(t) : t \geq 0\}$  satisfies the axioms.

The proof of the second claim is similar to the corresponding result for the case where the probabilities  $p_1(t)$  and  $p_2(t)$  are constant.

## Time sampling a Poisson Process (cont.)

PROOF: Since  $N(0) = 0$ , it follows that  $N_i(0) = 0$ ,  $i = 1, 2$  as well.

Let  $(s_1, t_1]$  and  $(s_2, t_2]$  be disjoint. Since  $\{N(t) : t \geq 0\}$  has independent increments, we have for  $i = 1, 2$ :

$$\begin{aligned} P(N_i(t_2) - N_i(s_2) = k | N_i(t_1) - N_i(s_1) = \ell) \\ &= \sum_{n=k}^{\infty} P(N_i(t_2) - N_i(s_2) = k | N(t_2) - N(s_2) = n, N_i(t_1) - N_i(s_1) = \ell) \\ &\quad \cdot P(N(t_2) - N(s_2) = n | N_i(t_1) - N_i(s_1) = \ell) \\ &= \sum_{n=k}^{\infty} P(N_i(t_2) - N_i(s_2) = k | N(t_2) - N(s_2) = n) \cdot P(N(t_2) - N(s_2) = n) \\ &= P(N_i(t_2) - N_i(s_2) = k) \end{aligned}$$

Hence,  $\{N_i(t) : t \geq 0\}$  have independent increments,  $i = 1, 2$ .

## Time sampling a Poisson Process (cont.)

Moreover, we have:

$$\begin{aligned}P(N_1(t+h) - N_1(t) = 1) &= P(N_1(t+h) - N_1(t) = 1 | N(t+h) - N(t) = 1) \cdot P(N(t+h) - N(t) = 1) \\ &+ P(N_1(t+h) - N_1(t) = 1 | N(t+h) - N(t) \geq 2) \cdot P(N(t+h) - N(t) \geq 2) \\ &= p_1(t) \cdot (\lambda h + o(h)) + o(h) \\ &= \lambda p_1(t)h + o(h)\end{aligned}$$

and:

$$P(N_1(t+h) - N_1(t) \geq 2) \leq P(N(t+h) - N(t) \geq 2) = o(h).$$

By similar arguments we get that:

$$\begin{aligned}P(N_2(t+h) - N_2(t) = 1) &= \lambda p_2(t)h + o(h) \\ P(N_2(t+h) - N_2(t) \geq 2) &= o(h).\end{aligned}$$

## Time sampling a Poisson Process (cont.)

Before we prove that  $\{N_1(t) : t \geq 0\}$  and  $\{N_2(t) : t \geq 0\}$  are independent, we note that, as a consequence of the first part of the proof, we have for  $s < t$  that:

$$P(N_i(t) - N_i(s) = k) = \frac{(m_i(t) - m_i(s))^k}{k!} e^{-(m_i(t) - m_i(s))}, \quad k = 0, 1, 2, \dots$$

where:

$$\begin{aligned} m_i(t) - m_i(s) &= \int_0^t \lambda p_i(u) du - \int_0^s \lambda p_i(u) du \\ &= \int_s^t \lambda p_i(u) du = \lambda(t-s) \int_s^t p_i(u) \frac{1}{t-s} du = \lambda \bar{p}_i(s, t)(t-s). \end{aligned}$$

Note also that since  $p_1(t) + p_2(t) = 1$ , we also have  $\bar{p}_1(s, t) + \bar{p}_2(s, t) = 1$ .

## Time sampling a Poisson Process (cont.)

To show that  $\{N_1(t) : t \geq 0\}$  and  $\{N_2(t) : t \geq 0\}$  are independent we let  $s < t$ , and consider:

$$\begin{aligned} & P[(N_1(t) - N_1(s) = k) \cap (N_2(t) - N_2(s) = \ell)] \\ &= P[(N_1(t) - N_1(s) = k) \cap (N(t) - N(s) = k + \ell)] \\ &= \binom{k + \ell}{k} \bar{p}_1(s, t)^k \cdot \bar{p}_2(s, t)^\ell \cdot \frac{[\lambda(t - s)]^{k + \ell}}{(k + \ell)!} e^{-\lambda(t - s)} \\ &= \frac{(\lambda \bar{p}_1(s, t)(t - s))^k}{k!} e^{-\lambda \bar{p}_1(s, t)(t - s)} \cdot \frac{(\lambda \bar{p}_2(s, t)(t - s))^\ell}{\ell!} e^{-\lambda \bar{p}_2(s, t)(t - s)} \\ &= P(N_1(t) - N_1(s) = k) \cdot P(N_2(t) - N_2(s) = \ell) \end{aligned}$$

Hence, we conclude that  $(N_1(t) - N_1(s))$  and  $(N_2(t) - N_2(s))$  are independent for all  $s < t$ , implying that  $\{N_1(t) : t \geq 0\}$  and  $\{N_2(t) : t \geq 0\}$  are independent.



## Example 5.25 – An $M/G/\infty$ queue

Clients arrive at a server according to homogeneous Poisson process  $\{N(t) : t \geq 0\}$  with rate  $\lambda$ :

$$N(t) = \text{Number of clients arriving in } [0, t], \quad t \geq 0.$$

We then introduce:

$$X_n = \text{The amount time it takes to serve the } n\text{th client}, \quad n = 1, 2, \dots$$

We assume that  $X_1, X_2, \dots$  are independent and identically distributed with cumulative distribution function  $G$ , and also that  $X_1, X_2, \dots$  are independent of  $\{N(t) : t \geq 0\}$ .

## Example 5.25 (cont.)

An  $M/G/c$  queue is a stochastic process where:

- Clients arrive according to a Markovian counting process, (i.e. a Poisson process), which explains the  $M$  in the notation
- The amount time it takes to serve a client has cdf  $G$
- The server has a capacity of  $c$ , i.e.,  $c$  clients can be served at the same time.

In this case  $X_1, X_2, \dots$  are independent and identically distributed, which is justified by assuming that the server has an **infinite capacity**, i.e.,  $c = \infty$ . Thus, the time it takes to serve a client is not affected by the number of clients presently being served.

So in this particular case we have an  $M/G/\infty$  queue.

## Example 5.25 (cont.)

We then assume that  $0 \leq s < t$ , and introduce:

$$D(s, t) = \text{Number of clients departing in } (s, t].$$

In order to find the probability distribution of  $D(s, t)$  we start by arguing that:

$$(D(s, t) | N(t) = n) \sim \text{Bin}(n, \bar{p}(s, t)), \quad t \geq 0,$$

where:

$$\bar{p}(s, t) = \frac{1}{t} \int_s^t G(u) du.$$

In order to explain this, we recall that conditional on the event that  $N(t) = n$ , the  $n$  arrival times in the interval  $[0, t]$  are independent and uniformly distributed.

## Example 5.25 (cont.)

Given that the arrival time of a client is  $u \in [0, t]$  and denoting the service time by  $X$ , the probability that this client departs in the interval  $(s, t]$  is:

$$P(s < u + X \leq t | u) = \begin{cases} G(t - u) - G(s - u) & \text{if } u < s \\ G(t - u) & \text{if } s \leq u < t \end{cases}$$

Hence, the unconditional probability that the client departs in  $[s, t]$  is:

$$\begin{aligned} P(s < u + X \leq t) &= \frac{1}{t} \cdot \left[ \int_0^s (G(t - u) - G(s - u)) du + \int_s^t G(t - u) du \right] \\ &= \frac{1}{t} \cdot \left[ \int_0^t G(t - u) du - \int_0^s G(s - u) du \right] \quad (\text{Subst.: } v = t - u \text{ and } v = s - u.) \\ &= \frac{1}{t} \cdot \left[ \int_0^t G(v) dv - \int_0^s G(v) dv \right] = \frac{1}{t} \int_s^t G(v) dv = \bar{p}(s, t) \end{aligned}$$

## Example 5.25 (cont.)

Since  $X$  is independent of the Poisson process, we have a series of  $n$  binomial experiments with the same probability of success.

Hence, we have  $(D(s, t) | N(t) = n) \sim \text{Bin}(n, \bar{p}(s, t))$ , ■

In the following we let  $D(t) = D(0, t)$ , and claim that  $\{D(t) : t \geq 0\}$  is a **non-homogeneous** Poisson process with intensity function:

$$\lambda(t) = \lambda \cdot G(t).$$

In order to show this, we must verify that the axioms (i), (ii), (iii) and (iv) of the definition are satisfied. Axiom (i) states that  $D(0) = 0$ , which is obviously satisfied.

In order to verify the other axioms we first find the **unconditional probability distribution** of  $D(s, t)$ .

## Example 5.25 (cont.)

The probability distribution of  $D(s, t)$  is obtained by conditioning on  $N(t)$ :

$$\begin{aligned}P(D(s, t) = k) &= \sum_{n=k}^{\infty} P(D(s, t) = k | N(t) = n) \cdot P(N(t) = n) \\&= \sum_{n=k}^{\infty} \binom{n}{k} [\bar{p}(s, t)]^k [1 - \bar{p}(s, t)]^{n-k} \cdot \frac{(\lambda t)^n}{n!} e^{-\lambda t} \\&= \frac{(\bar{p}(s, t)\lambda t)^k}{k!} e^{-\bar{p}(s, t)\lambda t} \sum_{n=k}^{\infty} \frac{((1 - \bar{p}(s, t))\lambda t)^{n-k}}{(n-k)!} e^{-(1-\bar{p}(s, t))\lambda t} \\&= \frac{(\bar{p}(s, t)\lambda t)^k}{k!} e^{-\bar{p}(s, t)\lambda t} \sum_{j=0}^{\infty} \frac{((1 - \bar{p}(s, t))\lambda t)^j}{j!} e^{-(1-\bar{p}(s, t))\lambda t} \\&= \frac{(\bar{p}(s, t)\lambda t)^k}{k!} e^{-\bar{p}(s, t)\lambda t}, \quad k = 0, 1, 2, \dots\end{aligned}$$

## Example 5.25 (cont.)

Thus, we conclude that  $D(s, t) \sim Po(\bar{p}(s, t) \cdot \lambda t)$ . By a similar argument it can also be shown that if  $(s_1, t_1]$  and  $(s_2, t_2]$  are disjoint intervals, then  $D(s_1, t_1)$  and  $D(s_2, t_2)$  are **independent**.

We recall that:

$$\bar{p}(s, t) = \frac{1}{t} \int_s^t G(u) du.$$

Hence, we get that:

$$\bar{p}(s, t) \cdot \lambda t = \left[ \frac{1}{t} \int_s^t G(u) du \right] \cdot \lambda t = \int_s^t \lambda G(u) du.$$

From this we get that:

$$D(s, t) \sim Po\left(\int_s^t \lambda G(u) du\right)$$

## Example 5.25 (cont.)

By **Taylor expansion** we have for a given function  $f$  and  $h > 0$  that:

$$f(h) = f(0) + f'(0)h + o(h)$$

Hence, we get:

$$f_1(h) = \int_t^{t+h} \lambda G(u) du = \lambda G(t)h + o(h)$$

$$f_2(h) = e^{-ah} = 1 - ah + o(h)$$

Hence, we get:

$$P(D(t, t+h) = 0) = e^{-(\lambda G(t)h + o(h))} = 1 - \lambda G(t)h + o(h)$$

$$P(D(t, t+h) = 1) = \frac{\lambda G(t)h + o(h)}{1!} e^{-(\lambda G(t)h + o(h))} = \lambda G(t)h + o(h)$$

$$P(D(t, t+h) \geq 2) = 1 - [1 - \lambda G(t)h + o(h) + \lambda G(t)h + o(h)] = o(h)$$



## Example 5.25 (cont.)

By combining all the above results, it follows that  $\{D(t) : t \geq 0\}$  is a **non-homogeneous** Poisson process with intensity function:

$$\lambda(t) = \lambda \cdot G(t).$$

NOTE:

$$\lim_{t \rightarrow \infty} \lambda(t) = \lambda \cdot \lim_{t \rightarrow \infty} G(t) = \lambda.$$

Hence, when  $t$  is large, the intensity function of the **departure process**  $\{D(t) : t \geq 0\}$  is approximately equal to the **arrival rate**  $\lambda$ .

## The non-homogeneous Poisson process (cont.)

Let  $\{N(t) : t \geq 0\}$  be a non-homogeneous Poisson process with intensity function  $\lambda(t)$ , and mean value function  $m(t)$ . Furthermore, let:

$S_n =$  The time of the  $n$ th event,  $n = 1, 2, \dots$

We have shown that the density of  $S_1 = T_1$  is given by:

$$f_{S_1}(t) = \lambda(t)e^{-m(t)}, \quad t \geq 0.$$

We shall now derive the density of  $S_n$ ,  $n = 1, 2, \dots$

In order to do so, it is convenient once again to introduce:

$$N(s, t) = N(t) - N(s), \quad 0 \leq s < t$$

## The non-homogeneous Poisson process (cont.)

Let  $h > 0$ . We then have:

$$\begin{aligned}P(t < S_n \leq t + h) &= P(N(t) = n - 1 \cap N(t, t + h) = 1) + o(h) \\&= P(N(t) = n - 1) \cdot P(N(t, t + h) = 1) + o(h) \\&= \frac{[m(t)]^{n-1}}{(n-1)!} e^{-m(t)} \cdot [\lambda(t)h + o(h)] + o(h) \\&= \frac{[m(t)]^{n-1}}{(n-1)!} \lambda(t) e^{-m(t)} h + o(h)\end{aligned}$$

Hence, the density of  $S_n$  becomes:

$$\begin{aligned}f_{S_n}(t) &= \lim_{h \rightarrow 0} \frac{P(t < S_n \leq t + h)}{h} = \lim_{h \rightarrow 0} \left[ \frac{[m(t)]^{n-1}}{(n-1)!} \lambda(t) e^{-m(t)} + \frac{o(h)}{h} \right] \\&= \frac{[m(t)]^{n-1}}{(n-1)!} \lambda(t) e^{-m(t)}.\end{aligned}$$

## The non-homogeneous Poisson process (cont.)

**NOTE 1.** If  $n = 1$ , we as before get:

$$f_{S_1}(t) = \frac{[m(t)]^{1-1}}{(1-1)!} \lambda(t) e^{-m(t)} = \lambda(t) e^{-m(t)}.$$

**NOTE 2.** If  $\lambda(t) = \lambda$ , then  $m(t) = \int_0^t \lambda du = \lambda t$ , and we get:

$$\begin{aligned} f_{S_n}(t) &= \frac{[m(t)]^{n-1}}{(n-1)!} \lambda(t) e^{-m(t)} \\ &= \frac{[\lambda t]^{n-1}}{(n-1)!} \lambda e^{-\lambda t} = \frac{\lambda^n}{\Gamma(n)} t^{n-1} e^{-\lambda t} \end{aligned}$$

Thus, in this case  $S_n \sim \text{Gamma}(n, \lambda)$  as before.