

# growthrates R package

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## What does the package do?

- `growthrates` offers various ways of assessing growth rates (and other growth parameters) in populations
- For example, finding the  $r$  in an exponential growth function, or  $r_{max}$  and  $K$  in a logistic growth function
- Can also estimate dose response curves
- It doesn't have its own model-fitting routines, but rather serves as a convenient wrapper for other packages

## Application

- The models can be applied to any type of population, from microbes to bison
- For the simplest applications, all you need is a time series of population size
- Can also handle multiple time series from a single experiment (see example)

## Example

- I will use a dataset on bacterial growth that comes with the package
- Three strains of bacteria (D = Donor, R = Recipient, T = transconjugant)
- Different concentrations of the antibiotic tetracycline
- Read off at 31 different times (0:30)
- Two replicates

## Load, inspect, subsample data

```
# Load dataset and show summary
```

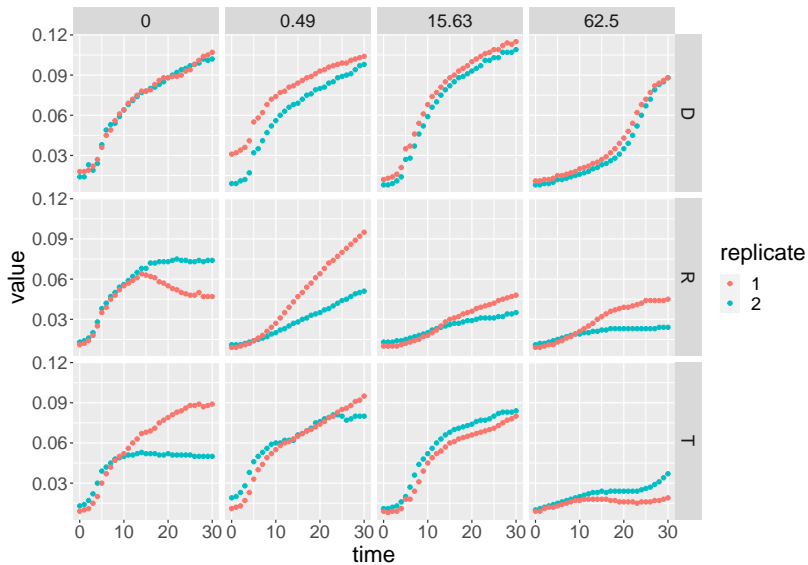
```
data(bactgrowth)
summary(bactgrowth)
```

##	strain	replicate	conc	time	value
##	D:744	Min. :1.0	Min. : 0.0000	Min. : 0	Min. :0.008
##	R:744	1st Qu.:1.0	1st Qu.: 0.8575	1st Qu.: 7	1st Qu.:0.019
##	T:744	Median :1.5	Median : 5.8600	Median :15	Median :0.036
##		Mean :1.5	Mean : 41.6467	Mean :15	Mean :0.045
##		3rd Qu.:2.0	3rd Qu.: 39.0625	3rd Qu.:23	3rd Qu.:0.070
##		Max. :2.0	Max. :250.0000	Max. :30	Max. :0.153

```
# Create subsample to fit graphs on one page
```

```
bactgrowth_small <- bactgrowth %>%
  filter(conc %in% sample(conc, 4))
```

## Plot data



## Simplest case: single dataset (time series)

- Three functions: `fit_easylinear`, `fit_growthmodels`, and `fit_splines`
- For single dataset (just one growth curve), need to subset data

```
# Subset bactgrowth data  
splitted.data <- multisplit(bactgrowth,  
                             c("strain", "conc", "replicate"))  
dat <- splitted.data[[1]]
```

This includes only strain D, replicate 1, and concentration 0

## Inspect dataset for single growth curve

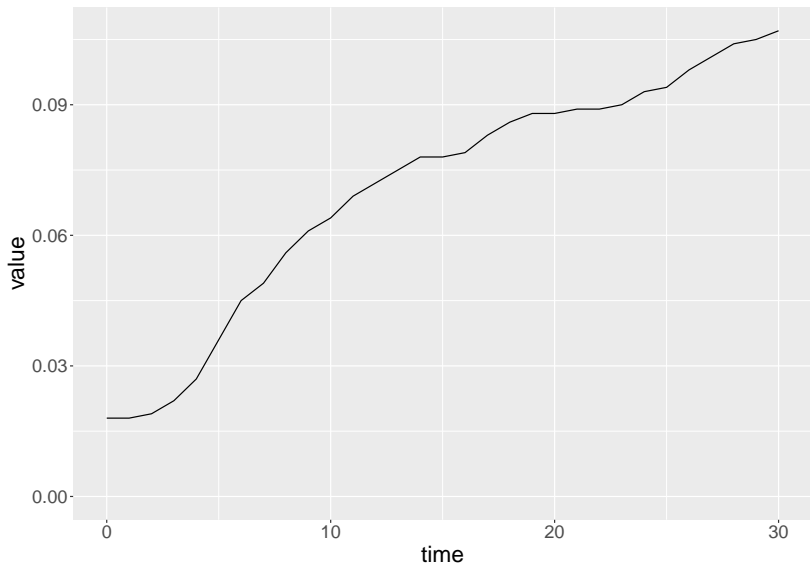
```
head(dat %>%  
  select(time, value))
```

```
##      time value  
## 1117     0 0.018  
## 1118     1 0.018  
## 1119     2 0.019  
## 1120     3 0.022  
## 1121     4 0.027  
## 1122     5 0.036
```

This is all the data you need to find  $r$ ,  $K$ , and other parameters.  
Make sure time starts at 0.



## Plot single growth curve



## Finding $r$

Exponential growth:

$$N_t = N_0 e^{rt}$$

Derivative of exponential growth:

$$\ln(N_t) = \ln(N_0) + rt$$

Can be evaluated as a linear function:

$$y = b_0 + b_1 t$$

where  $b_0 = \ln(N_0)$  and  $b_1 = r$ .

## Using growthrates to find $r$

The function `fit_easylinear` finds the maximum growth rate on the exponential segment of the growth curve.

`fit_easylinear` takes four arguments:

`fit_easylinear(time, y, h = 5, quota = 0.95)`

- `h` = number of data points (see next slide)
- `quota` = how much of adjacent data to include

## How `fit_easylinear`'s algorithm works

1. Fit linear regressions to all subsets of  $h$  consecutive data points. If for example  $h = 5$ , fit a linear regression to points 1 . . . 5, 2 . . . 6, 3 . . . 7 and so on. The method seeks the highest rate of exponential growth, so the dependent variable is log-transformed.
2. Find the subset with the highest slope  $b_{\max}$  and include also the data points of adjacent subsets that have a slope of at least  $quota \cdot b_{\max}$ , e.g. all data sets that have at least 95% of the maximum slope.
3. Fit a new linear model to the extended data window identified in step 2.

## Applying fit\_easylinear

```
fit <- fit_easylinear(dat$time, dat$value)
```

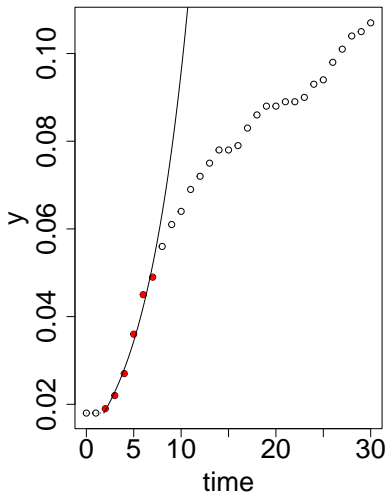
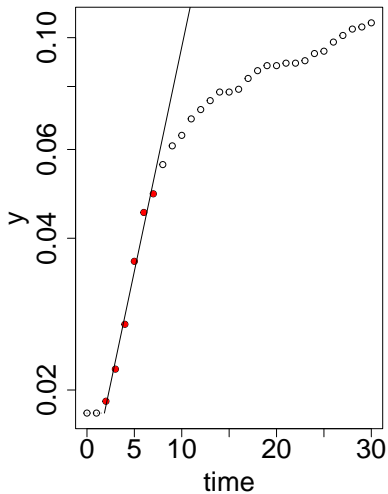
```
# Keeping defaults for h and quota
```

```
coef(fit)
```

```
##          y0      y0_lm      mumax      lag  
## 0.0180000 0.0123482 0.2048985 1.8392607
```

*mumax* is  $r$ .

## Plotting the results



## Using `fit_splines`

Splines fit models piecewise to a dataset, with a polynomial for each segment, and some fancy math to make it nice and smooth.

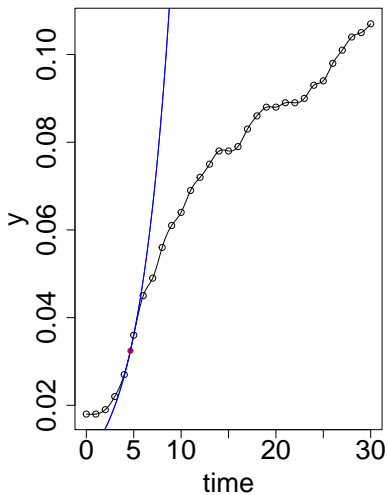
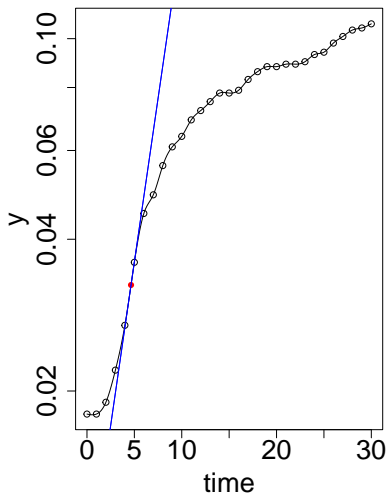
`growthrates` has the function `fit_splines` that can find  $r$  using this method

```
res <- fit_spline(dat$time, dat$value)

coef(res)
```

```
##           y0           mumax
## 0.008092223 0.298829681
```

## Plotting the result





## Fitting parametric nonlinear models

- `growthrates` can also be used to fit parametric nonlinear models with the `fit_growthmodel` function

```
fit_growthmodel(  
  FUN,  
  p,  
  time,  
  y,  
  lower = -Inf,  
  upper = Inf,  
  which = names(p),  
  method = "Marq",  
  transform = c("none", "log"), control = NULL,  
  ...)
```

## Applying `fit_growthmodel`

FUN defines the growth model; we will use `FUN = grow_logistic`

$$\frac{dN}{dT} = r_{max} \frac{(K - N)}{K} N$$

`p` sets start values for the parameters `y_0`, `mumax`, and `K`, where `mumax` is equivalent to  $r_{max}$ . Make your best guess based on an inspection of the data.

The other variables have defaults and we won't worry about them now.

## Applying fit\_growthmodel

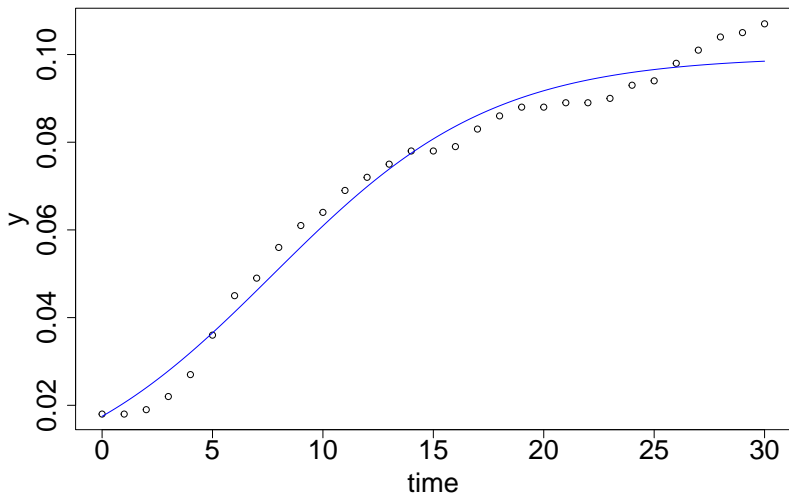
```
p <- c(y0 = 0.01, mumax = 0.2, K = 0.1)

fit1 <- fit_growthmodel(FUN = grow_logistic,
                        p = p,
                        dat$time,
                        dat$value)

coef(fit1)
```

```
##           y0      mumax           K
## 0.0174826 0.2000701 0.0996260
```

## Plotting results of logistic growth model



## Two-step differential equation model

Cells (or individuals) can be either inactive or active. For animals, inactive could mean an individual is not of reproductive age.

Each type has its own growth equation:

$$\frac{dy_i}{dt} = -k_w \cdot y_i$$

$$\frac{dy_a}{dt} = k_w \cdot y_i + \mu_{max} \cdot y_a \cdot \left(1 - \frac{y_a + y_i}{K}\right)$$

## Applying the two-step differential equation model

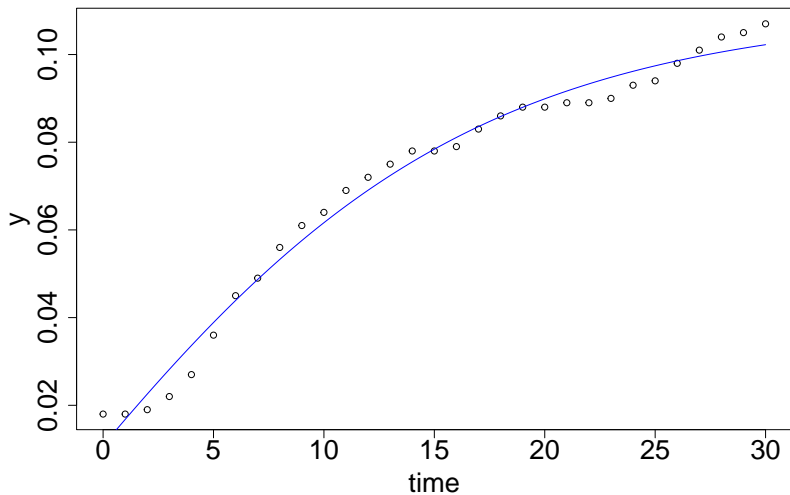
```
p <- c(yi = 0.02, ya = 0.001, kw = 0.1, mumax = 0.2, K = 0.1)

fit2 <- fit_growthmodel(FUN = grow_twostep,
                        p = p,
                        time = dat$time,
                        y = dat$value)

coef(fit2)
```

```
##           yi           ya           kw           mumax           K
## -0.08745055  0.09830086  0.02172016  0.06748615  0.11067716
```

## Plotting result of two-step model



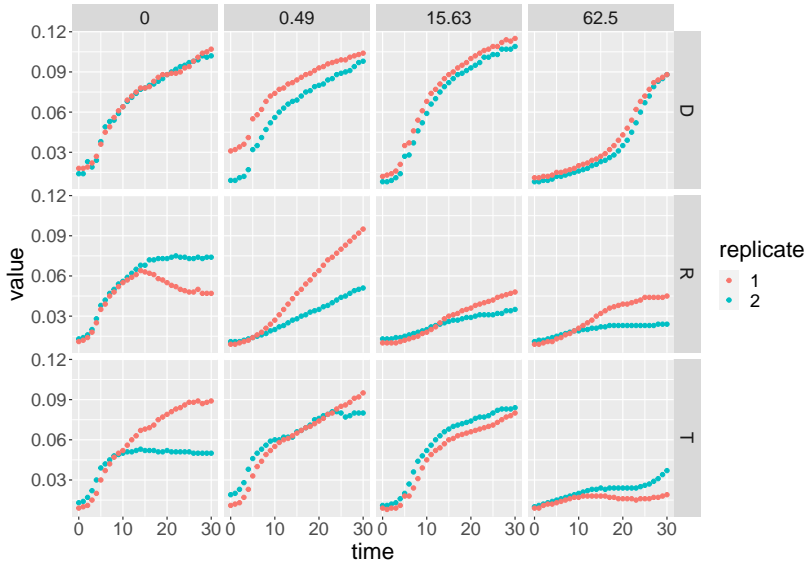
## Fitting models to multiple datasets

This applies when you have more than one growth curve. In `bactgrowth` we have a total of 72 growth curves, a combination of three strains, two replicates, and 12 different concentrations.



# Full bactgrowth dataset

Remember this plot of a subset with only four concentrations:



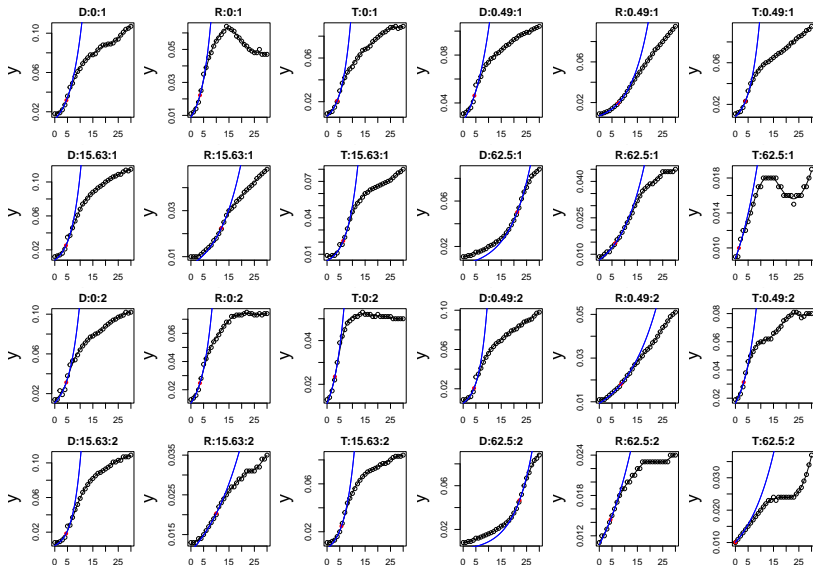


## Look at coefficients

```
head(coef(many_spline_fits), 5)
```

##		y0	mumax
##	D:0:1	0.012349620	0.20570733
##	R:0:1	0.008911212	0.25621722
##	T:0:1	0.006727476	0.28233842
##	D:0.24:1	0.016084542	0.17270804
##	R:0.24:1	0.013925666	0.05419363

# Plotting results for multiple splines



## Logistic growth models for multiple datasets

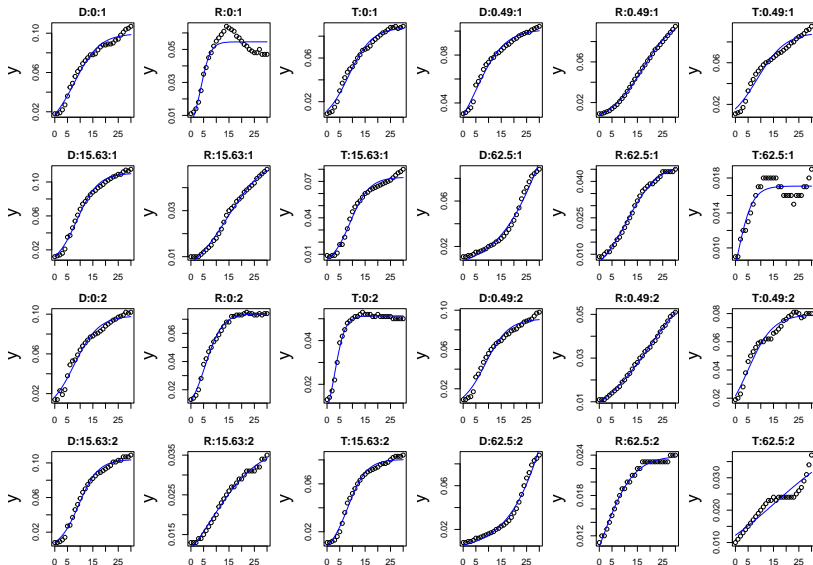
```
all_growthmodels(  
  formula,  
  data,  
  p,  
  lower = -Inf,  
  upper = Inf,  
  which = names(p),  
  FUN = NULL,  
  method = "Marq",  
  transform = c("none", "log"),  
  ...,  
  subset = NULL,  
  ncores = detectCores(logical = FALSE)  
)
```

## Applying all\_growthmodels with logistic growth

```
p <- c(y0 = 0.03, mumax = .1, K = 0.1)

many_logistic <- all_growthmodels(
  value ~ grow_logistic(time, parms) |
  strain + conc + replicate,
  data = bactgrowth,
  p = p)
```

# Plotting results

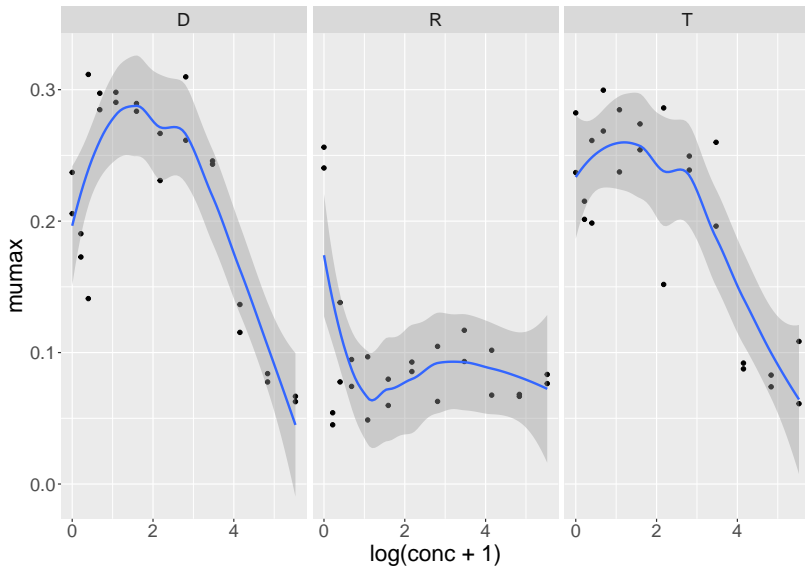


## Using results to estimate dose response curves

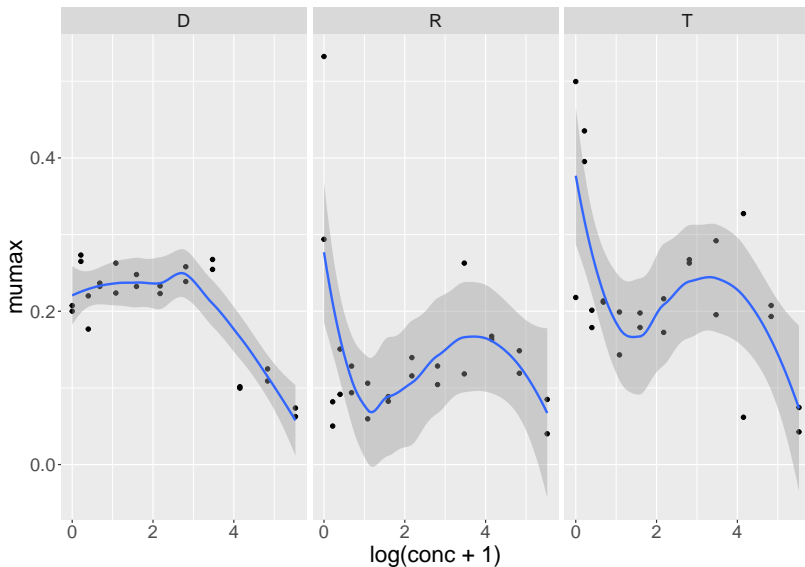
```
many_spline_res    <- results(many_spline_fits)
many_logistic_res  <- results(many_logistic)
```



## Plotting dose response curves for splines



## Plotting dose response curves for logistic



## Unique insight

You can write your own functions!

Example for a shift model (won't go into details of the model)

$$y(t) = \frac{K \cdot y_0}{y_0 + (K - y_0) \cdot e^{-\mu_{max} t}} + y_{shift}$$

## Code

```
# Define model
grow_logistic_yshift <- function(time, parms) {
  with(as.list(parms), {
    y <- (K * y0) / (y0 + (K - y0) * exp(-mumax * time)) + y_shift
    as.matrix(data.frame(time = time, y = y))
  })
}

# Convert to class `growthmodel`
grow_logistic_yshift <- growthmodel(grow_logistic_yshift,
                                     c("y0", "mumax", "K", "y_shift"))

# Now use `growthrates` function to fit model
fit <- fit_growthmodel(grow_logistic_yshift,
                       p = c(y0 = 1, mumax = 0.1, K = 10, K = 10,
                             y_shift = 1),
                       time = x, y = y)
```

## Advantages of growthrates package

- Adapted to problems of biological growth
- A lot simpler to use than the packages that contain the fitting routines
- Very flexible – can fit several different models; each function can be adapted
- Seems relatively fast
- Allows for user-defined functions
- Has built-in plotting function but also works well with ggplot
- Well documented

## Limitations of the package

- Would be even easier if some of the user-defined functions (like the shift model) were integrated into the package
- Overall the package does what it sets out to do, and I have no major complaints

## Sources

<https://tpetzoldt.github.io/growthrates/doc/Introduction.html>

[https://cran.r-](https://cran.r-project.org/web/packages/growthrates/growthrates.pdf)

[project.org/web/packages/growthrates/growthrates.pdf](https://cran.r-project.org/web/packages/growthrates/growthrates.pdf)

<https://github.com/tpetzoldt/growthrates>

My code:

[https:](https://github.com/linusblomqvist/ESM_211/tree/main/growthrates)

[//github.com/linusblomqvist/ESM\\_211/tree/main/growthrates](https://github.com/linusblomqvist/ESM_211/tree/main/growthrates)

## Portfolio assignment

Find  $r$  and  $K$  for the bison dataset using at least three different models (e.g. exponential, logistic, spline).

Hint: try functions `fit_easylinear`, `fit_growthmodels`, and `fit_splines`.

Do the different models agree on the parameter values?