

① Claim: In a pure birth process,

$$\sum_{n=0}^{\infty} P_n(t) = 1 \quad \forall t \quad \text{if and only if} \quad \sum_{n=0}^{\infty} \frac{1}{\lambda_n} = \infty.$$

Proof:

(\Rightarrow) Proof by contrapositive. Let $S_n \sim \text{Exp}(\lambda_n)$ be the waiting times. Assume $\sum_{n=0}^{\infty} \frac{1}{\lambda_n} < \infty$.

~~Then~~ ~~Then~~ ~~Then~~ $E\left[\sum_{n=0}^{\infty} S_n\right] = \sum_{n=0}^{\infty} E[S_n] = \sum_{n=0}^{\infty} \frac{1}{\lambda_n} < \infty.$

Hence the expected time for the population size to reach ∞ is finite.

Thus $P\left(\sum_{n=0}^{\infty} S_n < \infty\right) = 1$ which implies

that $\sum_{n=0}^{\infty} P_n(t) < 1$.

① P_f (continued):

(\Leftarrow) Assume $\sum_{n=0}^{\infty} \lambda_n^{-1} = \infty$.

Consider the moment generating function of the sum of waiting times.

mgf of exponentially distributed random variable.

$$E\left[e^{-\sum_{n=0}^{\infty} S_n}\right] = \lim_{N \rightarrow \infty} \prod_{n=0}^N E[e^{-S_n}] = \lim_{N \rightarrow \infty} \prod_{n=0}^N \frac{1}{1 + \lambda_n^{-1}}$$

$$= \lim_{N \rightarrow \infty} \exp\left[-\sum_{n=0}^{\infty} \ln(1 + \lambda_n^{-1})\right]$$

$$= \exp\left(-\sum_{n=0}^{\infty} \ln(1 + \lambda_n^{-1})\right) = 0, \quad \text{because } \sum_{n=0}^{\infty} \lambda_n^{-1} = \infty.$$

Thus, $\sum_{n=0}^{\infty} S_n = \infty$, i.e. the population size reaches ∞ in infinite time.

This implies $\sum_{n=0}^{\infty} P_n(t) = 1$.



① (comb.)

Derive an explosive process that explodes in finite time.

Consider the pure birth process with waiting times $S_n \sim \text{Exp}(\lambda_n) \quad \forall n \in \mathbb{N} \cup \{0\}$ with $\lambda_n = c \cdot n^2$, c -constant.

Please see Python Notebook for results on this.

□

② Claim: The birth and death process with immigration given by $\lambda_n = \lambda n$, $\mu_n = \mu \cdot n$, ν -rate of immigration has mean that follows $\frac{dn}{dt} = (\lambda - \mu)n + \nu$.

Proof: For this process, we have:

$$\begin{cases} P_0'(t) = -\lambda P_0(t) + \mu P_1(t), & n=0 \\ (\star) \begin{cases} P_n'(t) = (\lambda(n-1) + \nu)P_{n-1}(t) - (\lambda + \mu)n P_n(t) + \mu(n+1)P_{n+1}(t) \end{cases} & n \geq 1. \end{cases}$$

We will use the probability generating function (pgf) to obtain the ^{evolution} first moment of n in the following way:

$$\begin{aligned} \frac{\partial}{\partial z} \sum_{n=0}^{\infty} P_n'(t) \cdot z^n \Big|_{z=1} &= \sum_{n=0}^{\infty} n \cdot P_n'(t) \cdot z^{n-1} \Big|_{z=1} = \sum_{n=0}^{\infty} n \cdot P_n'(t) \\ &= \frac{d}{dt} \sum_{n=0}^{\infty} n \cdot P_n(t) = \frac{d}{dt} E[n]. \end{aligned}$$

② (cont.)

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Using (*) we know that:

$$\begin{aligned} R &:= \sum_{n=0}^{\infty} P_n'(t) z^{n+1} \\ &= \sum_{n=0}^{\infty} [(\lambda(n-1)+\nu) P_{n-1}(t) z^{n+1}] - \sum_{n=0}^{\infty} [(\lambda+\mu)n + \nu] P_n(t) z^{n+1} \\ &\quad + \sum_{n=0}^{\infty} \mu(n+1) P_{n+1}(t) z^{n+1} \end{aligned}$$

$$\begin{aligned} &= z^2 \lambda \sum_{n=0}^{\infty} (n-1) P_{n-1}(t) z^{n-1} + z^2 \nu \sum_{n=0}^{\infty} P_{n-1}(t) z^{n-1} \\ &\quad - z(\lambda+\mu) \sum_{n=0}^{\infty} n \cdot P_n(t) z^n - z \cdot \nu \sum_{n=0}^{\infty} P_n(t) z^n \\ &\quad + \mu \sum_{n=0}^{\infty} (n+1) P_{n+1}(t) z^{n+1} \end{aligned}$$

$$\text{So, } R = (z^2 \lambda - z(\lambda+\mu) + \mu) \cdot \sum_{n=0}^{\infty} n P_n(t) z^n + (z^2 \nu - z\nu) \sum_{n=0}^{\infty} P_n(t) \cdot z^n$$

$$\begin{aligned} \text{and } \frac{\partial}{\partial z} R &= (2z\lambda - (\lambda+\mu)) \cdot \sum_{n=0}^{\infty} n P_n(t) z^n + (\lambda - z(\lambda+\mu) + \mu) \sum_{n=0}^{\infty} n^2 P_n(t) z^{n-1} \\ &\quad + \nu(2z-1) \sum_{n=0}^{\infty} P_n(t) \cdot z^n + \nu(z^2-z) \cdot \sum_{n=0}^{\infty} n^2 P_n(t) z^{n-1}. \end{aligned}$$



② (cont.)

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Evaluate at $z=1$:

$$\begin{aligned} \frac{d}{dt} E[n] &= \frac{\partial}{\partial z} R \Big|_{z=1} = (2\lambda - \lambda - \mu) \sum_{n=0}^{\infty} n P_n(t) \\ &\quad + (\lambda - \lambda - \mu + \mu) \sum_{n=0}^{\infty} n^2 P_n(t) z^{n-1} \\ &\quad + \underbrace{V(2-1) \sum_{n=1}^{\infty} P_n(t)}_{=1} + V(1-1) \sum_{n=2}^{\infty} n^2 P_n(t) \end{aligned}$$

$$\frac{d}{dt} E[n] = (\lambda - \mu) \cdot E[n] + V.$$

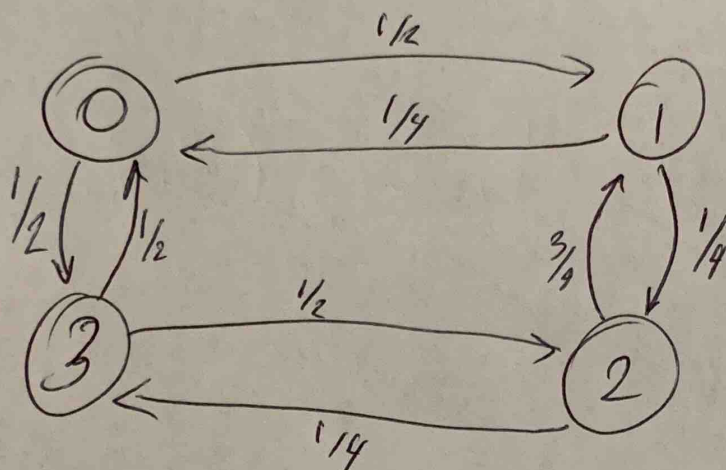
□

② Please see jupyter notebook for the numerical simulation regarding this question.

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$$P = \begin{pmatrix} 0 & 1/2 & 0 & 1/2 \\ 1/4 & 0 & 3/4 & 0 \\ 0 & 3/4 & 0 & 1/4 \\ 1/2 & 0 & 1/2 & 0 \end{pmatrix}$$

(a)



(b) Irreducibility.

Consider $P^7 = \begin{pmatrix} 0 & 2/3 & 0 & 1/3 \\ 1/3 & 0 & 2/3 & 0 \\ 0 & 2/3 & 0 & 1/3 \\ 1/3 & 0 & 2/3 & 0 \end{pmatrix}$ and $P^8 = \begin{pmatrix} 1/3 & 0 & 2/3 & 0 \\ 0 & 2/3 & 0 & 1/3 \\ 1/3 & 0 & 2/3 & 0 \\ 0 & 2/3 & 0 & 1/3 \end{pmatrix}$

Looking at P^7, P^8 , we see that for all states i, j , there exists $t, t+1$ such that:

$$P(X(t+t)=j \mid X(t)=i) > 0$$

$$\text{or } P(X(t+t+1)=j \mid X(t)=i) > 0$$

Therefore this Markov Chain (MC) is irreducible. \square

(3) (b) (cont).

Since the ^{MC} ~~matrix~~ is irreducible and has finite state space, it must also be positive recurrent. \square

Show periodicity.

The MC is periodic, because as shown early the probability of returning to a state is 1.

Also given P^7, P^8 earlier, we see that ^{for any state} the smallest number of steps possible to return is 2.

So the period is 2. \square

Alat

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③(c) Let π be the unique stationary distribution.

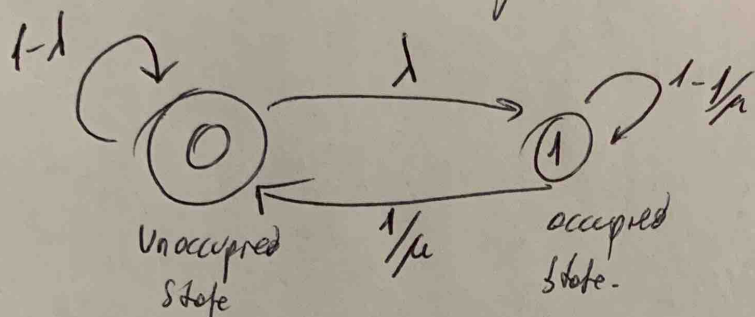
Then $\pi = \pi_0 \cdot P^n$ for n large enough
(in this case $n=8$ is large enough)
 \downarrow
arbitrary
initial
distribution.

Then (solving in Python), $\pi = [1/6, 1/3, 1/3, 1/6]$.

□

(4)

We can write this system as a Markov Chain (MC) given by:



with transition matrix

$$P = \begin{pmatrix} 1-l & l \\ 1/\mu & 1-1/\mu \end{pmatrix}$$

The long run fraction of time that the promoter is unoccupied is the fraction of time spent in state 0 ~~which~~ which is given by the stationary distribution,

$$\pi = [\pi_0, \pi_1], \text{ where we want } \pi_0.$$

$$\pi \text{ is given by } \pi P = \pi \quad \text{and} \quad \pi_0 + \pi_1 = 1.$$

$$\Rightarrow \pi_0(1-l) + \pi_1(1/\mu) = \pi_0$$

$$\pi_0(l) + \pi_1(1-1/\mu) = \pi_1$$

$$\text{Thus, } \pi_1 = \lambda\mu \cdot \pi_0$$

$$\text{So } \pi_0 + \lambda\mu\pi_0 = 1 \Rightarrow \pi_0 = \frac{1}{1+\lambda\mu}.$$

□

⑤ Assume that a spike train can be described by a Poisson process. Then for small Δt , the probability of ~~the~~ finding k action potentials in Δt is given by:

$$P(X(t+\Delta t) - X(t) = k) = \frac{(\lambda \Delta t)^k e^{-\lambda \Delta t}}{k!}.$$

For a fixed time t , let $T(t)$ be the time to the nearest AP in time.

Consider two cases: (1) spike at time $t+s$, $s \in \mathbb{R}$
 (2) spike at time $t-u$, $u \in \mathbb{R}$.

Case 1: $P(T(t) \leq s) = P(\text{no spike between } t \text{ and } t+s) = 1 - \frac{(\lambda s)^0}{0!} e^{-\lambda s} = 1 - e^{-\lambda s}$

Case 2: $P(T(t) \leq u) = P(\text{no spike between } t-u \text{ and } t) = 1 - \frac{(\lambda u)^0}{0!} e^{-\lambda u} = 1 - e^{-\lambda u}$

In any case, we ~~obtain~~ ^{see that} the CDF of $T(t)$ ~~is~~ ^{corresponds} to the exponential distribution with:

PDF: $f_T(s) = \lambda e^{-\lambda s}$

and mean: $E[T(t)] = 1/\lambda$.

□