

ST2302/MA8002 Exercises chapter 2 and 3

Exercise 2.1

Assume the stochastic growth rate $r(t)$ has expectation r and variance σ_r^2 . First, consider the expectation of ΔN , given by

$$E[\Delta N] = r N \left(1 - \frac{N}{K} \right)$$

This is equivalent to the deterministic version of the logistic model, hence it seems reasonable. The variance of ΔN is given by

$$\text{Var}(\Delta N) = N^2 \left(1 - \frac{N}{K} \right)^2 \sigma_r^2$$

This variance depends on N . Figure 1 shows how it changes with N , for $K = 70$ and $\sigma_r^2 = 0.1$. It does not seem realistic that the variance should decline as $N \rightarrow K$.

Exercise 2.4

The theta-logistic model is given by

$$r(N) = \begin{cases} r_1 \left(1 - \frac{N^\theta - 1}{K^\theta - 1} \right) & , \theta \neq 0 \\ r_1 \left(1 - \frac{\ln N}{\ln K} \right) & , \theta = 0 \end{cases}$$

In order to verify the different cases, we will insert the different values of θ in this model.

1. First, consider the case where $\theta = -1$.

$$\begin{aligned} r(N) &= r_1 \left(1 - \frac{\frac{1}{N} - 1}{\frac{1}{K} - 1} \right) \\ &= r_1 \left(1 - \frac{\frac{K}{N} - K}{1 - K} \right) \\ &= r_1 \left(\frac{1 - K - \frac{K}{N} + K}{1 - K} \right) \\ &= r_1 \left(\frac{1 - \frac{K}{N}}{1 - K} \right) \end{aligned}$$

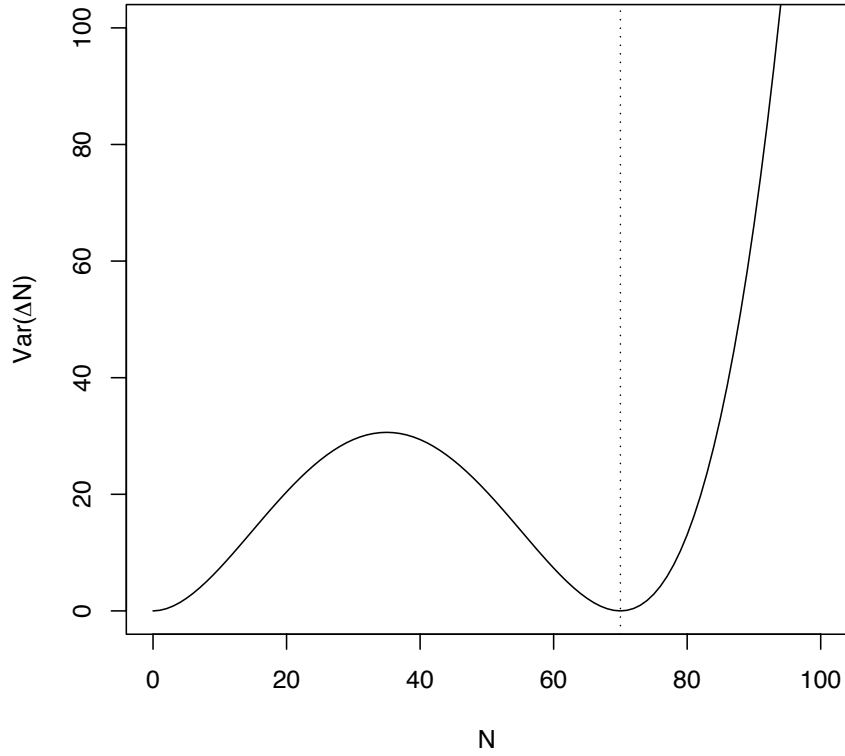


Figure 1: From exercise 2.1. How the variance in ΔN changes with N , for $K = 70$ (dashed line) and $\sigma_r^2 = 0.1$.

$$\begin{aligned}
 r(N) &= \Delta \ln N \approx \frac{\Delta N}{N} \\
 \Delta N &\approx r_1 N \left(\frac{1 - \frac{K}{N}}{1 - K} \right) \\
 &= r_1 \left(\frac{N - K}{1 - K} \right)
 \end{aligned}$$

Hence, in this case ΔN is a linear function of N .

2. For the case of $\theta = 0$, we use l'Hôpital's rule to find the limit as $\theta \rightarrow 0$:

$$r(N) = \lim_{\theta \rightarrow 0} r_1 \left(1 - \frac{N^\theta - 1}{K^\theta - 1} \right) = \lim_{\theta \rightarrow 0} r_1 \left(1 - \frac{N^\theta \ln N}{K^\theta \ln K} \right) = r_1 \left(1 - \frac{\ln N}{\ln K} \right)$$

This is Gompertz' type of density regulation, where $\Delta \ln N$ is a linear function of $\ln N$.

3. For the case of $\theta = 1$ we obtain

$$\begin{aligned}
 r(N) &= r_1 \left(1 - \frac{N-1}{K-1} \right) \\
 &= r_0 \left(1 - \frac{1}{K} \right) \left(1 - \frac{N-1}{K-1} \right) \\
 &= r_0 \left(1 - \frac{1}{K} - \frac{N-1}{K-1} + \frac{1}{K} \frac{N-1}{K-1} \right) \\
 &= r_0 \left(1 - \frac{K-1 + KN - K - N + 1}{K(K-1)} \right) \\
 &= r_0 \left(1 - \frac{N(K-1)}{K(K-1)} \right) \\
 &= r_0 \left(1 - \frac{N}{K} \right)
 \end{aligned}$$

This is the logistic model.

4. The limit as $\theta \rightarrow \infty$ (assuming $N < K$) is given by

$$\begin{aligned}
 \lim_{\theta \rightarrow \infty} r(N) &= \lim_{\theta \rightarrow \infty} r_1 \left(1 - \frac{N^\theta - 1}{K^\theta - 1} \right) \\
 &= \lim_{\theta \rightarrow \infty} r_1 \left(1 - \frac{\frac{1}{K^\theta - 1}}{\frac{1}{N^\theta - 1}} \right) \\
 &= r_1
 \end{aligned}$$

For $\theta \rightarrow \infty$ even a small increase in N above K would produce a growth rate $r(N) \rightarrow -\infty$. This is the "roof"-model, where the population grows exponentially until K , but never grow past this limit.

Exercise 3.1

From chapter 1 we know that the process $X_t|X_0$ is approximately normally distributed:

$$\begin{aligned}
 X_t|X_0 &\sim N(X_0 + st, \sigma_s^2 t) \\
 s &\approx r - \frac{1}{2} \sigma_e^2 - \frac{1}{2n} \sigma_d^2 \\
 \sigma_s^2 &\approx \sigma_e^2 + \frac{\sigma_d^2}{n}
 \end{aligned}$$

Hence, the infinitesimal mean and variance are given by

$$\begin{aligned}\mu_X(x) &= \mathbb{E}[\Delta X | X_t] = r - \frac{1}{2} \sigma_e^2 - \frac{1}{2e^x} \sigma_d^2 \\ \nu_X(x) &= \text{Var}(\Delta X | X_t) = \sigma_e^2 + \frac{\sigma_d^2}{e^x}\end{aligned}$$

Exercise 3.2

$$\begin{aligned}\mu_X(x^*) &= 0 \\ r - \frac{1}{2} \sigma_e^2 - \frac{1}{2e^{x^*}} \sigma_d^2 &= 0 \\ \frac{1}{2e^{x^*}} \sigma_d^2 &= r - \frac{1}{2} \sigma_e^2 \\ e^{x^*} = n^* &= \frac{\sigma_d^2}{2r - \sigma_e^2} \\ x^* &= \ln \left(\frac{\sigma_d^2}{2r - \sigma_e^2} \right)\end{aligned}$$

Exercise 3.3

Here, we use the transformation formulas for diffusion processes, with $X_t = g(N_t) = \ln N_t$, giving

$$\begin{aligned}\mu_X(x) &= g'(n)\mu(n) + \frac{1}{2}g''(n)\nu(n) \\ &= \frac{1}{n} r_1 n \left(1 - \frac{\ln n}{\ln K} \right) - \frac{1}{2n^2} \sigma_e^2 n^2 \\ &= r_1 \left(1 - \frac{\ln n}{\ln K} \right) - \frac{1}{2} \sigma_e^2 \\ &= r_1 - \frac{1}{2} \sigma_e^2 - \frac{r_1}{\ln K} x \\ \nu_X(x) &= g'(n)^2 \nu(n) \\ &= \frac{1}{n^2} \sigma_e^2 n^2 \\ &= \sigma_e^2.\end{aligned}$$

For the OU-process the infinitesimal mean and variance are given by

$$\begin{aligned}\mu_X(x) &= \alpha - \beta x \\ \nu_X(x) &= \sigma_e^2\end{aligned}$$

Hence, with $\alpha = r_1 - \sigma_e^2/2$ and $\beta = r_1/\ln K$ we see that X_t is an OU-process.

Exercise 3.4

We use the transformation formula for diffusion processes, with $X_t = g(N_t) = N_t^\theta$, giving

$$\begin{aligned}\mu_X(x) &= g'(n)\mu(n) + \frac{1}{2}g''(n)\nu(n) \\ &= \theta n^{\theta-1}rn \left(1 - \frac{n^\theta}{K^\theta}\right) + \frac{1}{2}\theta(\theta-1)n^{\theta-2}\sigma_e^2 n^2 \\ &= \theta rn^\theta - \frac{\theta rn^{2\theta}}{K^\theta} + \frac{1}{2}\theta(\theta-1)n^\theta\sigma_e^2 \\ &= \theta x \left(r \left[1 - \frac{x}{K^\theta}\right] + \frac{1}{2}(\theta-1)\sigma_e^2 \right)\end{aligned}$$

$$\begin{aligned}\nu_X(x) &= g'(n)^2\nu(n) \\ &= \theta^2 n^{2\theta-2}\sigma_e^2 n^2 \\ &= \theta^2 x^2 \sigma_e^2\end{aligned}$$

Exercise 3.5

Using the transformation formula for diffusion processes, with $X_t = g(N_t) = N_t^{-\theta}$, we obtain

$$\begin{aligned}X_t &= g(N_t) = N_t^{-\theta} \\ \mu_X(x) &= g'(n)\mu(n) + \frac{1}{2}g''(n)\nu(n) \\ &= -\theta n^{-\theta-1}rn \left(1 - \frac{n^\theta}{K^\theta}\right) + \frac{1}{2}\theta(-\theta-1)n^{-\theta-2}\sigma_e^2 n^2 \\ &= -\theta n^{-\theta}r + \frac{r\theta}{K^\theta} - \frac{1}{2}\theta(\theta+1)n^{-\theta}\sigma_e^2 \\ &= \frac{r\theta}{K^\theta} - \left(r\theta - \frac{1}{2}\theta(\theta+1)\sigma_e^2\right) x\end{aligned}$$

Hence, $\mu_X(x)$ is the infinitesimal mean of an OU-process in the form $\mu_X(x) = \alpha - \beta x$.

Exercise 3.6

In order to obtain a constant infinitesimal variance $\nu_X(x) = 1$ we use the isotropic scale transformation given by

$$\begin{aligned}
g(n) &= \int_a^n \frac{1}{\sqrt{\nu_N(z)}} dz \\
&= \int_a^n \frac{1}{\sigma_d \sqrt{z}} dz \\
&= \frac{2}{\sigma_d} [\sqrt{n} - \sqrt{a}]
\end{aligned}$$

We choose $a = 0$, giving

$$g(n) = \frac{2\sqrt{n}}{\sigma_d}$$

Exercise 3.12

The brownian motion, which is the process of $X = \ln N$, is defined by

$$\begin{aligned}
\mu(x) &= s \\
\nu(x) &= \sigma_e^2
\end{aligned}$$

Choosing $a = 0$ as lower integration limit, $s(x)$ is given by

$$\begin{aligned}
s(x) &= \exp\left(-2 \int_0^x \frac{\mu(z)}{\nu(z)} dz\right) \\
&= \exp\left(-2 \int_0^x \frac{s}{\sigma_e^2} dz\right) \\
&= \exp\left(-\frac{2s}{\sigma_e^2} x\right)
\end{aligned}$$

Using this, $S(x)$ is given by

$$\begin{aligned}
S(x) &= \int_0^x s(z) dz \\
&= \int_0^x \exp\left(-\frac{2s}{\sigma_e^2} z\right) dz \\
&= \begin{cases} \frac{\sigma_e^2}{2s} \left(1 - \exp\left(-\frac{2s}{\sigma_e^2} x\right)\right) & s \neq 0 \\ x & s = 0 \end{cases}
\end{aligned}$$

In order to find $u(x_0)$, we evaluate $S(a)$, $S(b)$ and $S(x_0)$ for $a = 0$ and $b \rightarrow \infty$, and consider the different cases $s > 0$, $s < 0$, and $s = 0$.

$$S(0) = 0 \quad \forall s$$

$$\lim_{b \rightarrow \infty} S(b) = \begin{cases} -\infty & s < 0 \\ \frac{\sigma_e^2}{2s} & s > 0 \\ \infty & s = 0 \end{cases}$$

$$S(x_0) = \begin{cases} \frac{\sigma_e^2}{2s} \left(1 - \exp\left(-\frac{2s}{\sigma_e^2} x_0\right)\right) & s \neq 0 \\ x & s = 0 \end{cases}$$

This gives

$$u(x_0) = \frac{S(x_0)}{S(b)}$$

$$= \begin{cases} 0 & s \leq 0 \\ 1 - \exp\left(-\frac{2s}{\sigma_e^2} x_0\right) & s > 0 \end{cases}$$

Exercise 3.15

The expression $G(x, x_0)\Delta x$ represents the expected time the population process will spend in a small interval $(x, x + \Delta x)$, before it is absorbed at a or b (see figure 2).

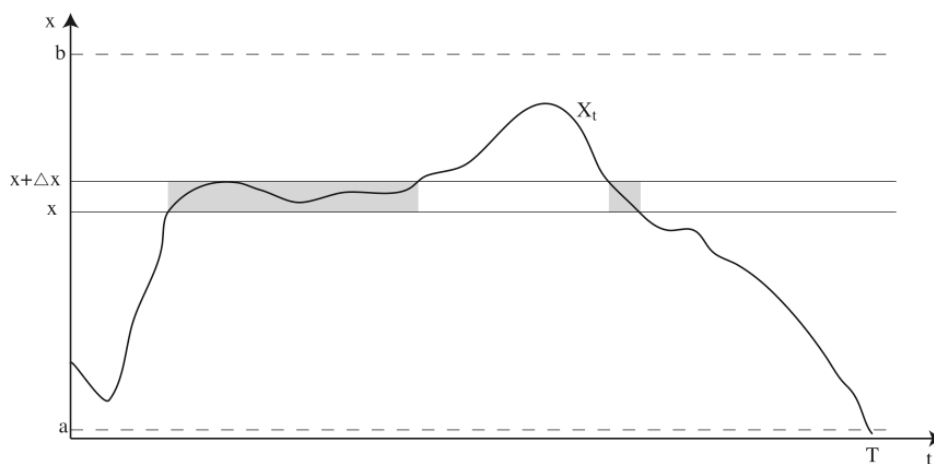


Figure 2: Illustration of how much time the process X_t spends in an interval $(x, x + \Delta x)$.

Let $T_x = G(x, x_0)\Delta x$. In the interval $(x, x + \Delta x)$ the value of the function $h(X_t)$ will be approximately a constant $h(x)$ as Δx becomes small. Then $E \left[\int_0^T h(X_t) dt \right]$ will become equal to $T_x h(x)$ in the interval $(x, x + \Delta x)$. In order to find the expectation of all x we summarize over all possible intervals between a and b . Letting $\Delta x \rightarrow 0$ we obtain the integral.

Exercise 3.19

Firstly, we have

$$Pr(N_t > n) = Pr(\ln N_t > \ln n) = Pr(X_t > x)$$

hence we may study $X_t = \ln N_t$ instead of N . Let X_t and X_t^* the processes without and with a barrier, respectively. Then X_t is normally distributed with expectation $x_0 + st$ and variance $\sigma_e^2 t$, and

$$Pr(X > x) = 1 - \Phi \left(\frac{x - x_0 - st}{\sigma_e \sqrt{t}} \right)$$

For the process with barrier we have (from exercise 3.18)

$$Pr(X_t^* > x) = 1 - \Phi \left(\frac{x - x_0 - st}{\sigma_e \sqrt{t}} \right) - \exp \left(-\frac{2x_0 s}{\sigma_e^2} \right) \Phi \left(\frac{st - x - x_0}{\sigma_e \sqrt{t}} \right)$$

Hence, the probability is lower if the extinction barrier is $N = 1$ ($X = 0$). The difference between the two probabilities is given by

$$Pr(X > x) - Pr(X_t^* > x) = \exp \left(-\frac{2x_0 s}{\sigma_e^2} \right) \Phi \left(\frac{st - x - x_0}{\sigma_e \sqrt{t}} \right)$$