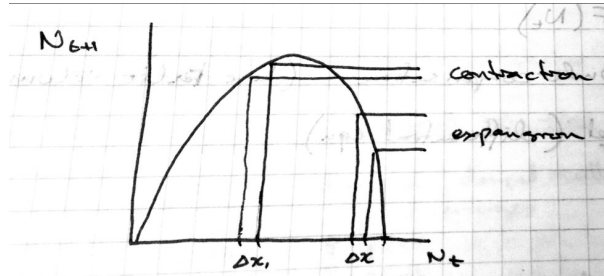


## Lecture 9 – 1-D Stability Analysis - Part 2

**Today:** 1D stability cont., non-dimensionalization, and paper discussion

**Next class:** 2 sp. LV competition (Bring laptops – *might* need them depending on how far we get)

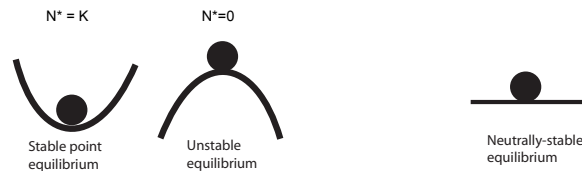
### Ricker plots & Intuitive notion of Lyapunov exponent



→ The larger  $r_d$ , the steeper the slopes, the more expansion.

### Local stability analysis

Through simulation we found  $r_d < 2$  for  $N^* = K$  to be stable  
(either monotonic dampening or damped oscillations).



Now let's determine this formally...

### Discrete-time model:

$$N_{t+1} = F(N_t)$$

**Step 1:** Solve  $F(N)$  for  $N^*$ :

$$F(N_t) = N_t + r_d N_t \left(1 - \frac{N_t}{K}\right)$$

By definition:  $F(N^*) = N_t$

$$F(N^*) = N_t = N_t + r_d N_t - \frac{r_d N_t^2}{K}$$

$$\text{Solve for } N_t: \quad 0 = r_d N_t - \frac{r_d N_t^2}{K}$$

$$\frac{r_d N_t^2}{K} = r_d N_t$$

$$r_d N_t^2 = r_d N_t K$$

$$\rightarrow N^* = K \text{ and } N^* = 0$$

**Step 2:** Find slope of  $F(N_t)$  evaluated at  $N^*$ :

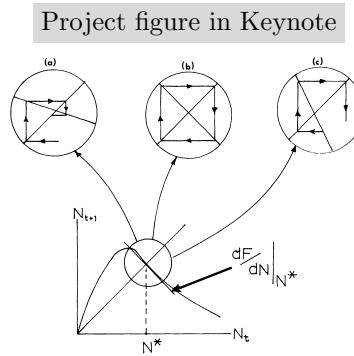
$$F'(N^*) = \left. \frac{dF(N_t)}{dN} \right|_{N^*}$$

If  $|F'(N^*)| < 1 \rightarrow \text{stable.}$

For discrete logistic:

$$\begin{aligned} F'(N^*) &= 1 + r_d - 2r_d \frac{N^*}{K} \\ &= 1 + r_d - 2r_d \frac{K}{K} \\ &= 1 - r_d \end{aligned}$$

Thus, discrete logistic reaches stable point equilibrium when  $0 < r_d < 2$ .




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**Continuous-time model:**

$$\frac{dN}{dt} = f(N) = rN \left( 1 - \frac{N}{K} \right)$$

**Step 1:** Solve  $f(N)$  for  $N^*$ :

By definition: At  $N^*$  when  $f(N^*) = 0$

$$\begin{aligned} 0 &= rN - \frac{rN^2}{K} \\ \frac{rN^2}{K} &= rN \\ rN^2 &= rNK \\ \rightarrow N^* &= K \text{ and } N^* = 0 \end{aligned}$$

**Step 2:** Find slope of  $f(N)$  at  $N^*$ .

$$f'(N^*) = \left. \frac{df(N_t)}{dN} \right|_{N^*}$$

If  $f'(N^*) < 0 \rightarrow$  stable.

For continuous-logistic:

$$\begin{aligned} f'(N^* = K) &= \frac{d}{dN} \left( rN - \frac{rN^2}{K} \right) \\ &= r - \frac{2rN}{K} \\ &= r - \frac{2rK}{K} \\ &= r - 2r \\ &= -r \end{aligned}$$

Thus, continuous logistic reaches stable point equilibrium when  $r > 0$ .

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### Summary

Step #1: Solve for  $N^*$ .

Step #2: Evaluate  $f'(N^*)$

For discrete:

Stable if  $|f'(N^*)| < 1$   
 (for discrete logistic, stable if  $0 < r_d < 2$ )

For continuous:

Stable if  $f'(N^*) < 0$   
 (for continuous logistic, stable if  $r > 0$ )

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**1-D Stability analysis - Dig deeper** (In discrete time, but same applies to continuous time models)

$$N_{t+1} = F(N_t) \rightarrow N^*$$

Now add small perturbation to  $N^*$  by adding  $n$ :

$$N_t = N^* + n_t$$

We therefore expect:

$$N_{t+1} = F(N^* + n_t)$$

We want to know if popn will return to  $N^*$ , but will ask a slightly different question to get the answer:

Since

$$n_t = N_t - N^*$$

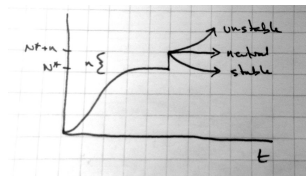
can write

$$n_{t+1} = N_{t+1} - N^*$$

Thus:

$$n_{t+1} = F(N^* + n_t) - N^*$$

**Thus the question is: Does  $n_t$  grow or shrink with time?**



Q: How do we find the solution of  $F(N^* + n_t)$ ?  
( $F$  could be a very complicated function!)

A: We approximate it:

$$\underbrace{F(N^* + n_t)}_y \approx \underbrace{F(N^*)}_{\text{intercept}} + \underbrace{F'(N^*)}_{\text{slope}} \cdot \underbrace{n_t}_x$$

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**Taylor Series**

Recall polynomial series:

$$y = \sum_{i=0} \beta_i x^i$$

Taylor series is similar, but with derivatives...

$$F(N^* + n_t) = \sum_{i=0}^{\infty} \frac{F^{(i)}(N^*)}{i!} n_t^i = F(N^*) + \underbrace{\frac{F'(N^*)}{1!} n_t^1 + \frac{F''(N^*)}{2!} n_t^2 + \frac{F'''(N^*)}{3!} n_t^3 + \dots}_{\text{h.o.t.}}$$

Show figure from 'Class-Ex-TaylorExp.R'.

*Higher order terms* get smaller and smaller.

First two terms are good approximation when  $n_t$  is small.

Thus:

$$\begin{aligned} n_{t+1} &= F(N^* + n_t) - N^* \\ &\approx F(N^*) + F'(N^*) \cdot n_t - N^* \\ &\approx N^* + F'(N^*) \cdot n_t - N^* \\ &\approx F'(N^*) \cdot n_t \\ &= \lambda n_t \quad (\lambda \text{ is the "eigenvalue" (for single-spp. model)}) \end{aligned}$$

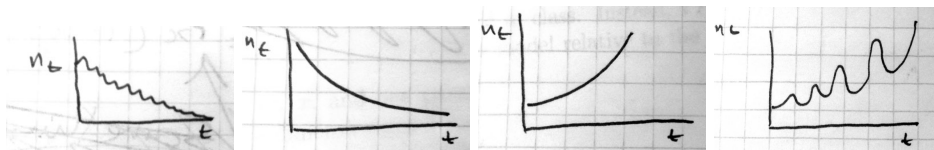
If  $\lambda < 1 \rightarrow n_{t+1} < n_t \rightarrow$  Perturbation decays (i.e. stable system)  
 If  $\lambda > 1 \rightarrow n_{t+1} > n_t \rightarrow$  Perturbation expands (i.e. unstable system)

Note that  $n_t$  could be a *removal* (i.e.  $n_t < 0$ ) of individuals (rather than an *addition*).

Thus **for discrete-time model:**

$$|F'(N^*)| < 1 \text{ for stability}$$

$-1 < \lambda < 0 \rightarrow$  decay w/ damped oscillations  
 $0 < \lambda < 1 \rightarrow$  geometric decay  
 $\lambda > 1 \rightarrow$  geometric growth  
 $\lambda < -1 \rightarrow$  divergent oscillations



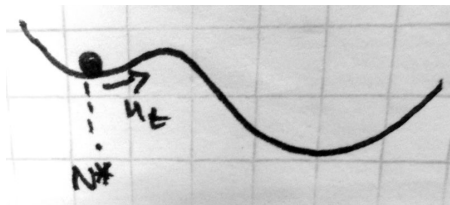
**For continuous model:**

$$\left. \frac{df(N)}{dN} \right|_{N^*} < 0 \text{ for stability}$$

We'll get much deeper into stability of continuous-time models from now on.

Will also talk about how oscillations occur and how their presence is analytically determined.

**Remember** that we're only dealing with **local** stability (i.e. small  $n_t$ ) not global stability!




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## Intro to Mathematica

### Local stability analysis of continuous logistic

Walk through Mathematica code: `'Class9-Stability-cLogistic.nb'`

Functions use square brackets [ ].

Important functions:

`Solve[y=ax,x]`

`D[f(x),x]`

`Simplify`

`func /. x -> y`

`var /. x`

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## Non-dimensionalization

The equation

$$\frac{dN}{dt} = rN \left(1 - \frac{N}{K}\right) = \lim_{\Delta t \rightarrow 0} \left(\frac{\Delta N}{\Delta t}\right)$$

has 2 parameters (+1 that's implicit!) and 1 variable.

$$r : \frac{\#}{\#time} \quad K : \# \quad N : \#$$

Define  $x$  to be the population size relative to the carrying capacity (i.e. fraction of the carrying capacity):

$$x := \frac{N}{K}$$

$x$  is dimensionless!

(Note: The symbol  $:=$  means *define*. Sometimes the symbol  $\equiv$  meaning *equivalent* is also used.)

Rearrange to  $N = xK$  and substitute:

$$\begin{aligned} \frac{dxK}{dt} &= rxK \left(1 - \frac{xK}{K}\right) \\ \frac{dx}{dt} &= rx(1 - x) \end{aligned}$$

Only 1 variable ( $x$ ) and 1 parameter ( $r$ ), same dynamical properties.

Can reduce further...

$$\tau := rt$$

( $\tau$  = 'tau') - dimensionless - the units of  $r$  are #/s per # per time (= 1/t).

That is,

$$\frac{d}{dt} = \frac{d}{d\tau} \cdot \frac{d\tau}{dt}$$

Rewriting  $r = \tau/t = d\tau/dt$ , this simplifies to

$$\frac{d}{dt} = \frac{d}{d\tau} r$$

Therefore

$$\begin{aligned} \frac{dx}{dt} &= rx(1 - x) \\ \frac{drx}{d\tau} &= rx(1 - x) \\ \frac{dx}{d\tau} &= x(1 - x) \end{aligned}$$

Only 1 variable and 0 parameters!!!

Of course, 'time-scale'  $\tau$  is tricky to conceptualize.

→ scaled realized rate of population dynamics (i.e.  $dN/dt$  or  $dx/dt$ )...  
...relative to the maximum growth rate of the population ( $r$ ).

Model is thus in terms of the realized growth relative to the maximum intrinsic growth.

Won't do all that much more non-dimensionalization (except in 2-spp. competition model, next), but can be extremely useful.

e.g., when absolute values of parameters are not known, but their relative values is (or can be approximated, or qualitatively known  $> 1$  or  $< 1$ )