

Thm 5.2 $S_1, \dots, S_n | N(t) = n \sim \text{i.i.d. } U[0, t]$
 Remember in Prop 5.2 the events were classified as type I or type II with probabilities p_1 and p_2 respectively.
 What happens if classification also involves time of event?
 Assume that an event occurring at time y be classified as a "type i " event, independently of previous events with a probability $P_i(y)$, $i=1, \dots, k$ $\sum_{i=1}^k P_i(y) = 1$

Proposition 5.3 If $N_i(t)$ represents the number of type i events occurring by time t , then $N_i(t)$, $i=1, \dots, k$ are independent Poisson random variables with means $E[N_i(t)] = \lambda \int_0^t P_i(s) ds$

mar. 13-10:12

Proof: Let n_1, \dots, n_k be integers $\sum_{i=1}^k n_i = n$
 $P(N_1(t) = n_1, \dots, N_k(t) = n_k) = P(N(t) = n, \sum_{i=1}^k N_i(t) = n)$
 $= P(N_1(t) = n_1, \dots, N_k(t) = n_k | N(t) = n) P(N(t) = n)$
 Consider an event $i \in [0, t]$. If it occurred at time s it would be a type i event with probability $P_i(s)$. Since the time of event is uniform in $[0, t]$, (Theorem 5.2) the probability that the event is type i is $P_i = \frac{1}{t} \int_0^t P_i(s) ds$, independent of other events.
 Hence, the joint conditional distribution given the number of events is multinomial $P(N_1(t) = n_1, \dots, N_k(t) = n_k | N(t) = n) = \frac{n!}{n_1! \dots n_k!} P_1^{n_1} \dots P_k^{n_k}$
 $\sum_{i=1}^k P_i = 1$

mar. 13-10:24

Hence $P(N_1(t) = n_1, \dots, N_k(t) = n_k) = \frac{(e^{-\lambda t})^k}{n_1! \dots n_k!} \cdot P_1^{n_1} \dots P_k^{n_k} \cdot \frac{(\lambda t)^{\sum n_i}}{(\sum n_i)!} e^{-\lambda t}$
 $= \prod_{i=1}^k \frac{(\lambda t P_i)^{n_i}}{n_i!} e^{-\lambda t P_i}$ since $\sum P_i = 1$
 But $\lambda t P_i = \lambda \int_0^t P_i(s) ds$

Example M/G/∞ queue
 • N : customers arrive according to a Poisson process rate λ
 • G : service time has a general distribution, μ with c.d.f G and an independent ∞ initially many servers.

mar. 13-10:34

Let $X(t)$ number of clients completed service by t
 $Y(t)$ — not completed —
 Distribution of $X(t)$ and $Y(t)$?
 type I: customer completed service by t
 type II: — not completed —
 Customer arrives at $s \leq t$ $\begin{cases} \text{type I with probability } G(t-s) \\ \text{type II} & 1 - G(t-s) \end{cases}$
 Using proposition 5.3 $X(t) \sim \text{Po}(\lambda \int_0^t G(y) dy)$
 since $\lambda \int_0^t G(t-s) ds = \int_0^t G(y) dy = \int_0^t G(y) dy$
 and $Y(t) \sim \text{Po}(\lambda \int_0^t (1 - G(y)) dy)$
 Also from prop 5.3 $X(t)$ and $Y(t)$ are independent

mar. 13-10:41

Joint distribution of $Y(t)$ and $Y(t+s)$?
 type I: arrives $[0, t]$ completes in $[t, t+s)$
 type 2: arrives $[t, t+s]$ completes $[t+s, \infty)$
 type 3: arrives $[t+s, \infty)$ completes $[t+s, \infty)$
 type 4: others.
 Now, $P_i(y)$ is the probability for a customer arriving at y being a type i customer
 Then $P_i(y) = \begin{cases} G(t+s-y) - G(t-y) & \text{if } y < t \\ 0 & \text{else} \end{cases}$
 because the service time is between $t-y$ and $t+s-y$
 $P_2(y) = \begin{cases} 1 - G(t+s-y) & \text{if } y < t \\ 0 & \text{else} \end{cases}$
 $P_3(y) = \begin{cases} 1 - G(t+s-y) & \text{if } t < y < t+s \\ 0 & \text{else} \end{cases}$
 $P_{type 4} = 1 - P_1(y) - P_2(y) - P_3(y)$

mar. 13-10:47

From proposition 5.3 if $N_i = N_i(t)$
 $E(N_i) = \lambda \int_0^t P_i(y) dy$
 $Y(t) = N_1 + N_2$ customers completing later than t
 $Y(t+s) = N_2 + N_3$ same
 Then $\text{Cov}(Y(t), Y(t+s)) = \text{Cov}(N_2, N_2) = \text{Var}(N_2)$
 since the N_i are independent $= \lambda \int_0^t [1 - G(t+s-y)] dy$
 $\approx \lambda \int_0^t [1 - G(y+s)] dy$
 since N_i are Poisson.
 Similarly $P(Y(t) = i, Y(t+s) = j) = P(N_1 + N_2 = i, N_2 + N_3 = j)$
 $= \sum_{l=0}^{\min(i,j)} P(N_2 = l, N_1 = i-l, N_3 = j-l)$
 $= \sum_{l=0}^{\min(i,j)} P(N_2 = l) P(N_1 = i-l) P(N_3 = j-l)$

mar. 13-10:55

5.4 Generalizations of the Poisson process
 5.4.1 Non-homogeneous / non-stationary Poisson process.
 In the non-homogeneous Poisson process the arrival rate is allowed to be a function of t .
 Definition: The counting process is 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) $P(N(t+h) - N(t) \geq 2) = o(h)$
 The function $m(t) = \int_0^t \lambda(y) dy$ is the mean value function of the non-homogeneous Poisson process

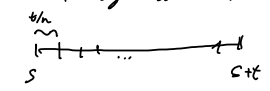
mar. 13-11:06

Theorem 5.3: If $\{N(t), t \geq 0\}$ is a non-homogeneous / non-stationary Poisson process with intensity function $\lambda(t), t \geq 0$, then $N(t+c) - N(t)$ is a Poisson random variable with mean/expectation function
 $m(t+c) - m(t) = \int_t^{t+c} \lambda(y) dy$
 Proof: Generalization of Theorem 5.1 where $\lambda(t) = \lambda$. Let $g(t) = E[e^{-uN(t)}]$ be the Laplace transform. Using independent increment requirement (i)
 $g(t+h) = E[e^{-u(N(t+h) - N(t))}] = e^{-u\lambda h} g(t)$
 $= g(t) \cdot e^{-u\lambda h}$
 where $N_1(h) = N(t+h) - N(t) = N(h)$
 Using (i) & (ii)
 $g(t+h) - g(t) = [1 - \lambda h + o(h)] e^{-u\lambda h} g(t) - g(t)$
 $= -\lambda h g(t) + o(h)$
 $\Rightarrow \lambda h = 0$ (Note: $N_1(h) = 1$ for $h > 0$)

mar. 13-11:24

such $g(t+h) - g(t) = g(t) \lambda h + o(h)$
 Let $h \rightarrow 0$
 $g'(t) = g(t) \lambda$
 $\frac{d}{dt} \log g(t) = \lambda$
 Integrating $\log(g(t)) - \log(g(0)) = \lambda t$
 $\log(g(t)) = \lambda t$
 $g(t) = e^{\lambda t}$
 so by same argument for the Laplace transform $N(t) \sim \text{Poisson}(\lambda t)$
 To conclude that $N(s+t) - N(s) = N_t(t)$ also is Poisson, note that $N_s(t)$ is non-stationary Poisson with intensity function $\lambda_s(t) = \lambda(s+t)$
 Hence $N_s(t) \sim \text{Poisson}(\int_s^{s+t} \lambda(y) dy)$
 But $\int_s^{s+t} \lambda(y) dy = \int_s^{s+t} \lambda(s+y) dy = \int_s^{s+t} \lambda(u) du = m(s+t) - m(s)$

mar. 13-11:33

Remark 5.4.1 Use of the Poisson approximation to the binomial distribution is also useful in the non-homogeneous case.

 Number of events is approximately equal to the number of intervals where event occurs. But this is a sum of $o(1)$ variables which are independent, and
 $P(\text{event in } i\text{th interval}) = \lambda(s + i \frac{h}{n}) \cdot \frac{h}{n} + o(\frac{h}{n})$
 and the expectation of sum is $\sum_{i=1}^n \lambda(s + i \frac{h}{n}) \cdot \frac{h}{n} \rightarrow \int_s^{s+t} \lambda(y) dy$
 and the distribution of the sum is approximately Poisson.

mar. 13-11:42

Remark 5.4.2 If events occur according to a homogeneous process the event is counted/sampled with probability $p(t)$ independently of what occurred prior to t .
 Then the number of counted/sampled events is a non-homogeneous Poisson process with mean function $\int_0^t \lambda(y) p(y) dy$.
 This generalizes to the situation where there are two types of event and the probabilities of an event being of type I or type II are $P_1(t)$ or $P_2(t)$ independent of what happened prior to t .

mar. 13-11:52

Then $N_1(t)$ and $N_2(t)$ are independent Poisson with $E[N_i(t)] = \int_0^t \lambda_i(s) ds$
 where $N_i(t)$ are the number of type i events occurred at time t .

mar. 13-11:57