

$$= \frac{\lambda^n t^{n-1}}{(n-1)!} e^{-\lambda t}.$$

### Theorem 4.3.4

For  $0 < s \leq t$ ,  $0 \leq k \leq n$ ,

$$(4.3.5) \quad P(N(s)=k \mid N(t)=n) = \frac{n!}{k!(n-k)!} \left(\frac{s}{t}\right)^k \left(1 - \frac{s}{t}\right)^{n-k}$$

Proof

$$P(N(s)=k \mid N(t)=n) = \frac{P(N(s)=k, N(t)=n)}{P(N(t)=n)}$$

$$= \frac{P(N(s)=k, N(t)-N(s)=n-k)}{P(N(t)=n)} \quad \downarrow \text{homogeneity}$$

$$= \frac{\left( e^{-\lambda s} \frac{(\lambda s)^k}{k!} \right) \left( e^{-\lambda(t-s)} \frac{(\lambda(t-s))^{n-k}}{(n-k)!} \right)}{e^{-\lambda t} \frac{(\lambda t)^n}{n!}}$$

$$= \frac{n!}{k!(n-k)!} \frac{s^k (t-s)^{n-k}}{t^n}$$

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The next result says that conditioned on a fixed total number of events in an interval, the times of occurrence of

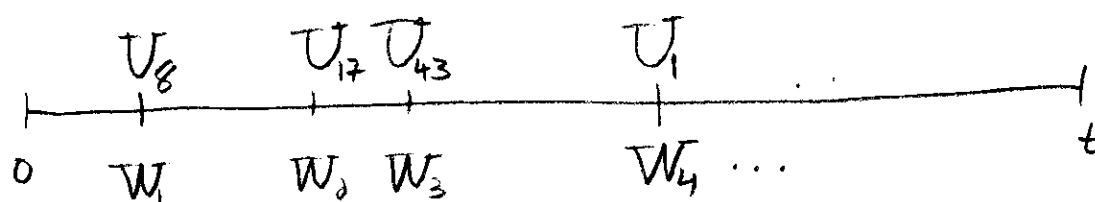
those events are uniformly distributed in a certain way.

We first compute a related probability density function. Consider an interval  $(0, t]$  and choose a fixed number  $n$  of points uniformly on the interval, denoting the positions by  $U_1, \dots, U_n$ . The p.d.f. is

$$f(s) = \begin{cases} \frac{1}{t}, & 0 \leq s \leq t, \\ 0, & \text{otherwise.} \end{cases}$$

Set  $\{W_1, \dots, W_n\}$  to be the positions

$\{U_1, \dots, U_n\}$  re-ordered from left to right.



The joint p.d.f. for  $W_1, W_2, \dots, W_n$  is

$$(4.3.6) \quad f_{W_1, \dots, W_n}(w_1, w_2, \dots, w_n) = n! t^{-n},$$

$$0 < w_1 < w_2 < \dots < w_n \leq t.$$

We can show this by induction.

$$\begin{aligned}
 f_{W_1, W_2}(w_1, w_2) \Delta w_1 \Delta w_2 &= P(w_1 < W_1 \leq w_1 + \Delta w_1, w_2 < W_2 \leq w_2 + \Delta w_2) \\
 &= P(w_1 < U_1 \leq w_1 + \Delta w_1, w_2 < U_2 \leq w_2 + \Delta w_2) \quad \downarrow \text{2 possible orders} \\
 &\quad + P(w_1 < U_2 \leq w_1 + \Delta w_1, w_2 < U_1 \leq w_2 + \Delta w_2) \\
 &= 2 \left( \frac{\Delta w_1}{t} \right) \left( \frac{\Delta w_2}{t} \right) = 2 \bar{t}^{-2} \Delta w_1 \Delta w_2
 \end{aligned}$$

Dividing by  $\Delta w_1 \Delta w_2$  and taking the limit gives (4.3.6). In general, there are  $n!$  arrangements of  $U_1, \dots, U_n$  leading to the same ordered  $W_1, \dots, W_n$ .

We now prove

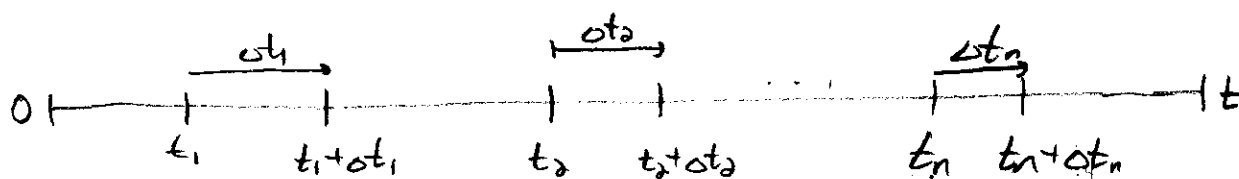
#### Theorem 4.3.5

Let  $T_1, \dots, T_n$  be arrival times in a Poisson process  $N(t)$  with rate  $\lambda > 0$ . Conditioned on  $N(t) = n$ , the random variables  $T_1, \dots, T_n$  have joint p.d.f.

$$(4.3.7) \quad \int_{T_1, \dots, T_n} f(t_1, \dots, t_n) = n! \bar{t}^{-n}, \quad 0 < t_1 < \dots < t_n \leq t.$$

#### Proof

We create some subintervals from a set of times  $t_1, \dots, t_n$  and increments  $\Delta t_1, \dots, \Delta t_n$



The event

$$\{t_i < T_i < t_i + \Delta t_i, i=1, \dots, n, N(t) = n\}$$

means no events occurred in  $(0, t_1]$ ,

$(t_1 + \Delta t_1, t_2]$ , ...,  $(t_n + \Delta t_n, t]$  and exactly one event occurred in each of  $(t_1, t_1 + \Delta t_1]$ , ...,  $(t_n, t_n + \Delta t_n]$ .

The intervals are disjoint and

$$\begin{aligned} P(N(t_1)=0, \dots, N(t) - N(t_n + \Delta t_n) = 0) \\ &= e^{-\lambda t_1} e^{-\lambda(t_2 - t_1 - \Delta t_1)} \dots e^{-\lambda(t_n - t_{n-1} - \Delta t_{n-1})} e^{-\lambda(t - t_n - \Delta t_n)} \\ &= e^{-\lambda t} e^{\lambda(\Delta t_1 + \dots + \Delta t_n)} \\ &= e^{-\lambda t} (1 + o(\max_i \Delta t_i)) \end{aligned}$$

while

$$\begin{aligned} P(N(t_1 + \Delta t_1) - N(t_1) = 1, \dots, N(t_n + \Delta t_n) - N(t_n) = 1) \\ &= \lambda(\Delta t_1) \dots \lambda(\Delta t_n) (1 + o(\max_i \Delta t_i)) \end{aligned}$$

Hence,

$$\begin{aligned}
 & \int_{T_1, \dots, T_n} (t_1, \dots, t_n) \Delta t_1 \cdots \Delta t_n \\
 &= P(t_1 < T \leq t_1 + \Delta t_1, \dots, t_n < T_n \leq t_n + \Delta t_n \mid N(t) = n) \\
 &\quad + O(\Delta t_1 \cdots \Delta t_n) \\
 &= \frac{P(t_1 < T_1 \leq t_1 + \Delta t_1, \dots, t_n < T_n \leq t_n + \Delta t_n, N(t) = n)}{P(N(t) = n)} + O(\Delta t_1 \cdots \Delta t_n) \\
 &= \frac{e^{-\lambda t} \lambda \Delta t_1 \cdots \lambda \Delta t_n}{\frac{e^{-\lambda t} (\lambda t)^n}{n!}} (1 + o(\max_i \Delta t_i)) \\
 &= n! e^{-\lambda t} \Delta t_1 \cdots \Delta t_n (1 + o(\max_i \Delta t_i))
 \end{aligned}$$

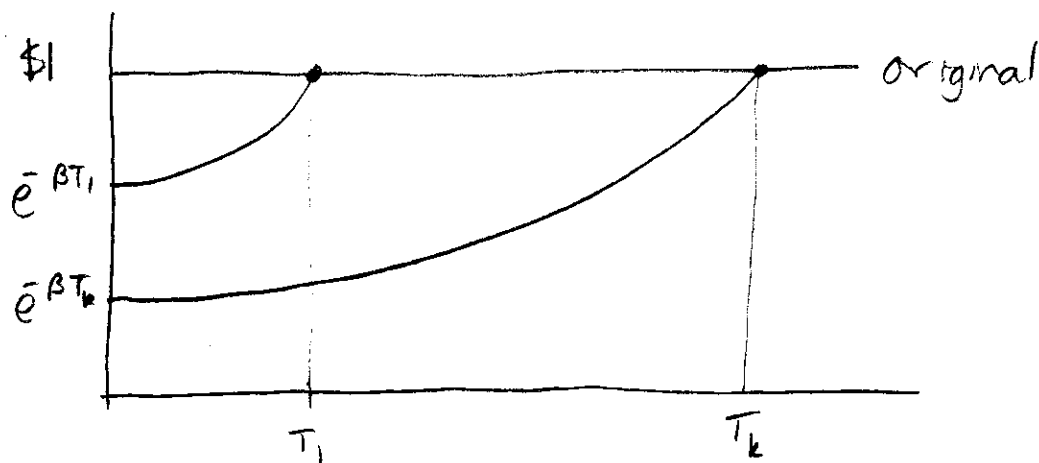
Dividing by  $\Delta t_1 \cdots \Delta t_n$  and letting  $\Delta t_1 \rightarrow 0, \dots, \Delta t_n \rightarrow 0$  gives the result.

### Example 4.3.2

Customers arrive at a facility according to a Poisson process of rate  $\lambda$ . Each customer pays \$1 on arrival. We want to evaluate the expected value of the total sum collected during the interval  $[0, t]$ , where the amounts are discounted back to time 0 according to a

discount rate  $\beta$ . If a customer pays \$1 at event time  $T_k$ , then the discounted amount is

$$e^{-\beta T_k} \times 1.$$



We want to compute

$$M = E \left( \sum_{k=1}^{N(t)} e^{-\beta T_k} \right)$$

We condition on  $N(t) = n$

$$M = \sum_{n=1}^{\infty} E \left( \sum_{k=1}^n e^{-\beta T_k} \mid N(t) = n \right) P(N(t) = n)$$

Let  $U_1, \dots, U_n$  be iid uniformly distributed variables in  $[0, t]$ . Using Theorem 4.3.5,

$$E \left( \sum_{k=1}^n e^{-\beta T_k} \mid N(t) = n \right) = E \left( \sum_{k=1}^n e^{-\beta U_k} \right) = n E(e^{-\beta U_1})$$

each term is treated the same way

$$= n \bar{E}' \int_0^t e^{-\beta u} du = \frac{n}{\beta t} (1 - e^{-\beta t})$$

So

$$M = \frac{1}{\beta t} (1 - e^{-\beta t}) \underbrace{\sum_{n=1}^{\infty} n P(N(t)=n)}_{E(N(t))}$$

$$= \frac{\lambda}{\beta} (1 - e^{-\beta t})$$

The proof of the strong Markov property Thm 4.2.9 for birth processes uses

- weak Markov property
- temporal homogeneity

The strong Markov property is very important in the analysis of continuous time Markov processes.

When applied to a birth process, it implies that the new process  $\tilde{N}(t)$  defined by

$$\tilde{N}(t) = N(t+T) - N(T), \quad t \geq 0,$$

conditional on  $\{N(T)=i\}$  is also a birth process whenever  $T$  is a stopping time for  $N$ .

Exercise: show the intensities are  $\lambda_i, \lambda_{i+1}, \dots$

In the case of a Poisson process,  $\tilde{N}(t) = N(T+t) - N(T)$  is also a Poisson process.

This leads to the observation of a fundamental characteristic.

#### Definition 4.3.1

A Poisson process  $N$  has stationary independent increments in the sense that

- (i) the distribution of  $N(t) - N(s)$  depends only on  $t - s$
- (ii) any finite set of increments  $\{N(t_i) - N(s_i), i=1, 2, \dots, n\}$  are independent if  $s_1 \leq t_1 \leq s_2 \leq t_2 \leq \dots \leq t_n$ .

It turns out that this property nearly characterizes a Poisson process.

#### Theorem 4.3.6

Suppose that  $M(t), t \geq 0$ , is a non-decreasing, right-continuous, integer valued stochastic process with



- (1)  $M(0) = 0$
- (2) stationary independent increments
- (3)  $M$  only has jump discontinuities of size 1 (implies the state space is  $\{0, 1, 2, 3, \dots\}$ )

Then  $M$  is a Poisson process.

### Outline of Proof

For  $u, v \geq 0$ , we have

$$\begin{aligned} E(M(u+v)) &= E(M(u)) + E(M(u+v) - M(u)) \\ &= E(M(u)) + E(M(v)) \end{aligned}$$

by the stationary increments assumption.

$E(M(u))$  is nondecreasing in  $u$ , so there is a  $\lambda$  such that

$$(4.3.8) \quad E(M(u)) = \lambda u, \quad u \geq 0$$

Let  $T = \sup\{t : M(t) = 0\}$  be the time of the first jump. Almost surely (right continuity),  $M(T) = 1$ , and  $T$  is a stopping time for  $M$ . (Exercise: explain). Now

$$(4.3.9) \quad E(M(s)) = E(E(M(s) | T)).$$

We have

$$E(M(s) | T) = 0 \quad s < T,$$

while for  $s \geq T$ ,

$$(4.3.10) \quad \begin{aligned} E(M(s) | T=t) &= E(M(t) | T=t) + E(M(s) - M(t) | T=t) \\ &= 1 + E(M(s-t)) \end{aligned} \quad \downarrow \text{exercise.}$$

by the stationary increments assumption. If

$F(t)$  is the distribution function for  $T$ , then using (4.3.10) in (4.3.9) gives

$$E(M(s)) = \int_0^s (1 + E(M(s-t))) dF(t)$$

Since  $E(M(s)) = \lambda s$ ,

$$(4.3.11) \quad \lambda s = F(s) + \lambda \int_0^s (s-t) dF(t).$$

This is an integral equation for the unknown function  $F$ . It may be solved e.g. using Laplace transforms. We find

$$F(t) = 1 - e^{-\lambda t}, \quad t \geq 0$$

so  $T$  has the exponential distribution.

Now we may argue as for the sojourn time formulation to show the "inter-jump" times of  $M$  are independent and have the exponential distribution.

Hence,  $M$  is a Poisson process with intensity  $\lambda$ .

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#### §4.4 Death Processes

This is the complement of a birth process. It moves through states  $N, N-1, \dots, 0$ , leading to absorption into 0, or extinction.

##### Definition 4.4.1

A death process  $X(t)$  with death parameters  $\mu_1, \dots, \mu_N$ ,  $\mu_i > 0$ , is a process with state space  $\{0, 1, 2, \dots, N\}$  such that

$$(1) X(0) = N$$

$$(2) s < t \Rightarrow X(s) \geq X(t)$$

(3)

$$P(X(t+h) = k-m | X(t) = k) = \begin{cases} \mu_k h + o(h), & m=1, \\ 1 - \mu_k h + o(h), & m=0, \\ o(h), & m>1. \end{cases}$$