

STAT253/317 Winter 2014 Lecture 11

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- 5.3 The Poisson Processes
- 5.4 Generalizations of the Poisson Processes

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The sum of two independent Poisson processes with respective rates  $\lambda_1$  and  $\lambda_2$ , called the **superposition** of the processes, is again a Poisson process but with rate  $\lambda_1 + \lambda_2$ .

The proof is straight forward from Definition 5.3 and hence omitted.

**Remark:** By repeated application of the above arguments we can see that the superposition of  $k$  independent Poisson processes with rates  $\lambda_1, \dots, \lambda_n$  is again a Poisson process with rate  $\lambda_1 + \dots + \lambda_n$ .

Why Poisson Processes Make Sense?

There is a useful result in probability theory which says that:

*if we take  $N$  independent counting processes and sum them up, then the resulting superposition process is approximately a Poisson process.*

Here

- ▶  $N$  must be "large enough" and
- ▶ the rates of the individual processes must be "small" relative to  $N$
- ▶ but the individual processes that go into the superposition can otherwise be arbitrary.

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Thinning

Consider a Poisson process  $\{N(t) : t \geq 0\}$  with rate  $\lambda$ . At each arrival of events, it is classified as a

$$\begin{cases} \text{Type 1 event with probability } p & \text{or} \\ \text{Type 2 event with probability } 1 - p, \end{cases}$$

independently of all other events. Let

$$N_i(t) = \# \text{ of type } i \text{ events occurred during } [0, t], \quad i = 1, 2.$$

Note that  $N(t) = N_1(t) + N_2(t)$ .

Proposition 5.2

$\{N_1(t), t \geq 0\}$  and  $\{N_2(t), t \geq 0\}$  are both Poisson processes having respective rates  $\lambda p$  and  $\lambda(1 - p)$ .

Furthermore, the two processes are independent.

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Proof of Proposition 5.2

First observe that given  $N(t) = n + m$ ,

$$N_1(t) \sim \text{Binomial}(n + m, p). \quad (\text{why?})$$

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

This proves the independence of  $N_1(t)$  and  $N_2(t)$  and that

$$N_1(t) \sim \text{Poisson}(\lambda p t), \quad N_2(t) \sim \text{Poisson}(\lambda(1 - p)t).$$

Both  $\{N_1(t)\}$  and  $\{N_2(t)\}$  inherit the stationary and independent increment properties from  $\{N(t)\}$ , and hence are both Poisson processes.

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Some "Converse" of Thinning & Superposition

Consider two indep. Poisson processes  $\{N_A(t)\}$  and  $\{N_B(t)\}$  w/ respective rates  $\lambda_A$  and  $\lambda_B$ . Let

$$\begin{aligned} S_n^A &= \text{arrival time of the } n\text{th } A \text{ event} \\ S_m^B &= \text{arrival time of the } m\text{th } B \text{ event} \end{aligned}$$

Find  $P(S_n^A < S_m^B)$ .

Approach 1:

Observe that  $S_n^A \sim \text{Gamma}(n, \lambda_A)$ ,  $S_m^B \sim \text{Gamma}(m, \lambda_B)$  and they are independent. Thus

$$P(S_n^A < S_m^B) = \int_{x < y} \lambda_A e^{-\lambda_A x} \frac{(\lambda_A x)^{n-1}}{(n-1)!} \lambda_B e^{-\lambda_B y} \frac{(\lambda_B y)^{m-1}}{(m-1)!} dx dy$$

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## Some "Converse" of Thinning & Superposition (Cont'd)

Let  $N(t) = N_A(t) + N_B(t)$  be the superposition of the two processes. Let

$$I_i = \begin{cases} 1 & \text{if the } i\text{th event in the superposition process is an } A \text{ event} \\ 0 & \text{otherwise} \end{cases}$$

The  $I_i, i = 1, 2, \dots$  are i.i.d. Bernoulli( $p$ ), where  $p = \frac{\lambda_A}{\lambda_A + \lambda_B}$ .

### Approach 2:

$$P(S_n^A < S_1^B) = P(\text{the first } n \text{ events are all } A \text{ events}) = \left(\frac{\lambda_A}{\lambda_A + \lambda_B}\right)^n$$

$$\begin{aligned} P(S_n^A < S_m^B) &= P(\text{at least } n \text{ } A \text{ events occur before } m \text{ } B \text{ events}) \\ &= P(\text{at least } n \text{ heads before } m \text{ tails}) \\ &= P(\text{at least } n \text{ heads in the first } n + m - 1 \text{ tosses}) \\ &= \sum_{k=n}^{n+m-1} \binom{n+m-1}{k} \left(\frac{\lambda_A}{\lambda_A + \lambda_B}\right)^k \left(\frac{\lambda_B}{\lambda_A + \lambda_B}\right)^{n+m-1+k} \end{aligned}$$

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## Example (Revision of Exercise 6.66 on p.364)

- Policyholders of a certain insurance company have accidents occurring according to a Poisson process with rate  $\lambda$ .
- The amount of time  $T$  from when the accident occurs until a claim is made has distribution  $G(t) = P(T \leq t)$ .
- Let  $N_c(t)$  be the number of claims made by time  $t$ .

Find the distribution of  $N_c(t)$ .

*Solution.* Suppose an accident occurred at time  $s$ . It is claimed by time  $t$  if  $s + T \leq t$ , i.e., with probability

$$p(s) = P(T \leq t - s) = G(t - s).$$

By Proposition 5.3,  $N_c(t)$  has a Poisson distribution with mean

$$\lambda \int_0^t p(s) ds = \lambda \int_0^t G(t - s) ds = \lambda \int_0^t G(s) ds$$

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## Proposition 5.4

Let  $\{N_1(t), t \geq 0\}$ , and  $\{N_2(t), t \geq 0\}$  be two independent nonhomogeneous Poisson process with respective intensity functions  $\lambda_1(t)$  and  $\lambda_2(t)$ , and let  $N(t) = N_1(t) + N_2(t)$ . Then

- $\{N(t), t \geq 0\}$  is a nonhomogeneous Poisson process with intensity function  $\lambda_1(t) + \lambda_2(t)$ .
- Given that an event of the  $\{N(t), t \geq 0\}$  process occurs at time  $t$  then, independent of what occurred prior to  $t$ , the event at  $t$  was from the  $\{N_1(t)\}$  process with probability

$$\frac{\lambda_1(t)}{\lambda_1(t) + \lambda_2(t)}.$$

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## Proposition 5.3 (Generalization of Proposition 5.2)

Consider a Poisson process with rate  $\lambda$ . If an event occurs at time  $t$  will be classified as a type  $i$  event with probability  $p_i(t)$ ,  $i = 1, \dots, k$ ,  $\sum_i p_i(t) = 1$ , for all  $t$ , independently of all other events. then

$$N_i(t) = \text{number of type } i \text{ events occurring in } [0, t], i = 1, \dots, k.$$

Note  $N(t) = \sum_{i=1}^k N_i(t)$ . Then  $N_i(t), i = 1, \dots, k$  are independent Poisson random variables with means  $\lambda \int_0^t p_i(s) ds$ .

Remark: Note  $\{N_i(t), t \geq 0\}$  are NOT Poisson processes.

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## 5.4.1 Nonhomogeneous Poisson Process

**Definition 5.4a.** A nonhomogeneous (a.k.a. non-stationary) Poisson process with intensity function  $\lambda(t) \geq 0$  is a counting process  $\{N(t), t \geq 0\}$  satisfying

- $N(0) = 0$ .
- having independent increments.
- $P(N(t+h) - N(t) = 1) = \lambda(t)h + o(h)$ .
- $P(N(t+h) - N(t) \geq 2) = o(h)$ .

**Definition 5.4b.** A nonhomogeneous Poisson process with intensity function  $\lambda(t) \geq 0$  is a counting process  $\{N(t), t \geq 0\}$  satisfying

- $N(0) = 0$ ,
- for  $s, t \geq 0$ ,  $N(t+s) - N(s)$  is independent of  $N(s)$  (independent increment)
- For  $s, t \geq 0$ ,  $N(t+s) - N(s) \sim \text{Poisson}(m(t+s) - m(s))$ , where  $m(t) = \int_0^t \lambda(t) dt$

The two definitions are equivalent

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## 5.4.2 Compound Poisson Processes

**Definition.** Let  $\{N(t)\}$  be a (homogeneous) Poisson process with rate  $\lambda$  and  $Y_1, Y_2, \dots$  are i.i.d random variables independent of  $\{N(t)\}$ . The process

$$X(t) = \sum_{i=1}^{N(t)} Y_i$$

is called a *compound Poisson process*, in which  $X(t)$  is defined as 0 if  $N(t) = 0$ .

A compound Poisson process has

- **independent increment**, since  $X(t+s) - X(s) = \sum_{i=1}^{N(t+s)-N(s)} Y_{i+N(s)}$  is independent of  $X(s) = \sum_{i=1}^{N(s)} Y_i$ , and
- **stationary increment**, since  $X(t+s) - X(s) = \sum_{i=1}^{N(t+s)-N(s)} Y_{i+N(s)}$  has the same distribution as  $X(t) = \sum_{i=1}^{N(t)} Y_i$

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## The Mean of a Compound Poisson Process

Suppose  $\mathbb{E}[Y_i] = \mu_Y$ ,  $\text{Var}(Y_i) = \sigma_Y^2$ . Note that  $\mathbb{E}[N(t)] = \lambda t$ .

$$\begin{aligned}\mathbb{E}[X(t)|N(t)] &= \sum_{i=1}^{N(t)} \mathbb{E}[Y_i|N(t)] \\ &= \sum_{i=1}^{N(t)} \mathbb{E}[Y_i] \quad (\text{since } Y_i\text{'s are indep. of } N(t)) \\ &= N(t)\mu_Y\end{aligned}$$

Thus

$$\mathbb{E}[X(t)] = \mathbb{E}[\mathbb{E}[X(t)|N(t)]] = \mathbb{E}[N(t)]\mu_Y = \lambda t\mu_Y$$

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## Variance of a Compound Poisson Process (Cont'd)

Similarly, using that  $\mathbb{E}[N(t)] = \text{Var}(N(t)) = \lambda t$ , we have

$$\begin{aligned}\text{Var}[X(t)|N(t)] &= \text{Var}\left(\sum_{i=1}^{N(t)} Y_i \middle| N(t)\right) \\ &= \sum_{i=1}^{N(t)} \text{Var}(Y_i|N(t)) \\ &= \sum_{i=1}^{N(t)} \text{Var}(Y_i) \quad (\text{since } Y_i\text{'s are indep. of } N(t)) \\ &= N(t)\sigma_Y^2\end{aligned}$$

$$\mathbb{E}[\text{Var}(X(t)|N(t))] = \mathbb{E}[N(t)\sigma_Y^2] = \lambda t\sigma_Y^2$$

$$\text{Var}(\mathbb{E}[X(t)|N(t)]) = \text{Var}(N(t)\mu_Y) = \text{Var}(N(t))\mu_Y^2 = \lambda t\mu_Y^2$$

Thus

$$\begin{aligned}\text{Var}(X(t)) &= \mathbb{E}[\text{Var}(X(t)|N(t))] + \text{Var}(\mathbb{E}[X(t)|N(t)]) \\ &= \lambda t(\sigma_Y^2 + \mu_Y^2) = \lambda t\mathbb{E}[Y_i^2]\end{aligned}$$

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## CLT of a Compound Poisson Process

As  $t \rightarrow \infty$ , the distribution of

$$\frac{X(t) - \mathbb{E}[X(t)]}{\sqrt{\text{Var}(X(t))}} = \frac{X(t) - \lambda t\mu_Y}{\sqrt{\lambda t(\sigma_Y^2 + \mu_Y^2)}}$$

converges to a standard normal distribution  $N(0, 1)$ .

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## 5.4.3 Conditional Poisson Processes

**Definition.** A *conditional (or mixed) Poisson process*  $\{N(t), t \geq 0\}$  is a counting process satisfying

- (i)  $N(0) = 0$ ,
- (ii) having stationary increment, and
- (iii) there is a random variable  $\Lambda > 0$  with probability density  $g(\lambda)$ , such that given  $\Lambda = \lambda$ ,

$$N(t+s) - N(s) \sim \text{Poisson}(\lambda t),$$

i.e.,

$$P(N(t+s) - N(s) = k) = \int_0^\infty e^{-\lambda t} \frac{(\lambda t)^k}{k!} g(\lambda) d\lambda, \quad k = 0, 1, \dots$$

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**Remark:** In general, a conditional Poisson process does NOT have independent increment.

$$\begin{aligned}P(N(s) = j, N(t+s) - N(s) = k) &= \int_0^\infty e^{-\lambda s} \frac{(\lambda s)^j}{j!} e^{-\lambda t} \frac{(\lambda t)^k}{k!} g(\lambda) d\lambda \\ &\neq \left( \int_0^\infty e^{-\lambda s} \frac{(\lambda s)^j}{j!} g(\lambda) d\lambda \right) \left( \int_0^\infty e^{-\lambda t} \frac{(\lambda t)^k}{k!} g(\lambda) d\lambda \right) \\ &= P(N(s) = j)P(N(t+s) - N(s) = k)\end{aligned}$$

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