# Deterministic functions for Modelling Biological Data

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Biol 520C: Statistical modelling for biological data

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- A reminder that if you want me to review anything in specific, let me know before next week.

The 'Linear' in Linear Regression

# **Linear Regression**



## **Linear Regression**



All of the models we've been working with so far are categorised as 'linear' deterministic functions.

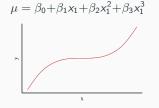
#### **Linear Regression**

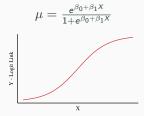


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$$\mu = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$





Even if we add polynomial terms, or fit GLMs with link functions the  $\beta$ s still combine linearly.

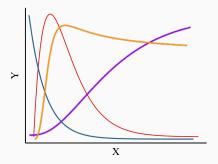
# Biology is not always linear



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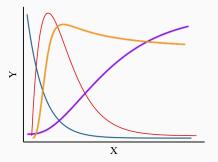
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# Biology is not always linear



Biological systems are not always linear, and you will need to become familiar with a wide range of deterministic functions.



Today we will learn about tools that can help you understand new functions, and explore a range of different functions that get used routinely.

**Finding Out About Functions** 

**Numerically and Analytically** 





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- 1. Numerically (plugging in numbers and observing changes)
- 2. Analytically (evaluate it mathematically using limits, derivatives, etc.)





R can be a useful too for evaluating functions numerically.



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Start by building a function() to describe the model



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Start by building a function() to describe the model, next define parameter values, run your function on a range of x values



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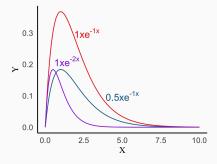
You would then repeat this process for multiple parameter values.

For the Ricker function  $(y = axe^{-bx})$ , the process would look like this:

```
ricker <- function(x, a = 1, b = 1) {
    a * x * exp(-b * x)
    }

x <- seq(0,10, 0.1)

y <- ricker(x)
    y2 <- ricker(x, a = 0.5)
    y3 <- ricker(x, b = 2)</pre>
```







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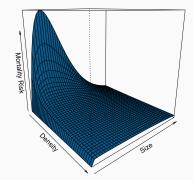
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If mortality risk can be modelled as a function of density (N) and size dependent attack rates ( $\alpha(s)$ ) using a Holling Type II functional response ( $y = \alpha(s)/(1 + \alpha(s)HN)$ ) (Vonesh & Bolker, 2005), then:

```
library(emdbook)
mortrisk <- function(N, size, H = .84) {
    a <- ricker(size)
    a/(1 + a * N * H)
}

curve3d(mortrisk(N = x, size = y),
    to = c(60,6),theta = 50,
    xlab = "Density",
    ylab = "Size",
    zlab = "Mortality Risk")</pre>
```



# Finding out about functions analytically



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1. Taking limits

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- 1. Taking limits
- 2. Using derivatives





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To understand the limiting behaviour of a function we look at what happens when x gets large  $(x \to \infty)$ , or when x gets small  $(x \to 0$  or  $x \to -\infty)$ 

As *x* tends towards these limits terms get dropped and we get a feel for what the tail ends of the function would look like.





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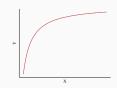
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What happens in the limit where  $x \to 0$ ?

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So we now know the limits of this function are 0 and a.





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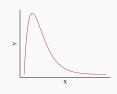




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So we now know the limits of this function are 0 and 0.

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Usefully, we can work out simple derivatives in R with the D() function.

# Michaelis-Menten derivative



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We know the Michaelis-Menten function limits to 0 and a:

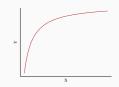
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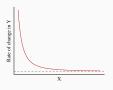
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But how does it approach its limits?

michmen = expression(a \* x / (b + x)) 
$$D(michmen, "x")$$
 a/(b + x) - a \* x/(b + x)^2



The rate of change in Y is greatest as  $X \to 0$ , and limits to 0 as  $X \to \infty$  (called a saturating function)

# Ricker derivative



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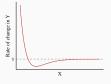


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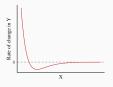


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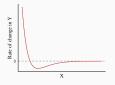


The rate of change in Y is greatest as  $X \to 0$ , it starts off growing but hits an inflection point

$$y = axe^{-bx}$$



But how does it approach its limits?



The rate of change in Y is greatest as  $X \to 0$ , it starts off growing but hits an inflection point, it then decays and the rate of change limits to 0 as  $X \to \infty$  (saturating)





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You can then change their values, shift or scale the functions, match them to biological parameters (remember they will all have units), etc.



If you know how to find out about a function's behaviour (numerically or analytically), you can get a better feeling of what each of the parameters are doing.

You can then change their values, shift or scale the functions, match them to biological parameters (remember they will all have units), etc.

All of this helps you get a better feel for how you can build functions to match the system you're modelling.

# Deterministic Functions for Modelling Biological Data

# **Polynomial functions**



Polynomial functions have the general form  $y = \sum_{i=1}^{n} \beta_i x^i$ 

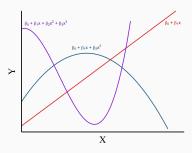
Examples:

**Linear**:  $f(x) = \beta_0 + \beta_1 x$ 

Quadratic:  $f(x) = \beta_0 + \beta_1 x + \beta_2 x^2$ 

**Cubic**:  $f(x) = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$ 

Range:  $-\infty, \infty$ 



**Advantages**: Easy to understand; easy to reduce; easy to extend to higher orders; can fit arbitrarily complex data.

**Disadvantage**: Anything beyond  $2^{\rm nd}$  order polynomials are hard to justify mechanistically; they don't level off as  $X \to \infty$  or  $-\infty$  (extrapolations are often unrealistic); higher order polynomials can be unstable.

# Piecewise polynomial functions



Polynomial functions can be made more flexible by using them as *piecewise* functions where different functions apply over different ranges of your predictor (x).

# Examples:

$$f(x) = a_1 \text{ if } x < s_1, \ a_2 \text{ if } x > s_1$$

#### Hockey stick:

$$f(x) = a + bx$$
 if  $x < s_1$ ,  $a + bs_1$  if  $x > s_1$ 

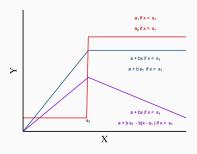
#### Piecewise linear:

$$f(x) = a + bx$$
 if  $x < s_1$ ,  $a + b_1s_1 + b_2(x - s_1)$  if  $x > s_1$ 

#### Cubic splines:

f(x) is complicated.

Range: 
$$-\infty, \infty$$



**Advantages**: Make sense and give added flexibility if there is a biological switching point.

**Disadvantage**: Hard to fit; discontinuous derivatives that may not make biological sense.

# **Rational functions**



Rational functions are ratios of polynomials with the general form:  $\frac{\sum a_i x^i}{\sum b_j x^j}$ 

Examples:

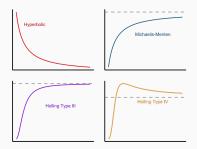
Hyperbolic: 
$$f(x) = \frac{a}{b+x}$$

Michaelis-Menten: 
$$f(x) = \frac{ax}{b+x}$$

Holling type III: 
$$f(x) = \frac{ax^2}{b^2 + x^2}$$

Holling type IV (c<0): 
$$f(x) = \frac{ax^2}{b+cx+x^2}$$

**Range**:  $0, \infty$ 

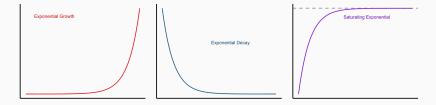


**Advantages**: Very flexible; often make mechanistic sense; simple to estimate parameters; easy to reduce down; reach finite asymptotes so are more stable than polynomials.

**Disadvantage**: Complicated derivatives; Approach their asymptotes very slowly, which can make these hard to estimate.

# **Exponential functions**

Exponential functions are based on exponential growth  $(ae^{bx})$ , exponential decay  $(ae^{-bx})$ , or saturating exponential functions  $(a(1-e^{-bx}))$ . Their range is  $0,\infty$ .



**Advantages**: Exponential growth/decay occur commonly in nature and these function make mechanistic sense; can be used to calculate doubling times or half-lives

**Disadvantage**: Similar behaviour to rational functions which makes it hard to distinguish between them without a lot of data.

# Comb. of exponentials with other fncs.



Exponential functions can be combined with other functions to increase their flexibility. Their ranges are  $0, \infty$ .

# Examples:

Ricker:  $f(x) = axe^{-bx}$ 

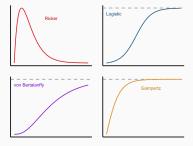
**Logistic**:  $f(x) = \frac{e^{a+bx}}{1+e^{a+bx}}$ 

### von Bertalanffy:

$$f(x) = a(1 - e^{-k(1-d)(x-x_0)})^{(\frac{1}{1-d})}$$

**Gompertz**:  $f(x) = e^{-ae^{-bx}}$ 

Range:  $0, \infty$ 



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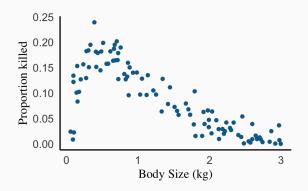
The nls() function allows fitting of non-linear relationships between a response variable and one or more explanatory variables using non-linear least squares.

# Kill rate data



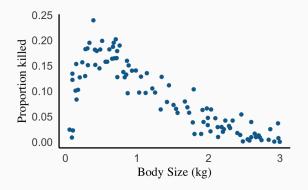


We'll work with a simulated dataset describing size-dependent predation rate.



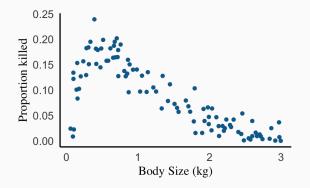


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Does a linear model look like a good option here?

We'll work with a simulated dataset describing size-dependent predation rate.



Does a linear model look like a good option here? What deterministic function do think we should try?

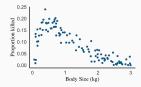
# Kill rate data cont.



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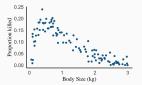


We can fit a Ricker function to the data using the nls() function.





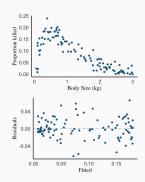
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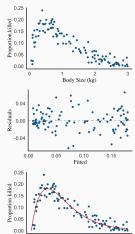
```
#Need to provide starting values for the parameters
FIT <- nls(prop ~ a * size * exp(-b * size),
           start = list(a = 1.
                        b = 2),
           data = DATA)
summary(FIT)
Formula: prop ~ a * size * exp(-b * size)
Parameters:
 Estimate Std. Error t value Pr(>|t|)
  0.96502
              0 04175
                        23 11
                               <2e-16 ***
                        35.79
  1.97821
              0.05528
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Residual standard error: 0.02352 on 98 degrees of freedom
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Residual standard error: 0.02352 on 98 degrees of freedom
#To plot fitted model need to code up the Ricker function
ricker <- function(x) {
  coef(FIT)[1] * x * exp(-coef(FIT)[2] * x)
x \leftarrow seq(0,3, 0.01)
v <- ricker(x)
```







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Unlike lm(), nls() requires that the formula includes all of the parameters you want to fit, including an intercept if you want one fitted. E.g., in lm() you would write the formula for linear regression as:

$$y \sim x$$

but to fit the same model in nls() you would have to write this as:

$$y \sim a + b*x$$





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If you combine these functions with a stochastic model and maximum likelihood estimation you can fit any model you can write down to data (Chapter 8 of Bolker's book).

# References

Vonesh, J.R. & Bolker, B.M. (2005). Compensatory larval responses shift trade-offs associated with predator-induced hatching plasticity. *Ecology*, 86, 1580–1591.

Bolker, B. M. (2008). Ecological models and data in R. Princeton University Press.