

A non-homogeneous Semi-Markov model for Interval Censoring

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Previous approaches to modelling interval-censored data have often relied on assumptions of homogeneity in the sense that the censoring mechanism, the underlying distribution of occurrence times, or both, are assumed to be time-invariant. In this work, we introduce a model which allows for non-homogeneous behaviour in both cases. In particular, we outline a censoring mechanism based on semi-Markov processes in which interval generation is assumed to be time-dependent and we propose a Markov point process model for the underlying occurrence time distribution. We prove the existence of this process and derive the conditional distribution of the occurrence times given the intervals. We provide a framework within which the process can be accurately modelled, and subsequently compare our model to homogeneous approaches by way of a parametric example.

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1 Introduction

In previous work [18], we developed statistical methods for state estimation on interval-censored data. The motivating example was that of determining the occurrence times of residential burglaries based on police reports. In the criminology literature, such data are known as aoristic crime data [21, 22]. Aoristic crime studies have mainly focused on ad hoc methods [1], which can be helpful but may miss dependencies such as the near-repeat effect [4]. We developed a Bayesian statistical method that can account for inter-event dependencies [18].

Our approach assumed that for each event occurrence the censoring mechanism is governed by a stochastic process. Specifically, an alternating renewal process was used to split time up into observable and partially observable periods according to the two phases of the renewal process. Either the event is fully observed, in which case the exact time of occurrence is recorded, or only the interval between two jumps is recorded. The approach was shown to lead to a tractable mark distribution and is therefore amenable to Monte Carlo methods for simulation.

The censoring mechanism based on alternating renewal processes imposes time-homogeneity. In reality, events rarely occur homogeneously in time. For instance, returning to the motivating example, there may be times of day that are more likely to be censored due to the periodic behaviour of potential victims, such

as being at work or asleep. Additionally, burglars may choose to commit crimes at different rates at certain times of the day based on their perception of victim behaviour. Thus, there may be inhomogeneity in both the underlying distribution of occurrence times and the censoring mechanism.

This paper introduces a new model that rectifies these shortcomings. For the censoring mechanism, we propose a non-homogeneous semi-Markov process [11, 12, 16, 24]. Conditional intensity-based methods [10] are used to guarantee existence and we derive the joint, marginal and conditional distributions of starting point and length for each occurrence time. We then propose a marked point process model [7] for the complete data using a non-homogeneous Markov point process [17] for the ground process of event occurrences and a mark kernel based on the semi-Markov process. We illustrate the model by means of parametric examples that can describe various types of non-homogeneous behaviour, culminating in a comparison of non-homogeneous and homogeneous models.

The plan of this paper is as follows. In Section 2 we recall the definition of a semi-Markov process on the half line and give an explicit expression for the joint distribution of age and excess. In Section 3 we formulate our marked point process model and study the conditional distribution of the ground process given the union of marks. In Section 4 we present some parametric examples; a demonstration of the model in action is given in Section 5.

2 The non-homogeneous semi-Markov process

2.1 Definition and notation

Let (Ω, \mathcal{A}, P) be a probability space. Consider the two-dimensional stochastic process (S_i, X_i) , $i \in \mathbb{N}_0$, on (Ω, \mathcal{A}, P) with values in $\{0, 1\} \times \mathbb{R}^+$. Here, S_i denotes the i -th state that the process is in and $0 = X_0 \leq X_1 \leq \dots$ are the jump times. Call a time interval that the process spends in state 0 a Z -phase and state 1 a Y -phase, in analogy to [18]. We set $S_0 = 1$, as is convention.

The tuple $(S_n, X_n)_{n=1}^\infty$ defines a *non-homogeneous semi-Markov process* if

$$\begin{aligned} \mathbb{P}(S_{n+1} = j, X_{n+1} \leq x \mid (S_0, X_0) = (s_0, x_0), \dots, (S_n, X_n) = (s_n, x_n)) \\ &= \mathbb{P}(S_{n+1} = j, X_{n+1} \leq x \mid (S_n, X_n) = (s_n, x_n)) \\ &= \mathbb{P}(S_{n+1} = j, X_{n+1} - X_n \leq x - x_n \mid (S_n, X_n) = (s_n, x_n)) \\ &= \mathbb{P}(S_1 = j, X_1 - X_0 \leq x - x_0 \mid (S_0, X_0) = (s_0, x_0)), \end{aligned} \tag{2.1}$$

i.e. the joint conditional probability of the sojourn time $T_{n+1} = X_{n+1} - X_n$ in the n -th state and the next state S_{n+1} depends only on the n -th state S_n and its jump time X_n , not on the entire history of the process [6, 12, 16, 24] nor on the index n . This process is only Markov at the jump times, hence the name *semi-Markov*.

It follows from (2.1) that the distribution of a non-homogeneous semi-Markov process is completely specified by the *starting state* (or its probability distribution) and a *semi-Markov kernel* G that describes

the transition rates from state i to state j . Formally, for $\tau \geq 0$, $x \geq 0$ and $i, j \in \{0, 1\}$,

$$G_{ij}(x, \tau) = \mathbb{P}(S_{n+1} = j, T_{n+1} \leq \tau \mid S_n = i, X_n = x), \quad (2.2)$$

regardless of $n = 0, 1, \dots$. As the process alternates, we can write $G_{10}(x, \tau) = G_Y(x, \tau)$ and $G_{01}(x, \tau) = G_Z(x, \tau)$, the subscript denoting the state that the process is in after jump time x . In the remainder of this paper, we shall assume that, for all $x \geq 0$, $G_Y(x, \cdot)$ and $G_Z(x, \cdot)$ are absolutely continuous with respect to Lebesgue measure and write $g_Y(x, \cdot)$ and $g_Z(x, \cdot)$ respectively for their Radon–Nikodym derivatives.

2.2 Conditional intensities and non-explosion conditions

The *conditional intensity*, also known as the stochastic intensity, of a temporal point process describes the infinitesimal conditional probability of occurrence given the history of the process [15]. More precisely, for $n = 0, 1, \dots$ and $0 = x_0 \leq x_1 \leq \dots \leq x_n \leq x$,

$$\lambda_{n+1}(x; x_1, \dots, x_n) dx = \mathbb{P}(X_{n+1} \leq x + dx \mid X_{n+1} \geq x, X_0 = 0, X_1 = x_1, \dots, X_n = x_n). \quad (2.3)$$

For a non-homogeneous semi-Markov process, the $\lambda_{n+1}(\cdot; \cdot)$ are closely related to the hazard rates of the sojourn times. To see this, recall that $S_0 = 1$ and assume that $n + 1$ is odd. Then the conditional intensity of the jump process at time x given jumps at times $0 \leq x_1 \leq x_2 \leq \dots \leq x_n$ can be simplified as

$$\begin{aligned} \lambda_{n+1}(x; x_1, \dots, x_n) dx &= \mathbb{P}(X_{n+1} \leq x + dx \mid X_{n+1} \geq x, X_n = x_n, S_n = 1) \\ &= \frac{\mathbb{P}(x - x_n \leq T_{n+1} \leq x - x_n + dx \mid X_n = x_n, S_n = 1)}{\mathbb{P}(T_{n+1} \geq x - x_n \mid X_n = x_n, S_n = 1)} \\ &= \frac{g_Y(x_n, x - x_n) dx}{1 - G_Y(x_n, x - x_n)} \end{aligned} \quad (2.4)$$

whenever well-defined and using absolute continuity of the semi-Markov kernel. When $G_Y(x_n, x - x_n) = 1$, the conditional intensity is set to zero. For even $n + 1$, a similar argument holds with g_Z and G_Z instead of g_Y and G_Y .

The conditional intensity is a convenient tool to guarantee the existence of the process. Indeed, [10] developed suitable comparison criteria under which explosion, the situation in which there are infinitely many transitions in a finite time span, can be prevented. Indeed, their Corollaries 2 and 5 imply, for two temporal point processes X_n and X_n^* with conditional intensities λ and λ^* , that if

- for every $n \in \mathbb{N}_0$, $\lambda_{n+1} \leq \lambda_{n+1}^*$;
- for every $n \in \mathbb{N}$, either $\lambda_{n+1}(x; x_1, \dots, x_n)$ or $\lambda_{n+1}^*(x; x_1, \dots, x_n)$ depends only on $x - x_n$,

then the probability of explosion at or before time x of the point process defined by λ is at most as big as that of the point process defined by λ^* . Under the same conditions [10, Corollary 1], for all $n \in \mathbb{N}$ and $x \geq 0$,

$$\mathbb{P}(X_n \leq x) \leq \mathbb{P}(X_n^* \leq x).$$

Below, we establish existence for two common families of sojourn time distributions, the Gamma and the Weibull.

Proposition 2.1. *Let $(S_n, X_n)_{n=1}^\infty$ be an alternating non-homogeneous semi-Markov process with values in $\{0, 1\} \times \mathbb{R}^+$ with $S_0 = 1, X_0 = 0$ and semi-Markov kernels $G_Y(x, \cdot), G_Z(x, \cdot)$ that follow Gamma distributions with shape and rate parameters $\theta_Y(x) = (k_Y(x), \lambda_Y(x))$ and $\theta_Z(x) = (k_Z(x), \lambda_Z(x))$ in $[1, \infty) \times (0, \infty)$ such that, for all $x \in \mathbb{R}^+$,*

$$\lambda_Y(x) \leq c; \quad \lambda_Z(x) \leq c$$

for some $c > 0$. Write $X_\infty = \lim_{n \rightarrow \infty} X_n$ for the time of explosion. Then $\mathbb{P}(X_\infty < \infty) = 0$.

Proof. The probability density and cumulative distribution functions of the Gamma distribution with shape and rate parameters $k(x)$ and $\lambda(x)$ are, for $\tau \geq 0$,

$$g(x, \tau; k(x), \lambda(x)) = \frac{\lambda(x)^{k(x)} \tau^{k(x)-1} e^{-\lambda(x)\tau}}{\Gamma(k(x))}; \quad G(x, \tau; k(x), \lambda(x)) = \frac{\gamma(k(x), \lambda(x)\tau)}{\Gamma(k(x))},$$

writing Γ for the gamma function and γ for the lower incomplete gamma function. The conditional intensity is, for $n = 0, 1, \dots$ and $0 = x_0 \leq x_1 \leq \dots \leq x_n \leq x$,

$$\begin{aligned} \lambda_{n+1}(x; x_1, \dots, x_n) &= \frac{g_T(x_n, x - x_n; k_T(x_n), \lambda_T(x_n))}{1 - G_T(x_n, x - x_n; k_T(x_n), \lambda_T(x_n))} \\ &= \frac{\lambda_T(x_n)^{k_T(x_n)} (x - x_n)^{k_T(x_n)-1} e^{-\lambda_T(x_n)(x-x_n)}}{\int_{\lambda_T(x_n)(x-x_n)}^\infty u^{k_T(x_n)-1} e^{-u} du}, \end{aligned}$$

where g_T is either g_Y or g_Z . We examine the limiting behaviour as $x \rightarrow \infty$. See that

$$\lim_{x \rightarrow \infty} g_T(x_n, x - x_n; k_T(x_n), \lambda_T(x_n)) = 0, \quad \lim_{x \rightarrow \infty} (1 - G_T(x_n, x - x_n; k_T(x_n), \lambda_T(x_n))) = 0.$$

Noting that both are differentiable on $(0, \infty)$, by L'Hôpital's rule,

$$\lim_{x \rightarrow \infty} \lambda_{n+1}(x; x_1, \dots, x_n) = \lim_{x \rightarrow \infty} \frac{\lambda_T(x_n)(x - x_n) - (k_T(x_n) - 1)}{x - x_n} = \lambda_T(x_n) \quad (2.5)$$

after simplifying.

To prove monotonicity, we must show that $\lambda_{n+1}(x; x_1, \dots, x_n)$ is increasing in $x \geq x_n$. Write $t = \lambda_T(x_n)(x - x_n)$. Then $\lambda_{n+1}(x; x_1, \dots, x_n)$ can be written as $\lambda_T(x_n)h(t)$ for

$$h(t) = \frac{t^{k_T(x_n)-1} e^{-t}}{\int_t^\infty u^{k_T(x_n)-1} e^{-u} du}.$$

Therefore, it suffices to show that the function $t \rightarrow \log h(t)$ is non-decreasing in $t > 0$. Now,

$$\frac{\partial}{\partial t} \log h(t) = \frac{k_T(x_n) - 1}{t} - 1 + \frac{t^{k_T(x_n)-1} e^{-t}}{\int_t^\infty u^{k_T(x_n)-1} e^{-u} du}.$$

If $t < k_T(x_n) - 1$, we see directly that the derivative is positive. Otherwise, use integration by parts to simplify the last term in the right-hand side to

$$1 - \int_t^\infty \frac{k_T(x_n) - 1}{u} u^{k_T(x_n)-1} e^{-u} du / \int_t^\infty u^{k_T(x_n)-1} e^{-u} du.$$

Consequently

$$\frac{\partial}{\partial t} \log h(t) = \int_t^\infty \left\{ \frac{k_T(x_n) - 1}{t} - \frac{k_T(x_n) - 1}{u} \right\} u^{k_T(x_n)-1} e^{-u} du / \int_t^\infty u^{k_T(x_n)-1} e^{-u} du$$

is non-negative. We conclude that $\lambda_{n+1}(x; x_1, \dots, x_n)$ is bounded by $\lambda_T(x_n)$ for all $k_T(x_n) \geq 1$.

Recall that we assume that $\sup_{x \in \mathbb{R}^+} \max(\lambda_Y(x), \lambda_Z(x)) \leq c$. We may then construct a Poisson process N^* with conditional intensity $\lambda_{n+1}^*(x; x_1, \dots, x_n) = c$. Clearly, λ^* satisfies the second condition of [10, Corollary 2]. Moreover, $\lambda_{n+1} \leq c = \lambda_{n+1}^*$ for every $n \in \mathbb{N}_0$. Since a Poisson process with constant intensity has probability zero to explode, we conclude that $\mathbb{P}(X_\infty < \infty) = 0$. \square

Important special cases include $k_T(x) = 1$ for exponential distributions or, more generally, $k_T(x) \in \mathbb{N}$ corresponding to Erlang distributed phases.

Proposition 2.2. *Let $(S_n, X_n)_{n=1}^\infty$ be an alternating non-homogeneous semi-Markov process with values in $\{0, 1\} \times \mathbb{R}^+$ with $S_0 = 1, X_0 = 0$ and semi-Markov kernels $G_Y(x, \cdot), G_Z(x, \cdot)$ that follow Weibull distributions with shape and rate parameters $\theta_Y(x) = (k_Y(x), \lambda_Y(x))$ and $\theta_Z(x) = (k_Z(x), \lambda_Z(x))$ in $(0, \infty) \times (0, \infty)$ such that (i) $\lambda_Y(x) \leq c, \lambda_Z(x) \leq c$ for some $c > 0$ and (ii) either $1 \leq k_Y(x) \leq k, 1 \leq k_Z(x) \leq k$ for some $k \geq 1$, or $k_Y(x) = k_Z(x) = k$ for some $k > 0$. Write $X_\infty = \lim_{n \rightarrow \infty} X_n$ for the time of explosion. Then $\mathbb{P}(X_\infty < \infty) = 0$.*

Proof. Let $G_T(x, \cdot)$ and corresponding $(\lambda_T(x), k_T(x))$ correspond to either Y - or Z -phase cases. The probability density and cumulative distribution functions of the Weibull distribution with shape and rate parameters $k(x)$ and $\lambda(x)$ are, for $\tau \geq 0$,

$$\begin{aligned} g(x, \tau; k(x), \lambda(x)) &= k(x)\lambda(x) (\lambda(x)\tau)^{k(x)-1} e^{-(\lambda(x)\tau)^{k(x)}}; \\ G(x, \tau; k(x), \lambda(x)) &= 1 - e^{-(\lambda(x)\tau)^{k(x)}}. \end{aligned}$$

The conditional intensity is therefore, for $n = 0, 1, \dots$ and $0 = x_0 \leq x_1 \leq \dots \leq x_n \leq x$,

$$\lambda_{n+1}(x; x_1, \dots, x_n) = k_T(x_n)\lambda_T(x_n) (\lambda_T(x_n)(x - x_n))^{k_T(x_n)-1}.$$

Since the conditional intensity is unbounded, we cannot use a Poisson process to bound λ_{n+1} . Instead we turn to a homogeneous renewal process N^* with sojourn times that are Weibull distributed with shape parameter k and rate parameter c . By the strong law of large numbers, since the expected sojourn times are strictly positive, N^* has explosion probability zero [24, Section 3.1]. Also,

$$\lambda_{n+1}(x; x_1, \dots, x_n) \leq \lambda_{n+1}^*(x; x_1, \dots, x_n) = kc^k(x - x_n)^{k-1}$$

and both conditional intensities are a function of $x - x_n$ only. By [10, Corollary 2], $\mathbb{P}(X_\infty < \infty) = 0$. \square

The case that $k = 1$ corresponds to exponential sojourn times.

2.3 Renewal function: existence and boundedness

The process counting the number of cycles having occurred by time $t \geq 0$ can be written as

$$N(t) = \sup \{n \in \mathbb{N}_0 : X_{2n} \leq t\}, \quad (2.6)$$

where a cycle is an interval of time within which each state occurs once. The distribution of X_{2n} , the jump time after completing the n -th cycle, is, for $n \in \mathbb{N}_0$ and $t \geq 0$,

$$F_{2n}(t) = \mathbb{P} \left(\sum_{i=1}^{2n} T_i \leq t \right) = \mathbb{P}(X_{2n} \leq t) = \mathbb{P}(N(t) \geq n).$$

The *renewal function* is defined, analogously to that of the classic alternating renewal process, as $M(t) = \mathbb{E}N(t)$, $t \geq 0$ [12]. In our case,

$$M(t) = \mathbb{E}N(t) = \sum_{n=0}^{\infty} \mathbb{P}(N(t) > n) = \sum_{n=1}^{\infty} \mathbb{P}(X_{2n} \leq t) = \sum_{n=1}^{\infty} F_{2n}(t),$$

a $2n$ -fold convolution.

The following corollaries to Propositions 2.1–2.2 hold.

Corollary 2.2.1. *Let $(S_n, X_n)_{n=1}^{\infty}$ be as in Proposition 2.1. Then its renewal function $M(t)$ satisfies $M(t) \leq ct$, $t \geq 0$.*

Proof. Construct a Poisson process $N^*(t)$ with intensity c as in the proof of Proposition 2.1 and write X_n^* for its jump times. By [10, Corollary 1], $\mathbb{P}(X_{2n} \leq t)$ is bounded from above by $\mathbb{P}(X_{2n}^* \leq t)$. Therefore,

$$\mathbb{E}N(t) = \sum_{n=1}^{\infty} \mathbb{P}(X_{2n} \leq t) \leq \sum_{n=1}^{\infty} \mathbb{P}(X_{2n}^* \leq t) = \mathbb{E}N^*(t) = ct.$$

□

Corollary 2.2.2. *Let $(S_n, X_n)_{n=1}^{\infty}$ be as in Proposition 2.2. Then its renewal function $M(t)$ is finite and bounded from above by the expectation $\mathbb{E}(N^*(t))$ of a renewal process $N^*(t)$ with Weibull distributed sojourn times having shape parameter k and rate parameter c .*

Proof. Construct the renewal process N^* as in the proof of Proposition 2.2. Then, as in the proof of Corollary 2.2.1, $\mathbb{E}(N(t)) \leq \mathbb{E}(N^*(t))$. Also $\mathbb{E}(N^*(t)) < \infty$ (see [2] or [24, Prop. 3.2.2.]). □

2.4 Age and excess distributions

Now that the theoretical groundwork for the censoring mechanism has been laid, we proceed by determining the joint distribution of age and excess. The age $A(t)$ is the time elapsed since the last phase change, and $B(t)$, the excess, is the time remaining until the next phase change. For all t where the process is in state 0, or the Z -phase, we assume that the occurrence time can be observed perfectly. Therefore we only consider age and excess with respect to state 1, or the Y -phase. Obtaining their joint distribution allows us to specify

the likelihood of intervals based on their starting point and length in terms of the semi-Markov kernel G_Y . See Figure 1 for a visualisation of the age and excess functions.

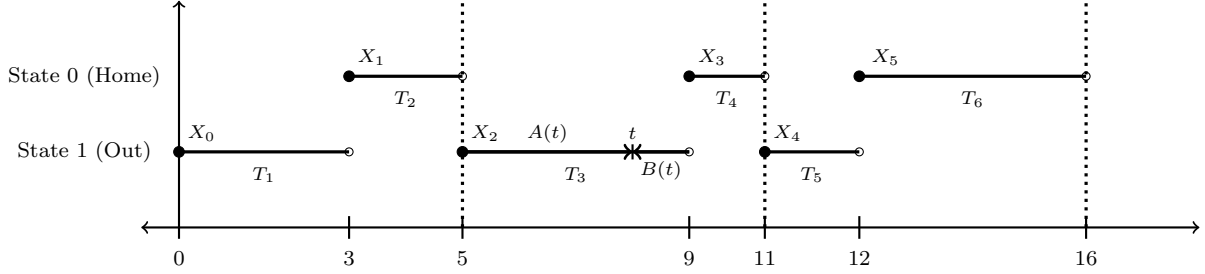


Figure 1: A visualisation of a semi-Markov process with initial values $S_0 = 1$ and $X_0 = 0$. At the dotted line, one cycle has passed - i.e. the process has taken both possible state values. The jump times correspond to a change of state. For a given time t in which the process is in state 1, a non-zero age $A(t)$ and excess $B(t)$ are recorded.

Proposition 2.3. Consider an alternating non-homogeneous semi-Markov process $(S_n, X_n)_{n=1}^{\infty}$ with values in $\{0, 1\} \times \mathbb{R}^+$ with $S_0 = 1$, $X_0 = 0$, semi-Markov kernels G_Y and G_Z and associated counting measure $N(t)$, $t \geq 0$. Let the age process with respect to the Y -phase be

$$A(t) = (t - X_{2N(t)}) \mathbf{1}\{X_{2N(t)+1} > t\}$$

and define the excess with respect to the Y -phase as

$$B(t) = (X_{2N(t)+1} - t) \mathbf{1}\{X_{2N(t)+1} > t\},$$

where $X_{2N(t)}$ is the jump time immediately after $N(t)$ cycles have been completed. Then, for $t \geq 0$ and $0 \leq x \leq t$ and $z \geq 0$,

$$\begin{aligned} \mathbb{P}(A(t) \leq x, B(t) \leq z) &= G_Y(0, t) - \int_{t-x}^t [1 - G_Y(s, t + z - s)] dM(s) - \int_0^{t-x} [1 - G_Y(s, t - s)] dM(s) \\ &\quad + \mathbf{1}\{x = t\} [G_Y(0, t + z) - G_Y(0, t)]. \end{aligned} \quad (2.7)$$

Proof. By construction, $X_0 = 0$ and $S_0 = 1$. Now, for $0 \leq x < t$,

$$\begin{aligned} \mathbb{P}(A(t) > x) &= \mathbb{P}(t - X_{2N(t)} > x, X_{2N(t)+1} > t \mid S_0 = 1, X_0 = 0) \\ &= \sum_{n=0}^{\infty} \mathbb{P}(t - X_{2n} > x, X_{2n+1} > t, N(t) = n \mid S_0 = 1, X_0 = 0) \\ &= 1 - \mathbb{P}(T_1 \leq t \mid S_0 = 1, X_0 = 0) + \sum_{n=1}^{\infty} \mathbb{P}(t - X_{2n} > x, X_{2n+1} > t \mid S_0 = 1, X_0 = 0) \end{aligned}$$

after simplifying and removing redundant conditions. Note that by (2.2) and as we know we are guaranteed to be in state 1, $\mathbb{P}(T_1 \leq t | S_0 = 1, X_0 = 0) = G_Y(0, t)$. Continuing,

$$\begin{aligned}\mathbb{P}(A(t) > x) &= 1 - G_Y(0, t) + \sum_{n=1}^{\infty} \mathbb{P}(X_{2n} < t - x; X_{2n+1} > t | S_0 = 1, X_0 = 0) \\ &= 1 - G_Y(0, t) + \int_0^{t-x} [1 - G_Y(s, t - s)] dM(s),\end{aligned}$$

using the law of total probability and Fubini's theorem. Considering the discrete components,

$$\mathbb{P}(A(t) = 0) = 1 - \mathbb{P}(A(t) > 0) = G_Y(0, t) - \int_0^t [1 - G_Y(s, t - s)] dM(s)$$

and

$$\mathbb{P}(A(t) = t) = \mathbb{P}(X_1 > t) = 1 - G_Y(0, t).$$

Next turn to the excess. For $z \geq 0$,

$$\begin{aligned}\mathbb{P}(B(t) > z) &= \mathbb{P}(X_{2N(t)+1} > t + z | S_0 = 1, X_0 = 0) \\ &= 1 - G_Y(0, t + z) + \int_0^t [1 - G_Y(s, t + z - s)] dM(s)\end{aligned}$$

and

$$\mathbb{P}(B(t) = 0) = 1 - \mathbb{P}(B(t) > 0) = G_Y(0, t) - \int_0^t [1 - G_Y(s, t - s)] dM(s).$$

Using similar arguments, we can find an expression for the joint probability $\mathbb{P}(A(t) > x, B(t) > z)$. For $z \in [0, \infty)$ and $x \in [0, t)$,

$$\begin{aligned}\mathbb{P}(A(t) > x, B(t) > z) &= \mathbb{P}(X_{2N(t)+1} > t + z, t - X_{2N(t)} > x | S_0 = 1, X_0 = 0) \\ &= 1 - G_Y(0, t + z) + \int_0^{t-x} [1 - G_Y(s, t + z - s)] dM(s).\end{aligned}$$

We can now handle the event $\{A(t) \leq x, B(t) \leq z\}$ for $0 \leq x < t, z \geq 0$ as follows:

$$\begin{aligned}\mathbb{P}(A(t) \leq x, B(t) \leq z) &= \mathbb{P}(A(t) > x, B(t) > z) + 1 - \mathbb{P}(B(t) > z) - \mathbb{P}(A(t) > x) \\ &= G_Y(0, t) - \int_{t-x}^t [1 - G_Y(s, t + z - s)] dM(s) - \int_0^{t-x} [1 - G_Y(s, t - s)] dM(s).\end{aligned}$$

Finally, for $x = t$,

$$\mathbb{P}(A(t) \leq t, B(t) \leq z) = 1 - \mathbb{P}(B(t) > z) = G_Y(0, t + z) - \int_0^t [1 - G_Y(s, t + z - s)] dM(s)$$

and we obtain the proposed expression. \square

From Proposition 2.3 we conclude that the probability that time $t \geq 0$ falls in a Z -phase is given by

$$w_t = \mathbb{P}(A(t) \leq 0, B(t) \leq 0) = G_Y(0, t) - \int_0^t [1 - G_Y(s, t - s)] dM(s). \quad (2.8)$$

This case constitutes the atomic part of (2.7). The singular component on the line $x = t$ has total mass $1 - G_Y(0, t)$ and represents the case that t falls before the first jump of the semi-Markov process.

The absolutely continuous component of (2.7) can be written as

$$\int_0^x \int_0^z g_Y(t-u, u+v) m(t-u) du dv$$

provided that the Radon–Nikodym derivatives m of M and g_Y of G_Y exist. Recall that in our proposed censoring mechanism, when t falls in a Y -phase, the entire interval $[t - A(t), t + B(t)]$ is reported, which may be parametrised by the left-most point $t - A(t)$ and length $A(t) + B(t)$. Suppose that $A(t) = u$ and $B(t) = v$, and apply the change of variables $a = t - u$ and $l = u + v$. We find that the joint probability density function of left-most point and length is

$$q_t(a, l) = \frac{m(a)g_Y(a, l)}{\int_0^t [1 - G_Y(s, t-s)] dM(s)} \mathbf{1}\{0 \leq a \leq t \leq a + l; l \geq 0\}, \quad (2.9)$$

upon scaling.

Proposition 2.4. *Let g_Y and m be as before, and let (A, L) be distributed according to $q_t(a, l)$ given by (2.9). Then the marginal probability density function of A at $a \in [0, t]$ is*

$$f_t(a) = \frac{m(a)[1 - G_Y(a, t-a)]}{\int_0^t [1 - G_Y(s, t-s)] dM(s)} \quad (2.10)$$

and the conditional probability density function of L given $A = a$ is, for $l \in [t - a, \infty)$,

$$f_{t, L|A=a}(l) = \frac{g_Y(a, l)}{1 - G_Y(a, t-a)}. \quad (2.11)$$

Proof. Assume that $0 \leq a \leq t \leq a + l$ and $l \geq 0$. The marginal distribution of the starting time $f_t(a)$ is

$$\begin{aligned} f_t(a) &= \int q_t(a, l) dl = \frac{m(a)}{\int_0^t [1 - G_Y(s, t-s)] dM(s)} \int_{t-a}^{\infty} g_Y(a, l) dl \\ &= \frac{m(a)[1 - G_Y(a, t-a)]}{\int_0^t [1 - G_Y(s, t-s)] dM(s)}, \end{aligned}$$

and

$$f_{t, L|A=a}(l) = \frac{q_t(a, l)}{f_t(a)} = \frac{g_Y(a, l)}{1 - G_Y(a, t-a)}.$$

□

The marginal and conditional distributions of the intervals can be used to generate interval samples.

3 A model for non-homogeneous interval-censoring

3.1 Model formulation

The ensemble of potentially censored occurrence times can be mathematically formalised as a marked point process [7]. The ground process of points represent the uncensored event occurrences, which we model by

a Markov point process [17] defined by a probability density with respect to a unit rate Poisson process. Temporal variations can be taken into account as well as interactions between the points. Each point is subsequently marked, independently of other points, either by an atom at the point when it is observed perfectly, or by the interval in which the point lies in case of censoring. The mark kernel that governs the random censoring is based on the distribution of age and excess in a non-homogeneous semi-Markov process.

Formally, let \mathcal{X} be an open set on the real line. The state space $\mathcal{N}_{\mathcal{X}}$ of a simple point process X consists of finite sets $\{x_1, x_2, \dots, x_n\} \subset \mathcal{X}$, $n \in \mathbb{N}_0$, which we equip with the Borel σ -algebra of the weak topology [7, Appendix A2]. Let p be a measurable, non-negative function on \mathcal{X} that integrates to unity and \sim a symmetric, reflexive relation on \mathcal{X} . A point process X on \mathcal{X} having probability density p with respect to a unit rate Poisson process is Markov with respect to \sim if, firstly, p is hereditary, that is, $p(\mathbf{x}) > 0$ implies that $p(\mathbf{y}) > 0$ for all subsets \mathbf{y} of \mathbf{x} , and, secondly, the conditional intensity, defined as $p(\mathbf{x} \cup \{t\})/p(\mathbf{x})$ with $a/0 = 0$ for $a \geq 0$, depends only on the neighbourhood $\{x \in \mathbf{x} : x \sim t\}$ of t in \mathbf{x} for every $t \in \mathcal{X} \setminus \mathbf{x}$ and every $\mathbf{x} = \{x_1, \dots, x_n\} \subset \mathcal{X}$ for which $p(\mathbf{x}) > 0$ [17, 23].

An interaction function is a family $\phi_0, \phi_1, \phi_2, \dots$ of non-negative functions ϕ_i defined on configurations of i points that take the value one whenever the configuration contains a pair $\{x_1, x_2\}$ of points that are unrelated, that is, $x_1 \not\sim x_2$. By the Hammersley–Clifford theorem [23], writing $|\cdot|$ for cardinality, a Markov density p can be factorised as

$$p(\mathbf{x}) = \prod_{\mathbf{y} \subset \mathbf{x}} \phi_{|\mathbf{y}|}(\mathbf{y}) \quad (3.1)$$

for some interaction function ϕ_i . The function $\phi_1(x)$ can be used to model temporal variations in the likelihood of events occurring. Higher order terms ϕ_2, ϕ_3, \dots govern interactions between pairs, triples or tuples of points.

The points x in a realisation \mathbf{x} of X are marked independently according to a mark kernel $\nu(\cdot|x)$ on $\mathbb{R} \times \mathbb{R}^+$. A mark (a, l) represents an interval $[a, a + l]$ that starts at a and has length l . The mark kernel ν formalises the semi-Markov censoring discussed in Section 2. For demonstrative purposes, we assumed a starting time of 0, which we now set to $-\infty$. Doing so also allows us to ignore the singular component. Hence the appropriate time-dependent mark kernel $\nu(\cdot|x)$, $x \in \mathcal{X}$, for a Borel subset $A \subset \mathbb{R} \times \mathbb{R}^+$ is

$$\begin{aligned} \nu(A|x) &= \left(1 - \int_{-\infty}^x [1 - G_Y(s, x - s)] dM(s)\right) \delta(\{(x, 0)\} \cap A) \\ &\quad + \int_{-\infty}^x \int_{x-a}^{\infty} \mathbf{1}\{(a, l) \in A\} G_Y(a, dl) dM(a). \end{aligned} \quad (3.2)$$

Write W for the marked point process defined by $p(\cdot)$ and $\nu(\cdot|x)$ [7, Prop. 4.IV]. A realisation \mathbf{w} is of the form

$$\mathbf{w} = \{w_1, w_2, \dots, w_n\} = \{(x_1, (a_1, l_1)), (x_2, (a_2, l_2)), \dots, (x_n, (a_n, l_n))\}$$

for $a_i \leq x_i \leq a_i + l_i$ for all $i = 1, 2, \dots, n$. We denote the set of realisations by $\mathcal{N}_{\mathcal{X} \times (\mathbb{R} \times \mathbb{R}^+)}$.

The model description is complete by noting that the observable pattern of marks after censoring is

$$U = \bigcup_{(x_i, (a_i, l_i)) \in W} \{(a_i, l_i)\}.$$

To obtain the probability distribution of U , write, for F in the Borel σ -algebra of the weak topology on $\mathcal{N}_{\mathbb{R} \times \mathbb{R}^+}$,

$$\mathbb{P}(U \in F | X = \mathbf{x}) = \int_{(\mathbb{R} \times \mathbb{R}^+)^n} \mathbf{1}(\{(a_1, l_1), \dots, (a_n, l_n)\} \in F) \prod_{i=1}^n d\nu((a_i, l_i) | x_i),$$

where $\mathbf{x} = \{x_1, \dots, x_n\}$, and then take the expectation with respect to X .

3.2 Conditional distribution

Write \mathbf{u} for a realisation of the interval set U . We are interested in the conditional distributions of X and W given $U = \mathbf{u}$.

Theorem 3.1. *Let W be a marked point process with ground process X on the open set $\mathcal{X} \subset \mathbb{R}$ defined by its probability density function p with respect to the distribution of a unit rate Poisson process having independent marks distributed according to the mark kernel $\nu(\cdot | x)$ for $x \in \mathcal{X}$ given by (3.2). Let \mathbf{u} be a realisation of U that consists of an atomic part $\{(a_1, 0), \dots, (a_m, 0)\}$, $m \in \mathbb{N}_0$, and a non-atomic part $\{(a_{m+1}, l_{m+1}), \dots, (a_n, l_n)\}$, $n \geq m$. Then the conditional distribution of X given $U = \mathbf{u}$ satisfies, for A in the Borel σ -algebra of the weak topology on $\mathcal{N}_{\mathcal{X}}$,*

$$\begin{aligned} \mathbb{P}(X \in A | U = \mathbf{u}) &= c(\mathbf{u}) \int_{\mathcal{X}^{n-m}} p(\{a_1, \dots, a_m, x_1, \dots, x_{n-m}\}) \mathbf{1}_A(\{a_1, \dots, a_m, x_1, \dots, x_{n-m}\}) \\ &\quad \sum_{\substack{D_1, \dots, D_{n-m} \\ \cup_j \{D_j\} = \{1, \dots, n-m\}}} \prod_{i=1}^{n-m} \mathbf{1}_{[a_{m+i}, a_{m+i} + l_{m+i}]}(x_{D_i}) dx_i \end{aligned}$$

provided that the normalisation constant

$$c(\mathbf{u}) = 1 / \int_{\mathcal{X}^{n-m}} p(\mathbf{x} \cup \{a_1, \dots, a_m\}) \sum_{\substack{D_1, \dots, D_{n-m} \\ \cup_j \{D_j\} = \{1, \dots, n-m\}}} \prod_{i=1}^{n-m} \mathbf{1}_{[a_{m+i}, a_{m+i} + l_{m+i}]}(x_{D_i}) dx_i$$

exists in $(0, \infty)$.

Proof. We must prove, for each A in the Borel σ -algebra of $\mathcal{N}_{\mathcal{X}}$ with respect to the weak topology and each F in the Borel σ -algebra of the weak topology on $\mathcal{N}_{\mathbb{R} \times \mathbb{R}^+}$, that

$$\mathbb{E}[\mathbf{1}_F(U) \mathbb{P}(X \in A | U)] = \mathbb{E}[\mathbf{1}_F(U) \mathbf{1}_A(X)],$$

as in equation 4 of [18]. From the model description, writing w_t for the modification of (2.8) over $(-\infty, t)$,

ℓ for Lebesgue measure, $|\cdot|$ for cardinality,

$$\begin{aligned} \mathbb{E}[1_F(U)1_A(X)] &= \sum_{n=0}^{\infty} \frac{e^{-\ell(\mathcal{X})}}{n!} \int_{\mathcal{X}^n} 1_A(\mathbf{x}) p(\{x_1, \dots, x_n\}) \sum_{C_0 \subset \{1, \dots, n\}} \frac{1}{(n - |C_0|)!} \prod_{i \in C_0} w_{x_i} \\ &\quad \int_{(\mathbb{R} \times \mathbb{R}_0^+)^{n - |C_0|}} 1_F(\{(a_1, l_1), \dots, (a_{n - |C_0|}, l_{n - |C_0|})\} \cup (\mathbf{x}_{C_0} \times \{0\})) \\ &\quad \sum_{\substack{C_1, \dots, C_{n - |C_0|} \\ \cup_j \{C_j\} = \{1, \dots, n\} \setminus C_0}} \prod_{j=1}^{n - |C_0|} m(a_j) g_Y(a_j, l_j) 1_{[a_j, a_j + l_j]}(x_{C_j}) da_j dl_j \prod_{i=1}^n dx_i. \end{aligned} \quad (3.3)$$

Following through for the left-hand side,

$$\begin{aligned} \mathbb{E}[1_F(U) \mathbb{P}(X \in A | U)] &= \sum_{n=0}^{\infty} \frac{e^{-\ell(\mathcal{X})}}{n!} \int_{\mathcal{X}^n} p(\{x_1, \dots, x_n\}) \sum_{C_0 \subset \{1, \dots, n\}} \frac{1}{(n - |C_0|)!} \prod_{i \in C_0} w_{x_i} \\ &\quad \int_{(\mathbb{R} \times \mathbb{R}_0^+)^{n - |C_0|}} 1_F(\{(a_1, l_1), \dots, (a_{n - |C_0|}, l_{n - |C_0|})\} \cup (\mathbf{x}_{C_0} \times \{0\})) \\ &\quad \mathbb{P}(X \in A | U = \{(a_1, l_1), \dots, (a_{n - |C_0|}, l_{n - |C_0|})\} \cup (\mathbf{x}_{C_0} \times \{0\})) \\ &\quad \sum_{\substack{C_1, \dots, C_{n - |C_0|} \\ \cup_j \{C_j\} = \{1, \dots, n\} \setminus C_0}} \prod_{j=1}^{n - |C_0|} m(a_j) g_Y(a_j, l_j) 1_{[a_j, a_j + l_j]}(x_{C_j}) da_j dl_j \prod_{i=1}^n dx_i. \end{aligned}$$

Next, we plug in the expression for $\mathbb{P}(X \in A | U = \mathbf{u})$ proposed in the statement of the theorem. Upon substitution, changing integration order and rearranging, we obtain

$$\begin{aligned} \mathbb{E}[1_F(U) \mathbb{P}(X \in A | U)] &= \sum_{n=0}^{\infty} \frac{e^{-\ell(\mathcal{X})}}{n!} \sum_{C_0 \subset \{1, \dots, n\}} \frac{1}{(n - |C_0|)!} \int_{\mathcal{X}^n} p(\mathbf{y} \cup \mathbf{x}_{C_0}) 1_A(\mathbf{y} \cup \mathbf{x}_{C_0}) \prod_{i \in C_0} w_{x_i} \\ &\quad \int_{(\mathbb{R} \times \mathbb{R}_0^+)^{n - |C_0|}} 1_F(\{(a_1, l_1), \dots, (a_{n - |C_0|}, l_{n - |C_0|})\} \cup (\mathbf{x}_{C_0} \times \{0\})) \\ &\quad c(\{(a_1, l_1), \dots, (a_{n - |C_0|}, l_{n - |C_0|})\} \cup (\mathbf{x}_{C_0} \times \{0\})) \\ &\quad \sum_{\substack{D_1, \dots, D_{n - |C_0|} \\ \cup_j \{D_j\} = \{1, \dots, n\} \setminus C_0}} \prod_{j=1}^{n - |C_0|} m(a_j) g_Y(a_j, l_j) 1_{[a_j, a_j + l_j]}(y_{D_j}) \\ &\quad \left(\int_{\mathcal{X}^{n - |C_0|}} p(\mathbf{x}) \sum_{\substack{C_1, \dots, C_{n - |C_0|} \\ \cup_j \{C_j\} = \{1, \dots, n\} \setminus C_0}} \prod_{j=1}^{n - |C_0|} 1_{[a_j, a_j + l_j]}(x_{C_j}) \prod_{j \notin C_0} dx_j \right) \prod_{j=1}^{n - |C_0|} da_j dl_j \\ &\quad \prod_{i \in C_0} dx_i \prod_{k=1}^{n - |C_0|} dy_k = \mathbb{E}[1_F(U)1_A(X)] \end{aligned}$$

since the term within brackets cancels out against the normalisation constant $c(\cdot)$. \square

Strikingly, although the marking mechanism is more complicated than that in [18], the conditional distribution of X has the same form.

The conditional distribution of W can be obtained in the same vein, by considering $1_A(W)$ instead of $1_A(X)$ for A a Borel set in $\mathcal{N}_{\mathcal{X} \times (\mathbb{R} \times \mathbb{R}^+)}$, the space of marked point configurations, is given by

$$\mathbb{P}(W \in A | U = \mathbf{u}) \propto \int_{\mathcal{X}^{n-m}} p(\{a_1, \dots, a_m, x_1, \dots, x_{n-m}\}) 1_A(\{(a_1, (a_1, 0)), \dots, (a_m, (a_m, 0)), (x_1, (a_{m+1}, l_{m+1})), \dots, (x_{n-m}, (a_{m+1}, l_{m+1}))\}) \prod_{i=1}^{n-m} 1_{[a_{m+i}, a_{m+i} + l_{m+i}]}(x_i) dx_i.$$

4 Modelling considerations

In this section, we will consider parametric forms for $p(\cdot)$ and $\nu(\cdot|x)$.

4.1 Non-homogeneous point process densities

We will first look at inhomogeneity that manifests itself via the occurrence time distribution. In view of (3.1), it is natural to add inhomogeneity by means of the first-order interaction function ϕ_1 , a procedure known as type I inhomogeneity [13]. The idea is to let $\phi_1(\{x\}) = \beta(x)$ vary over time according to a measurable function β that maps $x \in \mathcal{X}$ to $[0, \infty)$. In many applications, it may make sense to model β as a step function. More specifically, given a measurable partition B_k , $k = 1, \dots, K$, of \mathcal{X} , set

$$\beta(x) = \sum_{k=1}^K \beta_k \mathbf{1}_{B_k}(x), \quad x \in \mathcal{X} \quad (4.1)$$

where $\beta_k \geq 0$ is the value that β takes in the corresponding set B_k .

The function ϕ_1 can be combined with classic second and higher order interaction functions. For instance, the density of the non-homogeneous area-interaction point process [3] becomes

$$p(\mathbf{x}) = \alpha_p \left(\prod_{x \in \mathbf{x}} \beta(x) \right) \exp[-\log \gamma \ell(\mathcal{X} \cap U_r(\mathbf{x}))] \quad (4.2)$$

with respect to a unit rate Poisson process on \mathcal{X} . The parameter γ quantifies the interaction strength, r the radius of interaction, and $\alpha_p = c(\beta(\cdot), \gamma)$ is a normalisation constant [3] that depends on the function β as well as on γ . Additionally, $U_r(\mathbf{x}) = \bigcup_{i=1}^n B(x_i, r)$ where $B(x_i, r)$ is the closed interval $[x_i - r, x_i + r]$. We observe regularity for $\gamma < 1$, clustering for $\gamma > 1$, and $\gamma = 1$ corresponds to a non-homogeneous Poisson process with intensity function β . For further examples, we refer to [17].

4.2 Parametric modelling of the mark kernel

To proceed, parametric forms for G_Y and m must be developed. We begin by modelling G_Y , the semi-Markov kernel that determines the length of time until the next transition. We may take one of the time-dependent probability density functions considered in Section 2.2. For instance, $g_Y(a, l)$ could be the density function of an exponential distribution with rate

$$\lambda(a; \alpha) = \alpha (b + \sin(ca)), \quad a \in \mathbb{R}, \quad (4.3)$$

where c specifies the period and $b \geq 1$ the elevation away from 0. The parameter α determines the amplitude of the harmonic.

We could proceed in a similar fashion for g_Z . However, there are two problems with such an approach. From a probabilistic point of view, tractable expressions for the renewal density m in terms of the semi-Markov kernels G_Y and G_Z do not seem to exist, and, statistically speaking, lengths of Z phases cannot be observed. Therefore, we shall model m directly. The following proposition justifies this approach.

Proposition 4.1. *Let $(S_n, X_n)_{n=1}^\infty$ be a semi-Markov process on $\{1\} \times \mathbb{R}^+$ with $S_0 = 1$ and $X_0 = 0$ having semi-Markov kernel G_Y defined by a density function $g_Y(t, \tau)$, $t \in \mathbb{R}^+$, $\tau \in [0, \infty)$ and write \tilde{m} for the density of its renewal function*

$$\tilde{M}(t) = \sum_{n=1}^{\infty} \mathbb{P}(X_n \leq t).$$

If $h(t) : \mathbb{R}^+ \rightarrow [0, \infty)$ is a Borel-measurable function such that $h(t) \leq \tilde{m}(t)$, then there exists an alternating semi-Markov process on $\{0, 1\} \times \mathbb{R}^+$ with $G_{01} = G_Y$ and renewal density h .

Proof. As $0 \leq h(t)/\tilde{m}(t) \leq 1$, we may use a time-dependent thinning approach with retention probability $p(t) = h(t)/\tilde{m}(t)$. Algorithmically, the sought-after process can be constructed as follows. Initialise $\hat{S}_0 = 1$, $\hat{X}_0 = 0$ and $\hat{X}_1 = X_1$. Also set $\hat{S}_{2i} = 1$, $\hat{S}_{2i-1} = 0$ for $i \in \mathbb{N}$ and $j = 1$. For each jump time X_i , $i = 1, 2, \dots$,

- with probability $p(X_i)$, if j is even, update $\hat{X}_{j+1} = X_{i+1}$ and increment j by 1; for odd j update $\hat{X}_{j+1} = \hat{X}_j$, $\hat{X}_{j+2} = X_{i+1}$ and increment j by 2;
- else, if j is odd, update $\hat{X}_{j+1} = X_{i+1}$ and increment j by 1; for even j update $\hat{X}_j = X_{i+1}$ leaving j unchanged.

Because complete cycles correspond to intervals in between accepted points X_i , $i = 0, 1, 2, \dots$,

$$H(t) = \sum_{n=1}^{\infty} \mathbb{P}(\hat{X}_{2n} \leq t) = \sum_{n=1}^{\infty} \mathbb{P}(X_n \leq t; X_n \text{ retained}) = \int_0^t \frac{h(s)}{\tilde{m}(s)} d\tilde{M}(s).$$

We can therefore conclude that the intensity of the thinned process is $\frac{h(t)}{\tilde{m}(t)}\tilde{m}(t) = h(t)$ (see e.g. [7, pp. 78–79] and hence $(\hat{S}_n, \hat{X}_n)_{n=1}^\infty$ is a non-homogeneous alternating semi-Markov process that satisfies the proposed conditions. \square

As an illustration, suppose that h is a step function

$$m(t) = \sum_{j=1}^J \delta_j \mathbf{1}_{A_j}(t), \quad t \in \mathbb{R}^+, \quad (4.4)$$

that takes J different values $\delta_j > 0$ on Borel sets A_j forming a partition of the half line ($j = 1, \dots, J$, with $J \in \mathbb{N}$). The following corollary lays out conditions under which $h = m$ is the renewal density of an alternating renewal process whose Y -phases are governed by (4.3).

Corollary 4.1.1. *A sufficient condition for (4.4) to be the renewal density of an alternating semi-Markov process on $\{0, 1\} \times \mathbb{R}^+$ with G_Y given by (4.3) on \mathbb{R}^+ is that for all $j = 1, \dots, J$ we have $\delta_j \leq \alpha(b - 1)$.*

Proof. For (4.4) to induce a semi-Markov process, we require $h(t) \leq \tilde{m}(t)$, where $\tilde{m}(t)$ is the Radon-Nikodym derivative of the renewal function $\tilde{M}(t)$. In Proposition 4.1 we defined

$$\tilde{M}(t) = \sum_{n=1}^{\infty} \mathbb{P}(X_n \leq t),$$

with $(X_n)_{n=0}^{\infty}$ being its associated jump process of only Y -phases. By construction, its conditional intensity is $\tilde{\lambda}_{n+1}(t; t_1, \dots, t_n) = \lambda(t, \alpha)$ for all $0 \leq t_1 \leq \dots \leq t_n \leq t$.

Observe that $\inf\{\lambda(t; \alpha) : t \in \mathbb{R}\} = \alpha(b-1)$. Construct a Poisson process $N^*(t)$ with intensity $\nu = \alpha(b-1)$. By [10, Corollary 1], since $\lambda_{n+1}^*(t; t_1, \dots, t_n) \leq \tilde{\lambda}_{n+1}(t; t_1, \dots, t_n)$, we may conclude that the renewal function νt of $N^*(t)$ is bounded from above by $\tilde{M}(t)$ for all t . Hence also $\nu \leq \tilde{m}(t)$.

For $h = m$ as in (4.4), in order to have $\sum_{j=1}^J \delta_j \mathbf{1}_{A_j}(t) \leq \alpha(b-1)$, it is sufficient that $\delta_j \leq \alpha(b-1)$ for all $j = 1, \dots, J$ to guarantee that $m(t)$ is the renewal density of a semi-Markov process. \square

As noted before, in practice, the starting point 0 is moved back to $-\infty$. Realisations \mathbf{u} from the specified model may be obtained as follows. First, a set of points $\mathbf{x} \subset \mathcal{X}$ in time are chosen according to the probability density function $p(\cdot)$ by, for example, coupling from the past [14] or the Metropolis–Hastings algorithm [8]. Next, for each point $x \in \mathbf{x}$, it is determined whether or not it is an atom based on w_x . If this is not the case, we appeal to Proposition 2.4 and use rejection sampling with a proposal distribution that simulates a uniformly distributed point in $A_j \cap (-\infty, x]$ chosen with probability $\delta_j \ell(A_j \cap (-\infty, x]) / \sum_{i=1}^J \delta_i \ell(A_i \cap (-\infty, x])$ and acceptance probability $\exp[-\lambda(a; \alpha)(x - a)]$. The result is a sample a from $f_x(a)$, cf. (2.10). The length is then sampled according to an exponential distribution with parameter $\lambda(a; \alpha)$ shifted by $x - a$ (see (2.11)). It is interesting to observe that, in contrast to the alternating renewal case studied in [18], using the marginal distribution with respect to A and then the conditional given A is computationally simpler than sampling L first.

4.3 Statistical aspects

In practical applications, both the family of probability density functions $g_Y(t, \tau; \theta)$ for the sojourn times in phase Y and the function $m(t; \xi)$ rely on unknown parameters $\eta = (\theta, \xi)$ that must be estimated. The log-likelihood $L(\eta; \mathbf{u})$ follows directly from (3.3). Upon observing $\mathbf{u} = \{(a_1, 0), \dots, (a_m, 0), (a_{m+1}, l_{m+1}), \dots, (a_n, l_n)\}$,

$$L(\eta; \mathbf{u}) = \sum_{i=1}^m \log \left(1 - \int_{-\infty}^{a_i} [1 - G_Y(s, a_i - s; \theta)] m(s; \xi) ds \right) + \sum_{i=m+1}^n \log (m(a_i; \xi) g_Y(a_i, l_i; \theta)). \quad (4.5)$$

When the sojourn time distributions G_Y and G_Z and hence the renewal density $m \equiv (\mathbb{E}Y + \mathbb{E}Z)^{-1}$ are not time-varying, (4.5) reduces to the renewal likelihood in [18].

We will illustrate the procedure by means of a specific example. For the sojourn times, we take an exponential model; for the function m , we use (4.4). Assume that $G_Y(t, \cdot)$, $t \in \mathbb{R}$, is distributed exponentially

with rate parameter $\lambda(t)$ as in (4.3) and m given by (4.4). In the homogeneous case that $\lambda(t) \equiv \alpha > 0$ (that is, $b = 1$ and $c = 0$), $J = 1$, $A_1 = \mathbb{R}$ and $0 \leq \delta_1 \leq \alpha$,

$$L(\alpha, \delta_1; \mathbf{u}) = m \log \left(1 - \frac{\delta_1}{\alpha} \right) + (n - m) \log \delta_1 + (n - m) \log \alpha - \alpha \sum_{i=m+1}^n l_i.$$

In general, the atom probability for a given time $x \in \mathcal{X}$ is

$$w_x = 1 - \sum_{j=1}^J \delta_j \int_{A_j \cap (-\infty, x]} e^{-(x-s)\lambda(s)} ds. \quad (4.6)$$

The likelihood equation (4.5) after substitution and discarding of terms that do not depend on the parameters becomes

$$\begin{aligned} L(\delta, \alpha; \mathbf{u}) = & \sum_{i=1}^m \log \left(1 - \sum_{j=1}^J \delta_j \int_{(a_i - A_j) \cap [0, \infty)} e^{-\alpha r(b + \sin(ca_i - cr))} dr \right) + \sum_{i=m+1}^n \log \left(\sum_{j=1}^J \delta_j \mathbf{1}_{A_j}(a_i) \right) \\ & + (n - m) \log \alpha - \alpha \sum_{i=m+1}^n l_i (b + \sin(ca_i)). \end{aligned}$$

The resulting equations can be solved numerically to find optimal values for $\delta_k, k = 1, \dots, J$, and α under the inequality constraints $0 \leq \delta_j \leq \alpha(b - 1)$, $j = 1, \dots, J$.

The distribution of unobserved occurrence times may also be considered as a parameter to be estimated using the reported intervals. To do so, since the form of the conditional distribution of W given U according to Theorem 3.1 is identical to that for alternating renewal process-based censoring, the simulation techniques developed in [18] to obtain realisations of the marked occurrence times given a sample \mathbf{u} of U apply. Briefly, estimation of any parameters involved in $p(\cdot)$, for instance the β_k in (4.1), requires a Monte Carlo EM approach [9]. Once the parameters have been estimated, a Metropolis-Hastings algorithm [5, 19, 20] for a fixed number of points can be used. For further details and conditions under which the algorithm converges to the desired distribution, we refer to Propositions 4.3–4.5 in [18].

5 Illustrations in practice

To show how the non-homogeneous semi-Markov model behaves, we present a few examples that compare the new model with a homogeneous one. Recall that, broadly speaking, there are three sources of inhomogeneity: the interval lengths as governed by g_Y , the renewal density m , and the ground process responsible for the uncensored event occurrences. Throughout this section, we set $\mathcal{X} = (0, 1)$.

5.1 Model mis-specification

The first source of inhomogeneity in our model is the semi-Markov kernel $G_Y(a, l)$ for starting point $a \in \mathbb{R}$ and length $l \geq 0$, which determines the time until the next transition. For specificity, let us assume that the actual interval censoring mechanism is governed by a Weibull distribution with shape parameter $k = 1$

and rate parameter $\lambda_Y(t; \alpha) = \alpha(1.6 + \sin(2\pi t))$ for $\alpha = 1$. Regarding the other model ingredients, we take $p(\cdot)$ of the form given in (4.2) with $\beta = 400$ and $\gamma = 1$, that is, a homogeneous Poisson process on \mathcal{X} with intensity 400. We additionally set $m(t) = 0.6 \mathbf{1}_{[-0.2, 1)}(t)$.

To illustrate the effect of erroneously assuming a homogeneous model, we sample a realisation from the actual model and fit a Weibull distribution with parameters $k > 0$ and constant rate $\lambda_Y(t; \alpha) \equiv \alpha$ for $\alpha > 0$. We obtained parameter estimates $\hat{k} = 0.9$ and $\hat{\alpha} = 2.0$. The graphs of the survival time densities for $t = 0.6$ for both models are shown in Figure 2. The homogeneous model is able to roughly discern the shape of the distribution, but struggles with the scale. Compared to the actual model, for $t = 0.6$, it generates more intervals shorter than about 0.5 and fewer of longer length.

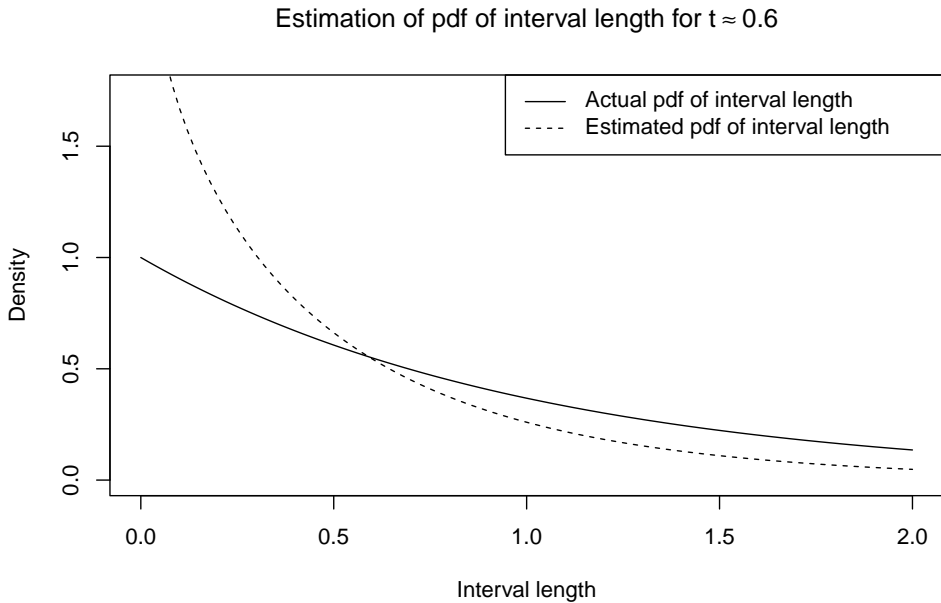


Figure 2: The solid line is the actual probability density of interval length for $k = 1$ and $\lambda(0.6; 1) = 1$. The broken line is the estimated survival time density.

5.2 Inhomogeneity in renewal density and survival time

In our second experiment, we add inhomogeneity in m to the the model and study the effect on f_x , cf. (2.10). As in Section 5.1, consider an exponential semi-Markov density g_Y with rate parameter either constant, $\lambda(t; \alpha) = 1.3\alpha$, or varying in time according to $\lambda(t; \alpha) = \alpha(1.3 + \sin(2\pi t))$. Furthermore, set $m(t) = 0.4$ for $t \in [-0.2, 1)$ in the constant case, and

$$m(t) = \begin{cases} 0.4 & t \in [-0.2, 0.4) \\ 0.1 & t \in [0.4, 1) \end{cases}$$

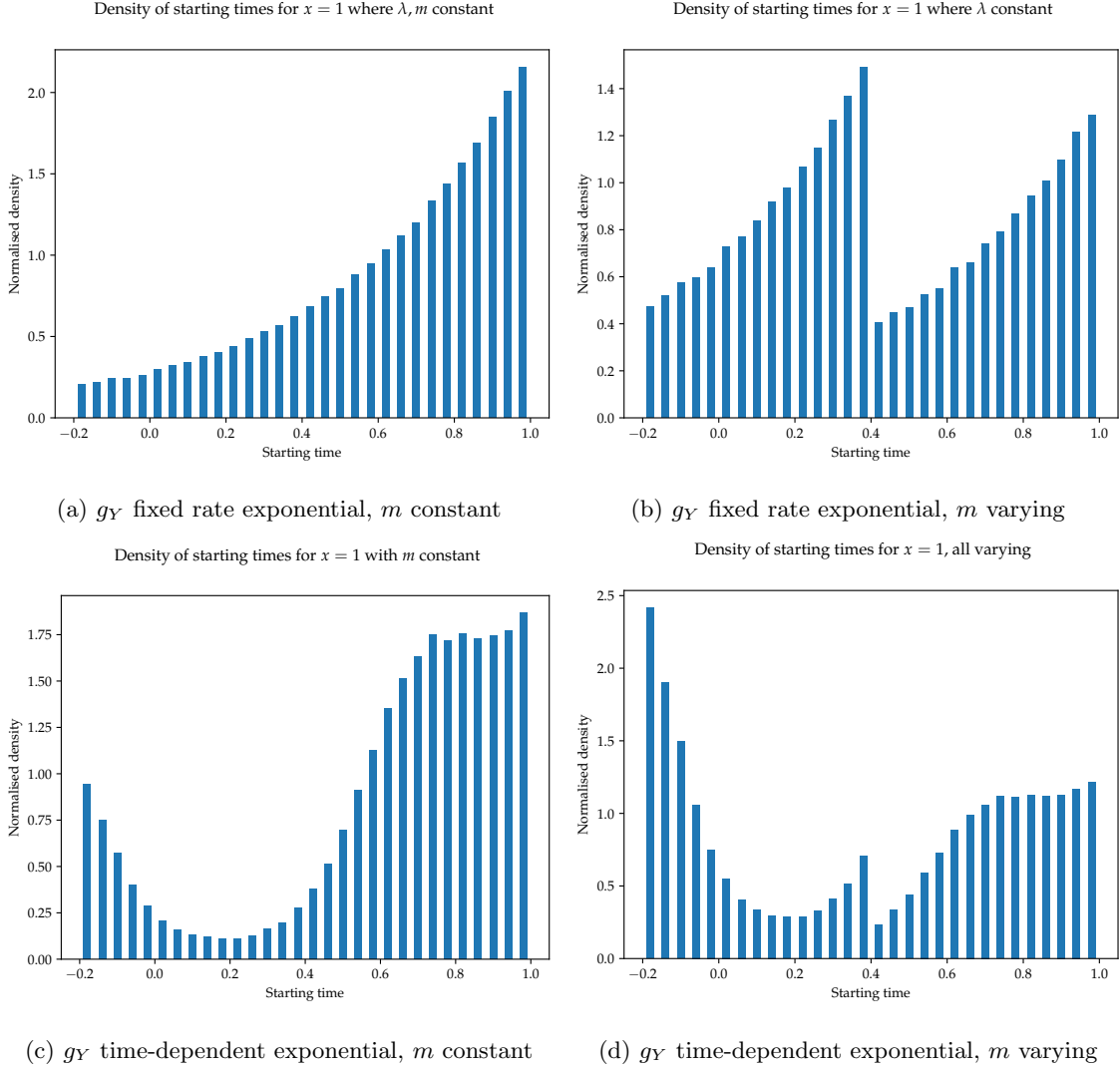


Figure 3: Probability density function of the starting time $f_x(\cdot)$ with $x = 1$ for various choices of g_Y and m .

in the time-varying case. We set $\alpha = 1.6$, so the largest value of δ_i which guarantees that g_Y is the Radon-Nikodym derivative of a semi-Markov kernel is $1.6 \times (1.3 - 1) = 0.48$. Figure 3 shows the graphs of $f_x(\cdot)$ for the four possible combinations of g_Y and m obtained from 200,000 samples from q_x for $x = 1$. In Figures 3a and 3b, we assume that λ is constant. When m is also constant as in Figure 3a, the marginal distribution of the starting times, by Proposition 2.4, is a shifted exponential distribution. If m is allowed to vary in time, the exponential curve is broken at $t = 0.4$, the discontinuity point of m , resulting in a zigzag pattern. In both Figures 3a and 3c, m is constant, but in Figure 3c the rate parameter of g_Y varies according to a harmonic. The resulting sinusoidal modulation is clearly visible. Finally, allowing m to vary too results in a break at its discontinuity point $t = 0.4$ as seen in Figure 3d.

5.3 Inhomogeneity in occurrence time distribution

In the previous subsections, we have assumed that the first order interaction function β of the point process X of occurrence times remains constant over the entire sampling window $(0, 1)$. In our final example, we relax this assumption in that we consider a ‘peak time’ in which events are more likely to occur and investigate the effect on the conditional distribution of occurrences. More precisely, we take an area-interaction model (4.2) with

$$\beta(y) = \begin{cases} 3 & y \in (0, c_1) \\ 5 & y \in [c_1, c_2) \\ 3 & y \in [c_2, 1) \end{cases}$$

and critical range $[c_1, c_2) = [0.81, 0.85)$. The radius of interaction is set to $r = 0.1$ and we consider both a regular ($\eta = -1.2$) and a clustered ($\eta = 1.2$) model.

As in [18], consider the set $\mathbf{u} = \{(0.45, 0.4), (0.51, 0), (0.58, 0)\}$ that contains one non-degenerate interval. Recall that the entries are parameterised as (a, l) , where a is the starting point and l is the length. Figure 4 plots the conditional distribution of the occurrence time on the interval $[0.45, 0.85]$ given \mathbf{u} for the regular and clustered model.

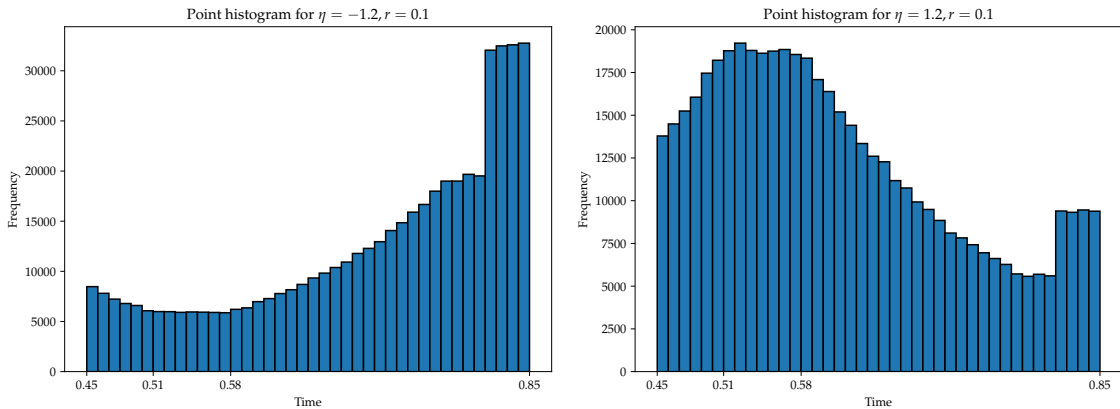


Figure 4: A comparison between a regular and clustered model with a ‘peak time’ added by changing the intensity function within a critical range.

To create this figure, a Metropolis-Hastings algorithm (see Algorithm 4.2, [18]) has been run for 600,000 time steps, with the first 100,000 iterations being thrown out due to burn-in. The general shape of the graphs is similar to the corresponding plots for constant $\beta = 3$ in Figures 2 and 3 in [18]. For the clustered model, the occurrence time is more likely to happen close to the atoms, for regular models the probability density is shifted away from the atoms. In the non-homogeneous case, the higher value of β during the peak times causes a clear bump in the range $[c_1, c_2) = [0.81, 0.85)$.

6 Conclusion

We introduced a time-dependent interval censoring mechanism that splits time into observable and partially observable phases by means of a non-homogeneous semi-Markov process on the real line. The process was shown to be well-defined for a range of Gamma and Weibull semi-Markov kernels. We extended tools from renewal theory to derive families of time-dependent joint distributions of age and excess, which in turn characterise the probability distribution of censored intervals. We then constructed a model wherein a possibly non-homogeneous point process provides a mechanism to select points on the real line, which are independently marked by the intervals resulting from the censoring mechanism. For this model, a conditional distribution form was posited and verified. The influence of the model components was demonstrated through parameterised examples. In future, we intend to apply this model to data on domestic burglaries and to add a spatial component.

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