

Stochastic Models

- Deterministic models (such as $\dot{N} = rN$) are unrealistic in that they ignore the element of chance. This element may be especially important in low population sizes
- Stochastic Elements

Environmental - Eg Storms, temperature, humidity give unpredictable birth & death rates

Demographic - Even if average birth & death rates are known, populations contain a discrete number of individuals whose behaviours are unpredictable

Overview

• Linear stochastic models

- analytical progress has been made
- simple birth processes studied by Yule (1924) & Furry (1937)
- simple birth & death processes studied by Feller (1939)
- Galton & Watson studied extinction of family names - even if $b > d$ there is a probability of extinction

• Nonlinear Stochastic Models

- include density-dependent probabilities for birth, death etc.
- without immigration or emigration, equilibrium solutions "statistically stable states" cannot be found
- if you cannot grow unboundedly you will eventually suffer a string of bad luck & die out
- on a fast timescale one may find a "quasi-stationary state" but as $t \rightarrow \infty$ this QSS "leaks" to zero.

Stochastic Processes

Defn ① If S is a sample space

(collection of all possible outcomes of an experiment) with a probability measure and N is a real-valued function defined over the elements of S then N is a random variable

② A family $\{N(t)\}$ indexed by a parameter t is called a stochastic process

③ A stochastic process $\{N(t)\}$ is called a Markov process iff it is history-independent. In the case with t discrete it is a one-step memory process

$$\begin{aligned} & \Pr \{ N(t_i) = n_1 \mid N(t_{i-1}) = n_2 \wedge N(t_{i-2}) = n_3 \wedge \dots \} \\ &= \Pr \{ N(t_i) = n_1 \mid N(t_{i-1}) = n_2 \} \end{aligned}$$

Linear Birth Process

- Markov process, continuous time, integer sample space

$N(t)$ = # individuals at time t (random variable)

$$P_n(t) = \Pr \{ N(t) = n \} \quad n = 0, 1, 2, \dots$$

For one individual

$$\Pr \{ 1 \text{ birth in } (t, t+\Delta t] \} = b \Delta t + O(\Delta t^2)$$

$$\Pr \{ > 1 \text{ birth in } (t, t+\Delta t] \} = O(\Delta t^2)$$

$$\Pr \{ 0 \text{ births in } (t, t+\Delta t] \} = 1 - b \Delta t + O(\Delta t^2)$$

For n individuals

$$\begin{aligned} \Pr \{ 1 \text{ birth in } (t, t+\Delta t] \} &= n b \Delta t (1 - b \Delta t)^{n-1} \\ &= n b \Delta t + O(\Delta t^2) \end{aligned}$$

$$\begin{aligned} m \leq n \quad \Pr \{ m \text{ births in } (t, t+\Delta t] \} &= \binom{n}{m} (b \Delta t)^m (1 - b \Delta t)^{n-m} \\ &= O(\Delta t^2) \end{aligned}$$

(A similar calculation shows $O(\Delta t^2)$ when $m > n$)

$$\Pr \{ 0 \text{ births in } (t, t+\Delta t] \} = 1 - n b \Delta t + O(\Delta t^2)$$

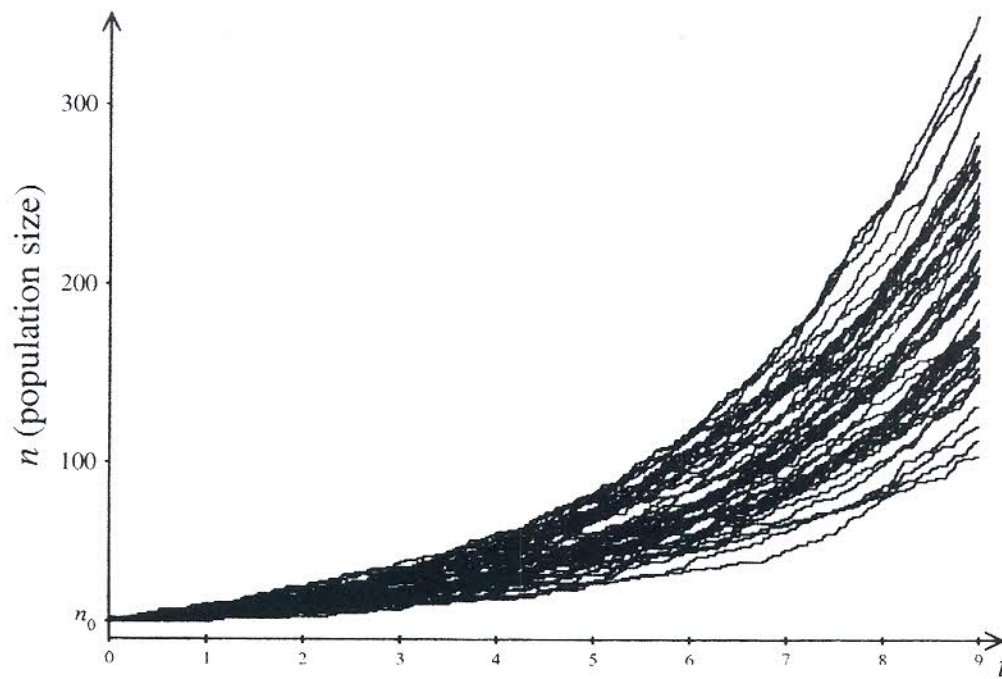


Figure 5.7. Stochastic simulation of the pure birth process given in (5.51). Parameters are $b = 1/3$ and $n_0 = 10$. Fifty different trajectories are given. They differ only in the seed for the random number generator used.

Thus

$$\begin{aligned}
 P_n(t+\Delta t) &= P_{n-1}(t) \cdot \Pr \{ 1 \text{ birth in } (t, t+\Delta t] \} \\
 &\quad + P_n(t) \cdot \Pr \{ 0 \text{ births in } (t, t+\Delta t] \} \\
 &\quad \quad \quad + O(\Delta t^2) \\
 &= P_{n-1}(t) (n-1)b\Delta t + P_n(t) (1 - nb\Delta t) + O(\Delta t^2)
 \end{aligned}$$

$$\Rightarrow \frac{P_n(t+\Delta t) - P_n(t)}{\Delta t} = b \{ (n-1) P_{n-1}(t) - n P_n(t) \}$$

As $\Delta t \rightarrow 0$ we have an infinite system of ODEs

$$\frac{d}{dt} P_n(t) = b \{ (n-1) P_{n-1}(t) - n P_n(t) \}$$

$$n = 0, 1, 2, 3, \dots \quad P_{-1} = 0 \quad \text{with initial data}$$

$$P_n(0) = \begin{cases} 1 & \text{if } n = n_0 \\ 0 & \text{otherwise.} \end{cases}$$

Note: As only birth is possible (i.e. no death)

$$P_n(t) = 0 \text{ for all } n < n_0 \text{ and } t \geq 0.$$

This can be expressed as an infinite dimensional system

$$\dot{p} = A p \quad p = \begin{pmatrix} p_0 \\ p_1 \\ \vdots \end{pmatrix}$$

$$A = \begin{pmatrix} 0 & 0 & 0 & 0 & \dots \\ 0 & -b & 0 & 0 & \dots \\ 0 & b & -2b & 0 & \dots \\ 0 & 0 & 2b & -3b & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

However, as $p_n(t)$ depends only upon $p_{n-1}(t)$ & $p_n(t)$ we can solve the ODEs in a chain

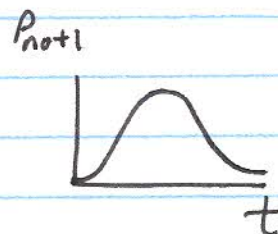
$$1. \left. \begin{aligned} \frac{d}{dt} p_{n_0} &= -b n_0 p_{n_0} \\ p_{n_0}(0) &= 1 \end{aligned} \right\} \Rightarrow p_{n_0}(t) = e^{-b n_0 t}$$



$$2. \frac{d}{dt} p_{n_0+1} = -b(n_0+1) p_{n_0+1} + b n_0 e^{-b n_0 t}$$

$$p_{n_0+1}(0) = 0$$

$$\Rightarrow p_{n_0+1}(t) = n_0 e^{-b n_0 t} (1 - e^{-bt})$$

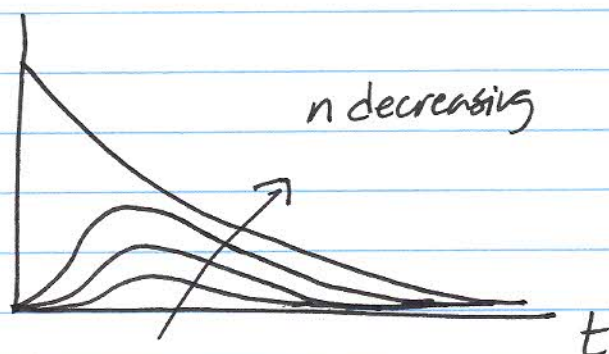


$$3. P_{n_0+k}(t) = \binom{n_0+k-1}{n_0-1} e^{-bn_0 t} (1 - e^{-bt})^k$$

writing $n = n_0 + k$ gives

$$P_n(t) = \binom{n-1}{n_0-1} e^{-bn_0 t} (1 - e^{-bt})^{n-n_0}$$

Negative binomial distribution with parameter $\phi = e^{-bt}$



$$M_1 = E(N(t)) = \sum_{n=n_0}^{\infty} n P_n(t) = \sum_{n=n_0}^{\infty} n \binom{n-1}{n_0-1} e^{-bn_0 t} (1 - e^{-bt})^{n-n_0}$$

$$= \sum_{k=0}^{\infty} (k+n_0) \binom{n_0+k-1}{k} e^{-bn_0 t} (1 - e^{-bt})^k$$

$$= n_0 e^{-bn_0 t} \sum_{k=0}^{\infty} \binom{k+n_0}{k} (1 - e^{-bt})^k$$

$$= n_0 e^{-bn_0 t} [e^{-bt}]^{-(n_0+1)} = n_0 e^{bt} \quad \text{exponential growth.}$$

The variance can be calculated as

$$\sigma^2 = n_0 e^{bt} (e^{bt} - 1)$$

$$CV = \frac{\sigma}{M_1} = \sqrt{\frac{1 - e^{-bt}}{n_0}} \rightarrow \frac{1}{\sqrt{n_0}} \text{ as } t \rightarrow \infty$$

An alternative method for calculating M_1 & σ^2 uses

$$\begin{aligned} \frac{d}{dt} \{E(N(t))\} &= \sum_{n=n_0}^{\infty} n \dot{p}_n(t) \\ &= \sum_{n=n_0}^{\infty} n [b(n-1)p_{n-1}(t) - b n p_n(t)] \\ &= \dots = b E(N(t)) \end{aligned}$$

$$\Rightarrow E(N(t)) = E(N(0)) e^{bt} = n_0 e^{bt}$$

A similar differential equation can be derived for M_2 & hence σ^2 can be calculated.