

FAST SIMULATION OF MULTISTAGE CLONAL EXPANSION MODELS FOR COLORECTAL CANCER

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ABSTRACT. We derive and demonstrate a method to simulate the Colorectal cancer model from [2]. The method is faster than previous ones while retaining similar accuracy.

1. DERIVATION

1.1. Poisson process with random start time. We will consider a non-homogeneous Poisson process with rate $\lambda(t) > 0$ which has a random start time $\tau \geq 0$ with distribution p . For fixed τ the number of occurrences at time $t \geq \tau$ given start time τ , $N(t) | \tau$ has the characteristic function [3, chapter 4, eqn. (2.1)]

$$(1.1) \quad \begin{aligned} \varphi_{N(t)|\tau}(u) &= \exp [m(t - \tau) \{e^{iu} - 1\}] \\ m(t) &= \int_0^t \lambda(s) ds. \end{aligned}$$

The by the law of total expectation, the characteristic function of $N(t)$ is given by

$$\begin{aligned} \varphi_{N(t)}(u) &= E [\varphi_{N(t)|\tau}(u)] \\ &= \int_0^t \exp [m(t - \tau) \{e^{iu} - 1\}] p(\tau) d\tau + \int_t^\infty p(\tau) d\tau. \end{aligned}$$

Comparing this expression to a Poisson process with different rate yields the first theorem.

Theorem 1.1. *Let $N(t)$ follow a non-homogeneous Poisson process with rate $\lambda(t) \geq 0$ starting at a random time $\tau \geq 0$ with probability density function $p(\tau)$. Let $M(t)$ follow a non-homogeneous Poisson process starting at time 0 with rate*

$$(1.2) \quad \nu(t) = \int_0^t \lambda(t - \tau) p(\tau) ds = (\lambda * p)(t) .$$

Then for the characteristic functions $\varphi_{N(t)}$ and $\varphi_{M(t)}$ there holds

$$(1.3) \quad \max_{t \in [0, \sigma]} |\varphi_{N(t)} - \varphi_{M(t)}| \leq 2(\exp(2m(\sigma)) - 2m(\sigma) - 1) = O(m(\sigma)^2)$$

where m is the mean value function of $N(t)$ as defined in eqn. (1.1).

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Proof. Let h be the mean value function (eqn. (1.1)) of $M(t)$, then there holds

$$\frac{d}{dt} \int_0^t m(t-\tau) p(\tau) d\tau = \int_0^t m'(t-\tau) p(\tau) d\tau = \int_0^t \lambda(t-\tau) p(\tau) d\tau = \frac{d}{dt} \nu(t) .$$

We used the Leibniz integration rule and $m(0) = 0$ in the first step. Because $h(0) = 0$ has to hold, we get

$$h(t) = \int_0^t m(t-\tau) p(\tau) d\tau = (m * p)(t)$$

For $\varphi_{N(t)}(u)$, using $k := \{e^{iu} - 1\}$, we obtain

$$\begin{aligned} \varphi_{N(t)}(u) &= \int_0^t \exp[m(t-\tau)k] p(\tau) d\tau + \int_t^\infty p(\tau) d\tau \\ &= 1 + k \int_0^t m(t-\tau) p(\tau) d\tau + \sum_{j=2}^\infty \frac{k^j}{j!} \int_0^t m(t-\tau)^j p(\tau) d\tau . \end{aligned}$$

For $\varphi_{M(t)}(u)$ we obtain

$$\varphi_{M(t)}(u) = \exp(h(t)k) = 1 + kh(t) + \sum_{j=2}^\infty \frac{k^j}{j!} h(t)^j .$$

Let $t \in [0, \sigma]$ then there holds

$$\begin{aligned} |\varphi_{N(t)} - \varphi_{M(t)}| &= \left| \sum_{j=2}^\infty \frac{k^j}{j!} \int_0^t m(t-\tau)^j p(\tau) d\tau - \sum_{j=2}^\infty \frac{k^j}{j!} h(t)^j \right| \\ &\leq \sum_{j=2}^\infty \frac{|k|^j}{j!} \left| \int_0^t m(t-\tau)^j p(\tau) d\tau - \left(\int_0^t m(t-\tau) p(\tau) d\tau \right)^j \right| \\ &\leq \sum_{j=2}^\infty \frac{|k|^j}{j!} \left(|m(\sigma)|^j + |m(\sigma)|^j \right) \\ &= 2 \sum_{j=2}^\infty \frac{(2m(\sigma))^j}{j!} \\ &= 2(\exp(2m(\sigma)) - 2m(\sigma) - 1) . \end{aligned}$$

We used that $\int_0^t p(\tau) d\tau = 1$ and that $m(\cdot)$ is positive and monotonically increasing. \square

Remark 1.2. Theorem 1.1 is useful if $m(\sigma) \ll 1$ because it then implies that a Poisson process with random start time can be viewed (and simulated) as a Poisson process with rate $h = (m * p)$. This makes intuitive sense, because if $m(\sigma)$, i.e. the expected number of occurrences for $N(\sigma)$ starting at 0, is much smaller than 1 the correlation that is introduced through the random starting time is negligible.

The formulas for the mean and the variance are

$$\begin{aligned} E[N(\sigma)] &= h(\sigma) , \\ E[M(\sigma)] &= h(\sigma) , \\ \text{Var}(N(\sigma)) &= h(\sigma) + \int_0^\sigma m^2(t-\tau)p(\tau) d\tau - \left(\int_0^\sigma m(t-\tau)p(\tau) d\tau \right)^2 , \\ \text{Var}(M(\sigma)) &= h(\sigma) . \end{aligned}$$

While the mean is consistent, the difference in variance is of second order in m .

1.2. Two Stage Poisson Process. We will consider a two stage Poisson process. The first process has rate $\nu(t)$ and each occurrence of the first process is the starting point of a second-stage process with rate $\lambda(t)$. We are interested in the number $N(t)$ of occurrences from the first process and the arrival times u_j of the second-stage processes. It is vital that we do not need the arrival times of the first process.

Theorem 1.3. *Let $N(t)$ be the number of occurrences of a non-homogeneous Poisson process with rate $\nu(t)$, mean value function $\eta(t)$ starting at time 0. Let $u_1, \dots, u_{N(t)}$ denote the arrival times of this process.*

For each $j = 1, \dots, N(t)$ let $Y(t, u_j)$ denote the number of occurrences of a non-homogeneous Poisson process with rate $\lambda(t)$, mean value function $m(t)$ starting at time u_j .

The process

$$Y(t) = \sum_{j=1}^{N(t)} Y(t, u_j)$$

is called a filtered Poisson process [3, chapter 4, eqn. (5.42)]. For $t \in [0, \sigma]$, if we neglect terms of order $O(m(\sigma)^2)$:

- i) *Conditioned on $N(\sigma)$ the arrival times of the process $Y(t)$ follow a Poisson process with rate*

$$\mu_N(t) = \frac{N(\sigma)}{\eta(\sigma)} (\nu * \lambda)(t) \quad \forall t \in [0, \sigma] .$$

Proof. By Proposition 2.206 in [1, p. 147] (actually this only guarantees the property for a homogeneous process. I am quite certain that this also holds for the non-homogeneous case but I am lacking a source.) we have that conditioned on $N(\sigma)$ the distribution for u_j (note that the u_j are not ordered) is given by $p(u) = \nu(u)/\eta(\sigma)$ and all u_j are i.i.d.. Then we know by Theorem 1.1 that $Y(t, u_j)$ can be approximated up to order 2 by a Poisson process with rate

$$\mu_j(t) = \int_0^t \lambda(t-u) \frac{\nu(u)}{\eta(\sigma)} du = \frac{(\lambda * \nu)}{\eta(\sigma)}(t) \quad \forall t \in [0, \sigma] .$$

Because the sum of $N(\sigma)$ independent Poisson process is again a Poisson process, we know that $Y(t)$ can be approximated up to order 2 by a Poisson process with rate

$$\mu_N(t) = \frac{N(\sigma)}{\eta(\sigma)} (\nu * \lambda)(t) .$$

□

Remark 1.4. Theorem 1.3 is useful if $m(\sigma) \ll 1$ because it then implies that a two stage Poisson process can be simulated as follows. a) Draw $N(\sigma)$ at random from a Poisson distribution with mean $\eta(\sigma)$. b) Simulate a Poisson process with rate

$$\frac{N(\sigma)}{\eta(\sigma)} (\nu * \lambda)(t) .$$

The direct solution would be to simulate the first Poisson process fully and obtain arrival times u_j . For each arrival time one would simulate a Poisson process with rate $\lambda(t - u_j)$. This means on average $\eta(\sigma)$ many Poisson process simulations. The method proposed here can, under the circumstances described, generate a very good approximation with only two Poisson process simulations. This advantage comes from marginalizing out (approximately) the arrival times u_j .

For the Colorectal cancer model from [2] the first rate is of order 10^2 , $\sigma = 50$ and the second rate is of order 10^{-6} . The direct approach results in approximately 5000 Poisson process simulations. The approximate method yields a theoretic speedup factor of 1000. Also $m(\sigma) \approx 10^{-4}$ and thus the approximation extremely accurate.

2. NUMERICAL EXPERIMENTS

In this section we present numerical experiments for all theorems presented in this paper.

2.1. Poisson process with random start time. In Figure 1 the model as described in Theorem 1.1 is simulated with a sample size of 10^7 . For $\lambda = 10^{-2}$ the approximation is already very accurate. The relative error in variance is $\lambda/6 \approx 1.7 \times 10^{-3}$ for $\lambda = 10^{-2}$.

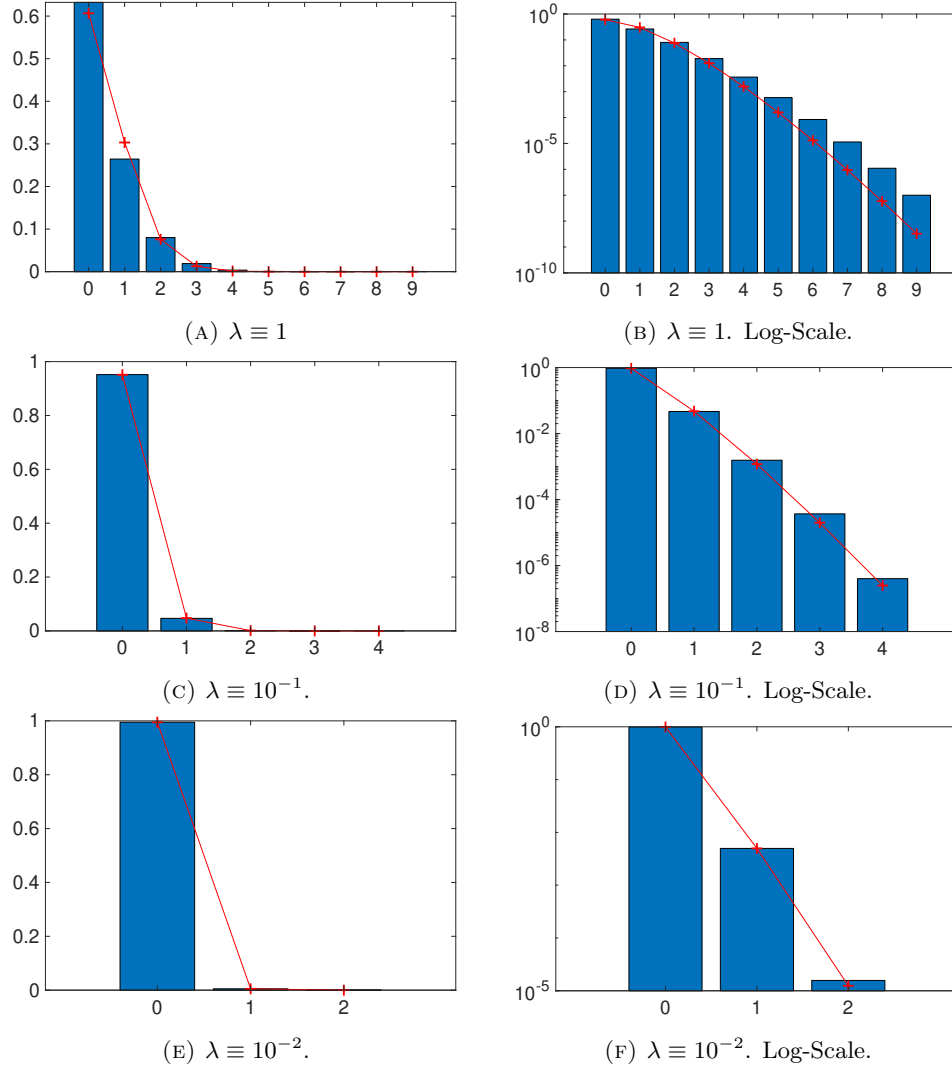


FIGURE 1. 10^7 samples. $\sigma = 1$. $\tau \sim \text{unif}(0, 1)$. For this example there holds $E[N] = \lambda/2$ and $\text{Var}(N) = \lambda/2 + \lambda^2/12$

2.2. Two Stage Poisson Process.

REFERENCES

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