

Friday, Feb 9

The Von Bertalanffy Growth Model

Consider the data frame `walleye` from the package `alr4`.

```
library(alr4)
head(walleye)
```

```
   age length period  periodf
1    1  215.3      1 pre-1991
2    1  193.3      1 pre-1991
3    1  202.6      1 pre-1991
4    1  201.5      1 pre-1991
5    1  232.0      1 pre-1991
6    1  191.0      1 pre-1991
```

The `period` variable refers to three distinct management periods: pre 1990, 1991-1996, and 1997-2000. It will be useful to explicitly define that as a categorical variable (i.e., a `factor` in R) with descriptive category labels.

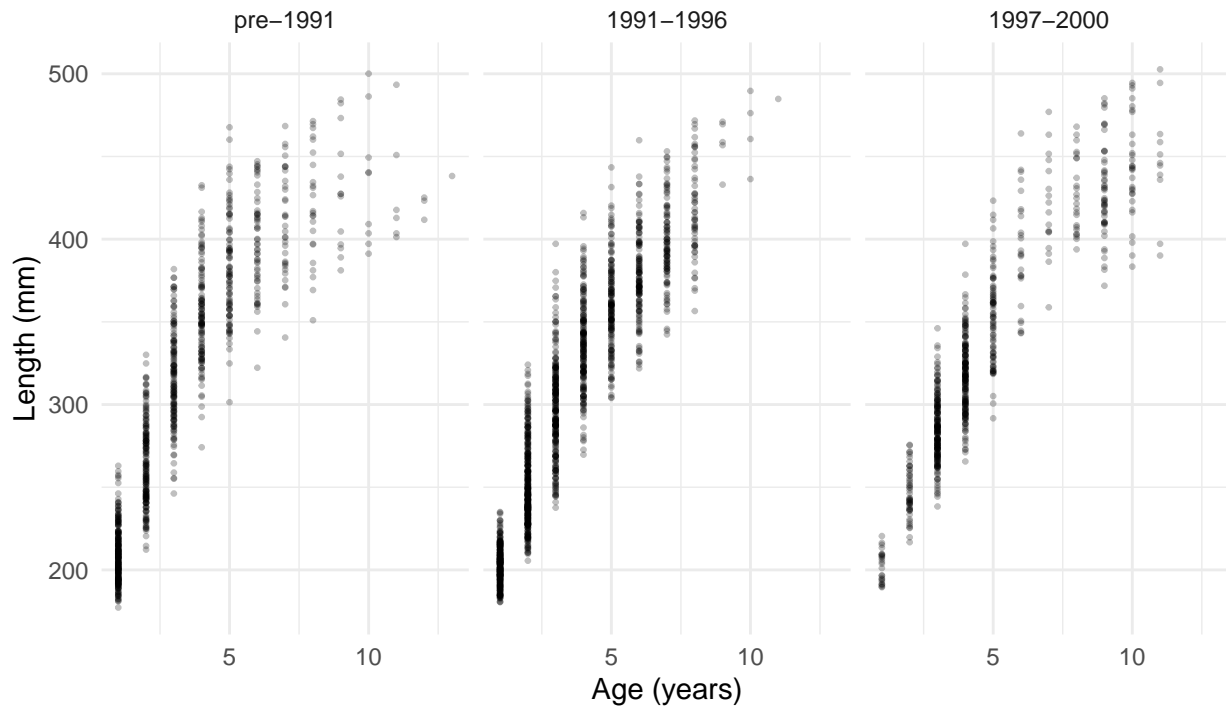
```
walleye$periodf <- factor(walleye$period, levels = c(1,2,3),
  labels = c("pre-1991", "1991-1996", "1997-2000"))
head(walleye)
```

```
   age length period  periodf
1    1  215.3      1 pre-1991
2    1  193.3      1 pre-1991
3    1  202.6      1 pre-1991
4    1  201.5      1 pre-1991
5    1  232.0      1 pre-1991
6    1  191.0      1 pre-1991
```

Let's visualize the data.

```
p <- ggplot(walleye, aes(y = length, x = age)) + facet_wrap(~ periodf) +
  theme_minimal() + geom_point(alpha = 0.25, size = 0.5) +
  labs(x = "Age (years)", y = "Length (mm)",
    title = "Length and Age of Walleye During Three Management Periods",
    subtitle = "Butternut Lake, Wisconsin",
    caption = "Source: Weisberg, S. (2014). Applied Linear Regression, 4th edition. Hoboken, NJ: Wiley.")
plot(p)
```

Length and Age of Walleye During Three Management Periods Butternut Lake, Wisconsin



Source: Weisberg, S. (2014). Applied Linear Regression, 4th edition. Hoboken, NJ: Wiley.

A common nonlinear regression model for these kind of data is the Von Bertalanffy growth model. This model can be written many different ways. One that is similar to the exponential model we used earlier is

$$E(L) = \alpha + (\delta - \alpha)2^{-a/\gamma},$$

where L and a are length and age, respectively. The parameters can be interpreted as follows.

1. α is the asymptote of $E(L)$ as a increases.
2. δ is the value of $E(L)$ when $a = 0$.
3. γ is the value of a at which $E(L)$ is half way between δ and α .

It is worth noting that this is *not* the parameterization of the model that is usually used in fisheries research. The parameterization I have used here is more closely related to the exponential model we considered for the `ToothGrowth` data.

Consider first a model in which there are no differences in the function between management periods. The starting values were obtained by “eyeballing” the plot.

```
m <- nls(length ~ alpha + (delta - alpha) * 2^(-age / gamma),
  data = walleye, start = list(alpha = 500, delta = 200, gamma = 5))
cbind(summary(m)$coefficients, confint(m))
```

	Estimate	Std. Error	t value	Pr(> t)	2.5%	97.5%
alpha	487.724	4.7688	102.27	0.00e+00	478.878	497.394
delta	140.729	2.0780	67.72	0.00e+00	136.654	144.732
gamma	3.424	0.1021	33.54	1.46e-211	3.236	3.632

Now suppose we want to allow the α and γ parameters to vary over management periods, but not δ . The

model we want could be written case-wise as

$$E(L_i) = \begin{cases} \alpha_1 + (\delta - \alpha_1)2^{-a_i/\gamma_1}, & \text{if the } i\text{-th observation is from the first period,} \\ \alpha_2 + (\delta - \alpha_2)2^{-a_i/\gamma_2}, & \text{if the } i\text{-th observation is from the second period,} \\ \alpha_3 + (\delta - \alpha_3)2^{-a_i/\gamma_3}, & \text{if the } i\text{-th observation is from the third period.} \end{cases}$$

Perhaps the easiest way to specify this model is to use the `case_when` function from the **dplyr** package.

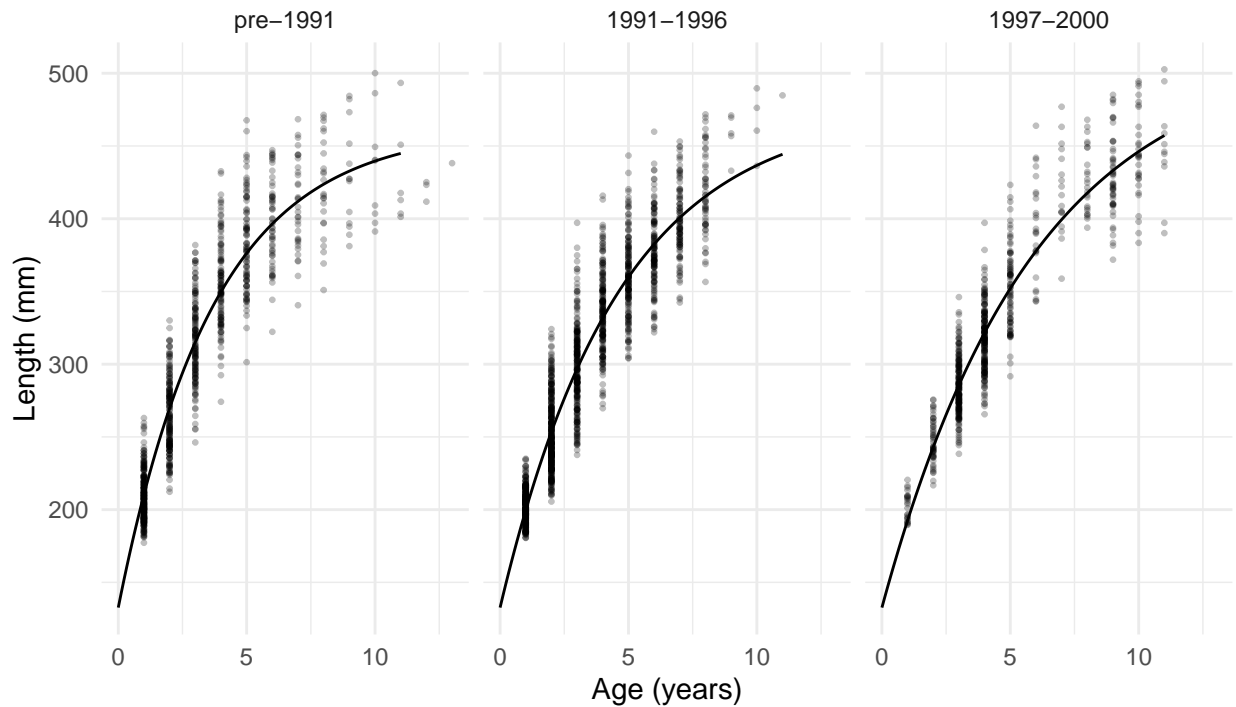
```
library(dplyr)
m <- nls(length ~ case_when(
  periodf == "pre-1991" ~ alpha1 + (delta - alpha1) * 2^(-age / gamma1),
  periodf == "1991-1996" ~ alpha2 + (delta - alpha2) * 2^(-age / gamma2),
  periodf == "1997-2000" ~ alpha3 + (delta - alpha3) * 2^(-age / gamma3)
), start = list(alpha1 = 500, alpha2 = 500, alpha3 = 500,
  delta = 200, gamma1 = 5, gamma2 = 5, gamma3 = 5), data = walleye)
cbind(summary(m)$coefficients, confint(m))
```

	Estimate	Std. Error	t value	Pr(> t)	2.5%	97.5%
alpha1	461.912	4.82053	95.82	0.000e+00	453.119	471.429
alpha2	475.839	6.30129	75.51	0.000e+00	464.110	489.135
alpha3	516.907	7.76416	66.58	0.000e+00	502.581	532.897
delta	132.667	2.22347	59.67	0.000e+00	128.307	136.939
gamma1	2.574	0.08383	30.70	1.299e-181	2.423	2.740
gamma2	3.194	0.12046	26.51	3.746e-140	2.971	3.448
gamma3	4.095	0.15206	26.93	4.080e-144	3.817	4.410

```
d <- expand.grid(age = seq(0, 11, length = 100),
  periodf = levels(walleye$periodf))
d$yhat <- predict(m, newdata = d)

p <- ggplot(walleye, aes(y = length, x = age)) + facet_wrap(~ periodf) +
  theme_minimal() + geom_point(alpha = 0.25, size = 0.5) +
  geom_line(aes(y = yhat), data = d) +
  labs(x = "Age (years)", y = "Length (mm)",
  title = "Length and Age of Walleye During Three Management Periods",
  subtitle = "Butternut Lake, Wisconsin",
  caption = "Source: Weisberg, S. (2014). Applied Linear Regression, 4th edition. Hoboken, NJ: Wiley.")
plot(p)
```

Length and Age of Walleye During Three Management Periods Butternut Lake, Wisconsin



Source: Weisberg, S. (2014). Applied Linear Regression, 4th edition. Hoboken, NJ: Wiley.

Here `summary` and `confint` provide inferences for each parameter in each period, but do not provide inferences about the *differences* in the parameters *between* periods. But we can use `lincon` to do this. Suppose we wanted to compare the second and third periods with the first.

```
library(trtools) # for lincon
lincon(m, a = c(-1,1,0,0,0,0,0)) # alpha2 - alpha1
```

	estimate	se	lower	upper	tvalue	df	pvalue
(-1,1,0,0,0,0,0),0	13.93	6.758	0.675	27.18	2.061	3191	0.03942

```
lincon(m, a = c(-1,0,1,0,0,0,0)) # alpha3 - alpha1
```

	estimate	se	lower	upper	tvalue	df	pvalue
(-1,0,1,0,0,0,0),0	54.99	8.449	38.43	71.56	6.509	3191	8.75e-11

```
lincon(m, a = c(0,0,0,0,-1,1,0)) # gamma2 - gamma1
```

	estimate	se	lower	upper	tvalue	df	pvalue
(0,0,0,0,-1,1,0),0	0.6199	0.1061	0.4118	0.8281	5.84	3191	5.736e-09

```
lincon(m, a = c(0,0,0,0,-1,0,1)) # gamma3 - gamma1
```

	estimate	se	lower	upper	tvalue	df	pvalue
(0,0,0,0,-1,0,1),0	1.521	0.145	1.237	1.805	10.49	3191	2.372e-25

Sometimes it is helpful to write the model as a *function* to keep the code tidy. We can program the function

$$f(a) = \alpha + (\delta - \alpha)2^{-a/\gamma}$$

as follows.

```
vbf <- function(age, alpha, delta, gamma) {
  alpha + (delta - alpha) * 2^(-age / gamma)
}
```

Now we can use vbf in nls.

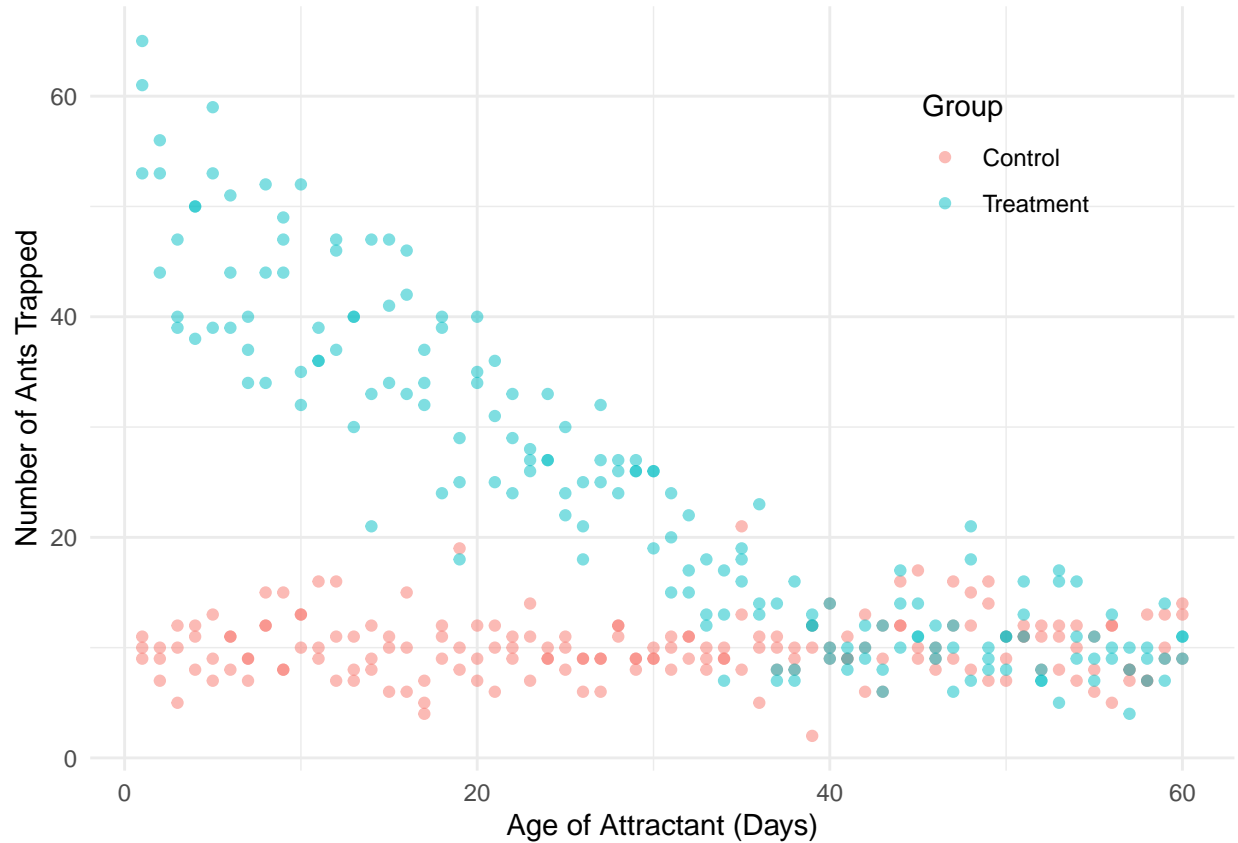
```
m <- nls(length ~ case_when(
  periodf == "pre-1991" ~ vbf(age, alpha1, delta, gamma1),
  periodf == "1991-1996" ~ vbf(age, alpha2, delta, gamma2),
  periodf == "1997-2000" ~ vbf(age, alpha3, delta, gamma3)
), start = list(alpha1 = 500, alpha2 = 500, alpha3 = 500,
  delta = 200, gamma1 = 5, gamma2 = 5, gamma3 = 5), data = walleye)
cbind(summary(m)$coefficients, confint(m))
```

	Estimate	Std. Error	t value	Pr(> t)	2.5%	97.5%
alpha1	461.912	4.82053	95.82	0.000e+00	453.119	471.429
alpha2	475.839	6.30129	75.51	0.000e+00	464.110	489.135
alpha3	516.907	7.76416	66.58	0.000e+00	502.581	532.897
delta	132.667	2.22347	59.67	0.000e+00	128.307	136.939
gamma1	2.574	0.08383	30.70	1.299e-181	2.423	2.740
gamma2	3.194	0.12046	26.51	3.746e-140	2.971	3.448
gamma3	4.095	0.15206	26.93	4.080e-144	3.817	4.410

Segmented Regression as a Linear Model

Consider data from a study of the effect of attractant age on attracting fire ants.

```
library(trtools) # for fireants data
p <- ggplot(fireants, aes(x = day, y = count, color = group)) +
  geom_point(alpha = 0.5) + theme_minimal() +
  theme(legend.position = c(0.8,0.8)) +
  labs(x = "Age of Attractant (Days)", y = "Number of Ants Trapped",
  color = "Group")
plot(p)
```



Consider first this model for only the treatment group:

$$E(Y_i) = \beta_0 + \beta_1 x_i + \beta_2 \mathbf{1}(x_i < \delta)(x_i - \delta),$$

where Y_i and x_i are the fire ant count and age of attractant, respectively, and $\mathbf{1}$ is an *indicator function* defined as

$$\mathbf{1}(x_i < \delta) = \begin{cases} 1, & \text{if } x_i < \delta, \\ 0, & \text{if } x_i \geq \delta. \end{cases}$$

In general, an indicator function is a function such that

$$\mathbf{1}(\text{statement}) = \begin{cases} 1, & \text{if the statement is true,} \\ 0, & \text{if the statement is false.} \end{cases}$$

Writing the model case-wise for $x_i < \delta$ versus $x_i \geq \delta$ we have

$$E(Y_i) = \begin{cases} \beta_0 - \beta_2 \delta + (\beta_1 + \beta_2)x_i, & \text{if } x_i < \delta, \\ \beta_0 + \beta_1 x_i, & \text{if } x_i \geq \delta. \end{cases}$$

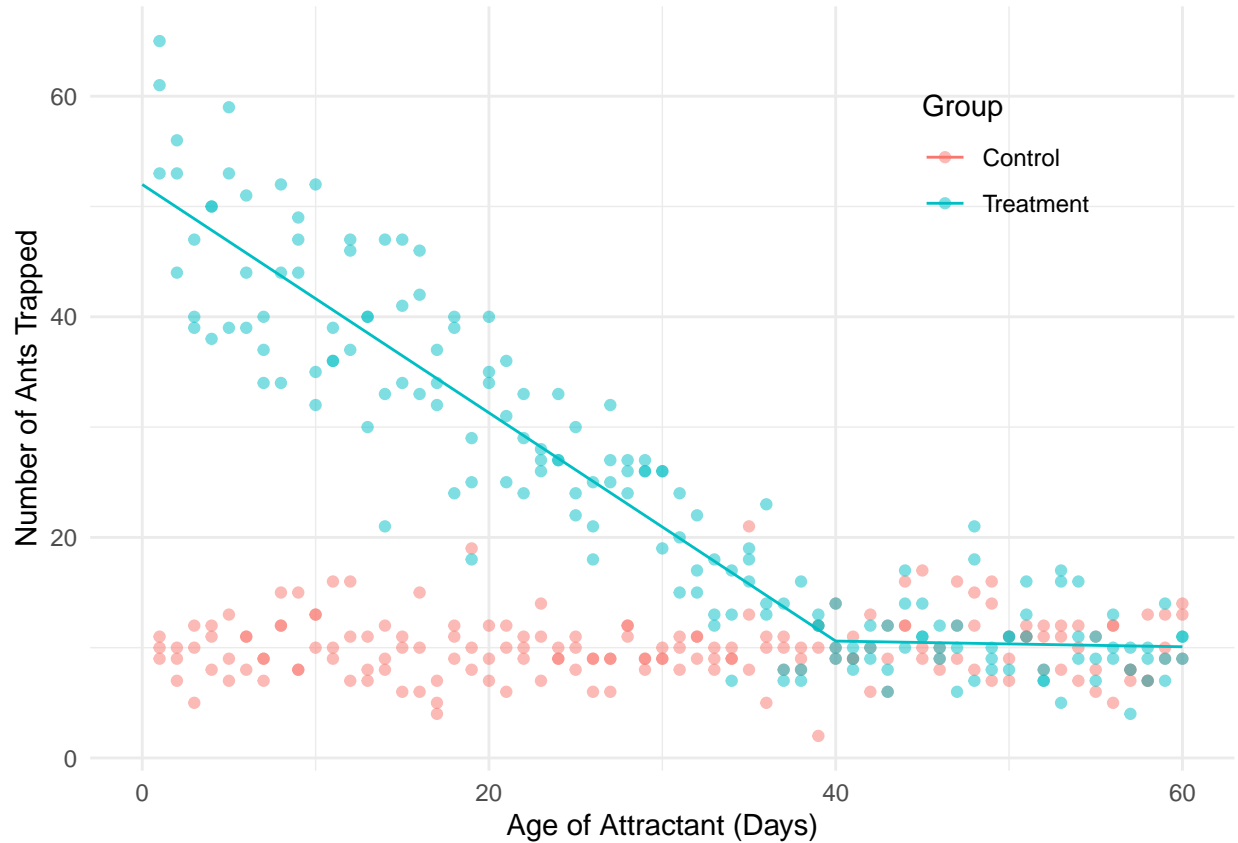
This is sometimes called *segmented*, *piece-wise*, or *broken-stick* regression. It is also a special case of a *spline*. The δ is called a “knot” of the spline. If the knot is known then this is a *linear* model.

```
treated <- subset(fireants, group == "Treatment")
m <- lm(count ~ day + I((day < 40)*(day - 40)), data = treated)
summary(m)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	11.62723	3.74415	3.1054	2.213e-03
day	-0.02574	0.07898	-0.3259	7.449e-01
I((day < 40) * (day - 40))	-1.00914	0.10389	-9.7138	3.798e-18

Note that we can write the indicator function $\mathbf{1}(x_i < 40)$ as `(day < 40)` in R.

```
d <- expand.grid(day = seq(0, 60, length = 100), group = "Treatment")
d$yhat <- predict(m, newdata = d)
p <- p + geom_line(aes(y = yhat), data = d)
plot(p)
```



Now it would be useful to extend the model to include the control group, but subject to a couple of constraints:

1. The relationship between expected count and age for the *control* group should not have a break (because there is no attractant to wear off).
2. After 40 days the relationship between expected count and age should be *identical* for the control and treatment groups (because the attractant has worn off).

Here's a model that will accomplish that:

$$E(Y_i) = \beta_0 + \beta_1 x_i + \beta_2 \mathbf{1}(x_i < \delta)(x_i - \delta)g_i,$$

where

$$g_i = \begin{cases} 1, & \text{if the } i\text{-th observation is from the treatment group,} \\ 0, & \text{otherwise,} \end{cases}$$

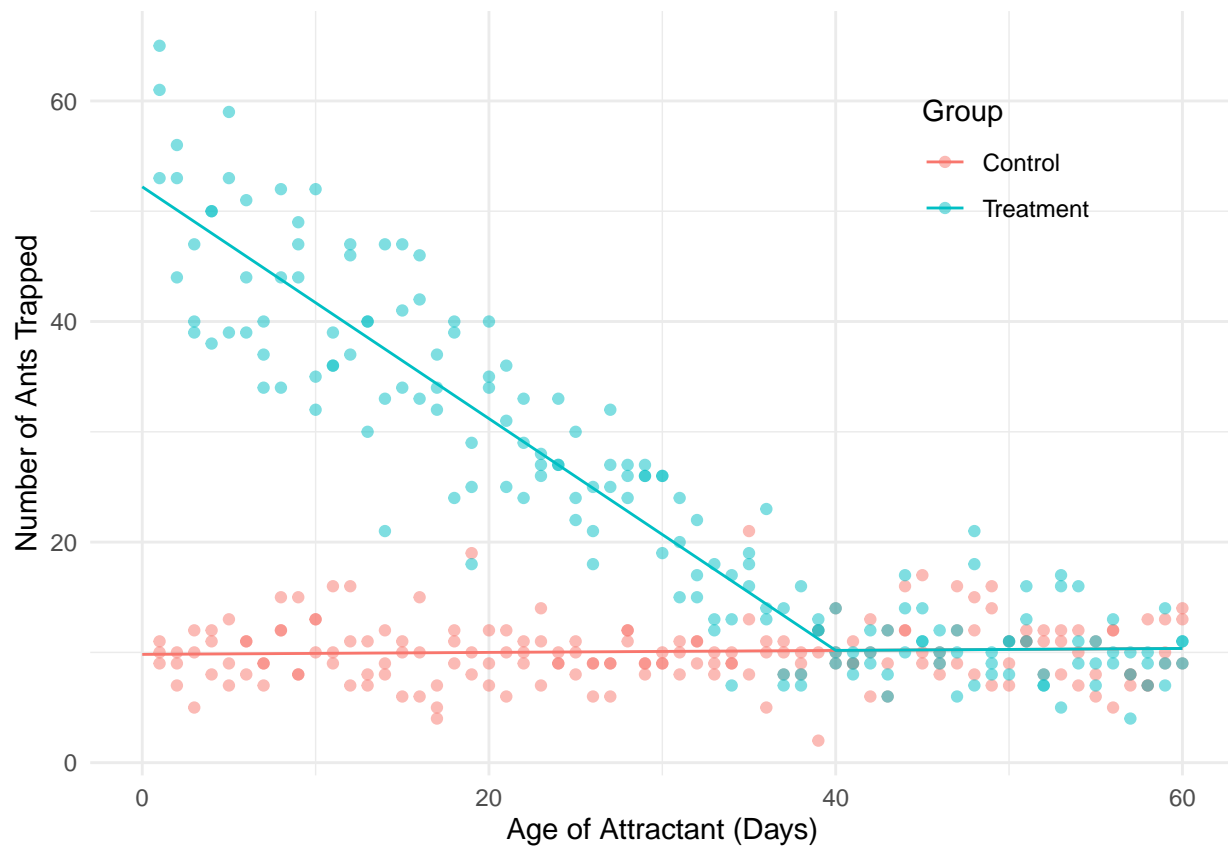
so that the model can be written as

$$E(Y_i) = \begin{cases} \beta_0 - \beta_2 \delta + (\beta_1 + \beta_2)x_i, & \text{if the } i\text{-th observation is from the treatment group and } x_i < \delta, \\ \beta_0 + \beta_1 x_i, & \text{otherwise.} \end{cases}$$

```
m <- lm(count ~ day + I((day < 40)*(day - 40)*(group == "Treatment")),
data = fireants)
```

```
d <- expand.grid(day = seq(0, 60, length = 100),
  group = c("Control", "Treatment"))
d$yhat <- predict(m, newdata = d)

p <- ggplot(fireants, aes(x = day, y = count, color = group)) +
  geom_point(alpha = 0.5) + theme_minimal() +
  theme(legend.position = c(0.8, 0.8)) +
  labs(x = "Age of Attractant (Days)",
    y = "Number of Ants Trapped", color = "Group") +
  geom_line(aes(y = yhat), data = d)
plot(p)
```



Now we can make some inferences.

```
# expected counts at day 0
contrast(m, a = list(group = c("Control", "Treatment"), day = 0),
  cnames = c("Control", "Treatment"))
```

	estimate	se	lower	upper	tvalue	df	pvalue
Control	9.819	0.5982	8.642	11.00	16.41	357	1.665e-45
Treatment	52.211	0.6770	50.880	53.54	77.12	357	1.145e-224

```
# expected counts at day 40
contrast(m, a = list(group = c("Control", "Treatment"), day = 40),
  cnames = c("Control", "Treatment"))
```

	estimate	se	lower	upper	tvalue	df	pvalue
Control	10.18	0.2573	9.671	10.68	39.56	357	1.523e-132


```
Treatment    10.18 0.2573 9.671 10.68 39.56 357 1.523e-132
```

```
# slopes before day 40
```

```
contrast(m,
  a = list(group = c("Control", "Treatment"), day = 1),
  b = list(group = c("Control", "Treatment"), day = 0),
  cnames = c("Control", "Treatment"))
```

	estimate	se	lower	upper	tvalue	df	pvalue
Control	0.008954	0.01509	-0.02072	0.03863	0.5935	357	5.532e-01
Treatment	-1.050865	0.01926	-1.08873	-1.01299	-54.5726	357	2.658e-175

```
# slopes after day 40
```

```
contrast(m,
  a = list(group = c("Control", "Treatment"), day = 41),
  b = list(group = c("Control", "Treatment"), day = 40),
  cnames = c("Control", "Treatment"))
```

	estimate	se	lower	upper	tvalue	df	pvalue
Control	0.008954	0.01509	-0.02072	0.03863	0.5935	357	0.5532
Treatment	0.008954	0.01509	-0.02072	0.03863	0.5935	357	0.5532

```
# difference in expected counts at day 20
```

```
contrast(m,
  a = list(group = "Treatment", day = 20),
  b = list(group = "Control", day = 20))
```

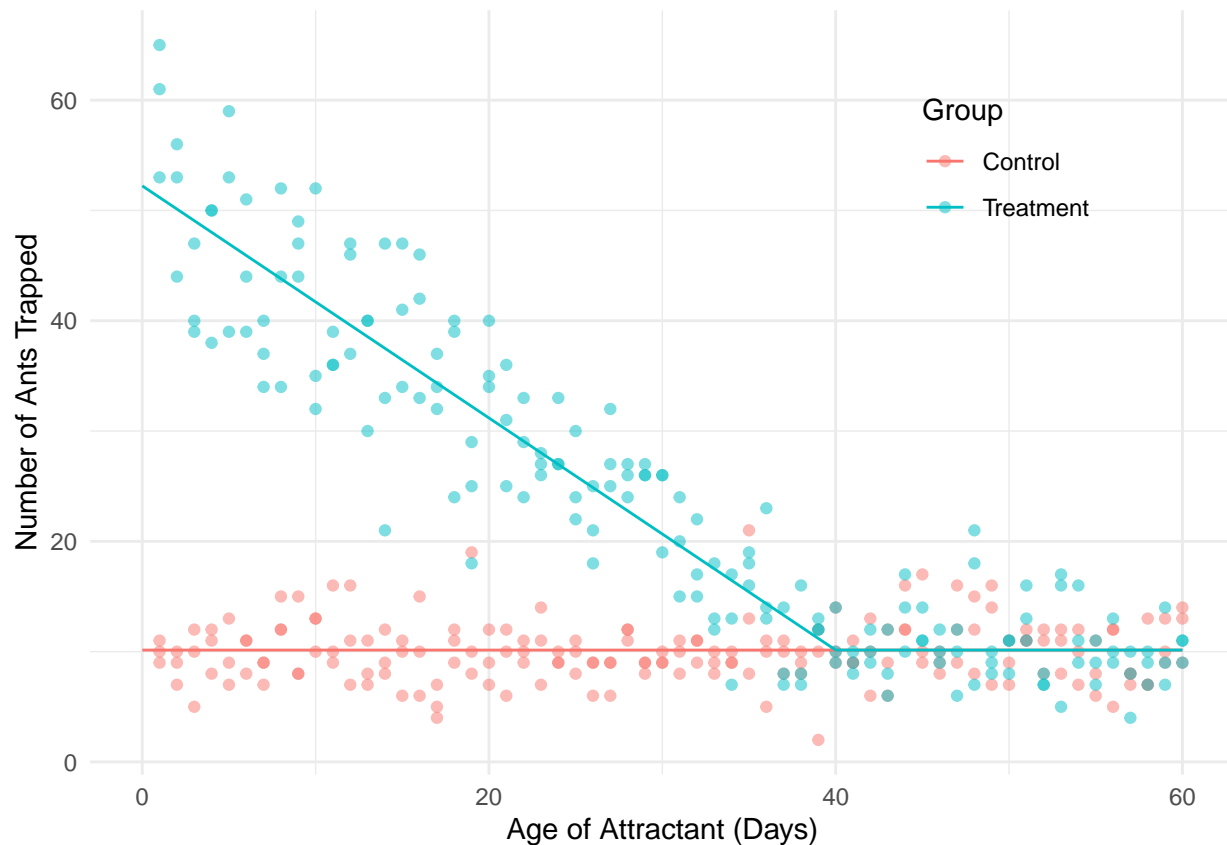
	estimate	se	lower	upper	tvalue	df	pvalue
	21.2	0.4602	20.29	22.1	46.05	357	2.908e-152

We could go one step further by assuming that for the control group and after the knot the expected count is constant. This would require us to drop the term $\beta_1 x_i$.

```
m <- lm(count ~ I((day < 40) * (day - 40) *
  (group == "Treatment")), data = fireants)

d <- expand.grid(day = seq(0, 60, length = 100),
  group = c("Control", "Treatment"))
d$yhat <- predict(m, newdata = d)

p <- ggplot(fireants, aes(x = day, y = count, color = group)) +
  geom_point(alpha = 0.5) + theme_minimal() +
  theme(legend.position = c(0.8, 0.8)) +
  labs(x = "Age of Attractant (Days)",
    y = "Number of Ants Trapped", color = "Group") +
  geom_line(aes(y = yhat), data = d)
plot(p)
```



Now consider the following inferences.

```
# slopes before day 40
```

```
contrast(m,
  a = list(group = c("Control", "Treatment"), day = 1),
  b = list(group = c("Control", "Treatment"), day = 0),
  cnames = c("Control", "Treatment"))
```

	estimate	se	lower	upper	tvalue	df	pvalue
Control	0.000	0.0000	0.00	0.000	NaN	358	NaN
Treatment	-1.052	0.0191	-1.09	-1.015	-55.08	358	7.001e-177

```
# slopes after day 40
```

```
contrast(m,
  a = list(group = c("Control", "Treatment"), day = 41),
  b = list(group = c("Control", "Treatment"), day = 40),
  cnames = c("Control", "Treatment")) # slopes after day 40
```

	estimate	se	lower	upper	tvalue	df	pvalue
Control	0	0	0	0	NaN	358	NaN
Treatment	0	0	0	0	NaN	358	NaN

Segmented Regression as a Nonlinear Model

If the knot δ is *known* then the model is *linear*. We can write

$$E(Y_i) = \beta_0 + \beta_1 x_i + \beta_2 \mathbf{1}(x_i < \delta)(x_i - \delta)g_i$$

as

$$E(Y_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2},$$

where $x_{i1} = x_i$ (day) and $x_{i2} = \mathbf{1}(x_i < \delta)(x_i - \delta)g_i$, provided we *know* δ . But what if δ is unknown and is to be estimated? Then we have a *nonlinear* model.

Let's start estimating a *linear* model with `nls` by guessing the value of δ . This will give us some good starting values.

```
m <- nls(count ~ b0 + b1 * day + b2 * (day < 40) * (day - 40) *
  (group == "Treatment"), data = fireants,
  start = list(b0 = 0, b1 = 1, b2 = 1))
cbind(summary(m)$coefficients, confint(m))
```

	Estimate	Std. Error	t value	Pr(> t)	2.5%	97.5%
b0	9.818633	0.59822	16.4131	1.665e-45	8.64216	10.99511
b1	0.008954	0.01509	0.5935	5.532e-01	-0.02072	0.03863
b2	-1.059819	0.02301	-46.0541	2.908e-152	-1.10508	-1.01456

Now consider a model where the knot (δ) is a *parameter*, using the estimate from the linear model as starting values.

```
m <- nls(count ~ b0 + b1 * day + b2 * (day < delta) * (day - delta) *
  (group == "Treatment"), data = fireants,
  start = list(b0 = 10, b1 = 0, b2 = -1, delta = 40))
cbind(summary(m)$coefficients, confint(m))
```

	Estimate	Std. Error	t value	Pr(> t)	2.5%	97.5%
b0	9.807069	0.60056	16.3298	3.885e-45	8.62598	10.98816
b1	0.008604	0.01516	0.5674	5.708e-01	-0.02122	0.03843
b2	-1.052444	0.03597	-29.2590	9.772e-97	-1.12822	-0.98318
delta	40.200079	0.75454	53.2776	1.061e-171	38.60885	41.69578

We can use `lincon` provided that the quantity of interest is a linear combination of parameters. For example, recall that the model can be written as

$$E(Y_i) = \begin{cases} \beta_0 - \beta_2\delta + (\beta_1 + \beta_2)x_i, & \text{if } x_i < \delta \text{ and treatment,} \\ \beta_0 + \beta_1x_i, & \text{otherwise,} \end{cases}$$

so the slope before the knot for the treatment group is $\beta_1 + \beta_2$. This can be written as

$$\ell = a_0\beta_0 + a_1\beta_1 + a_2\beta_2 + a_3\delta + b$$

where $a_0 = 0$, $a_1 = 1$, $a_2 = 1$, $a_3 = 0$, and $b = 0$.

```
# slope before knot for treatment group
lincon(m, a = c(0, 1, 1, 0))
```

	estimate	se	lower	upper	tvalue	df	pvalue
(0,1,1,0),0	-1.044	0.03262	-1.108	-0.9797	-32	356	8.718e-107

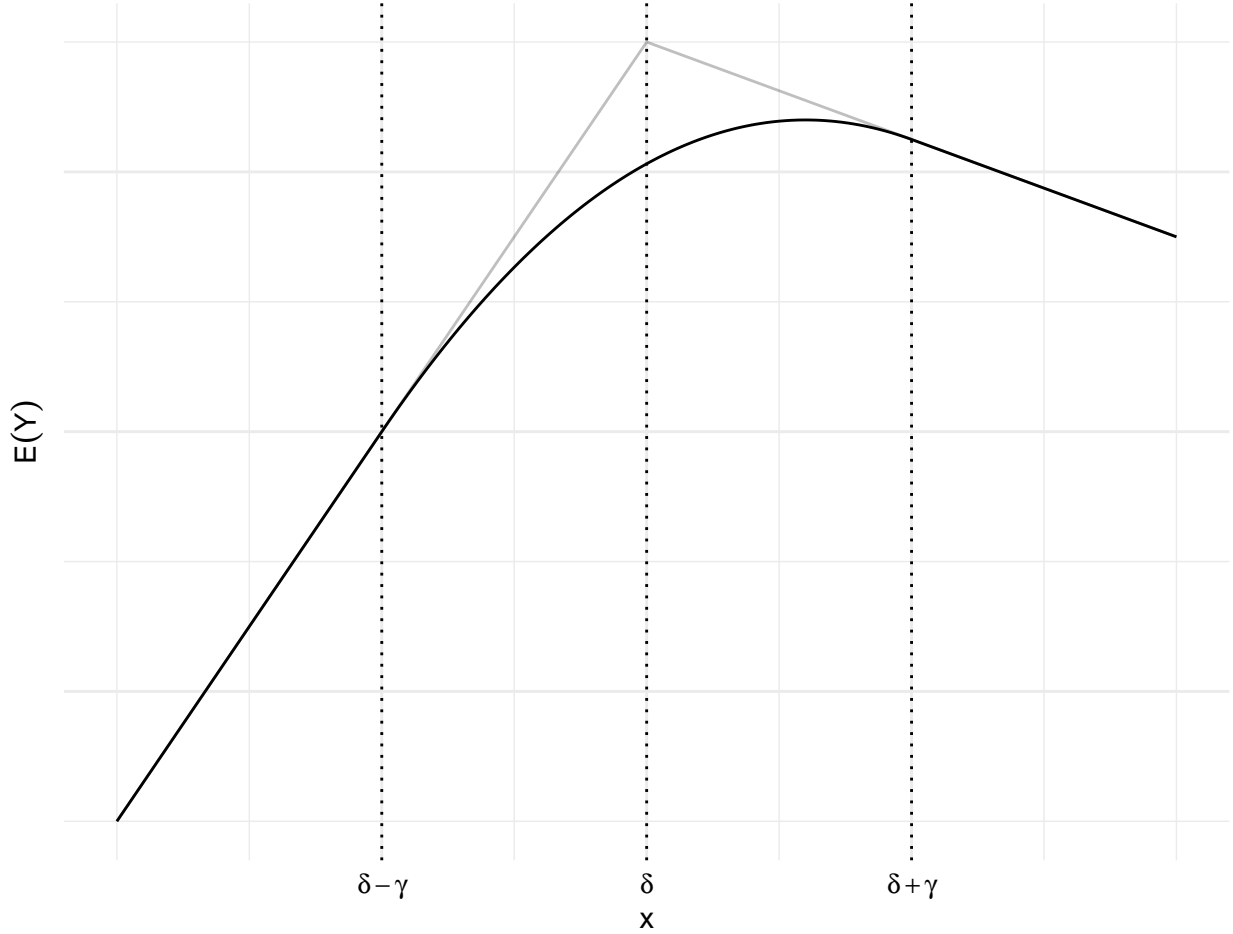
Bent Cable Regression

The data frame `children` in the package `npregfast` contains 2500 observations of the age and height of children.

```
library(ggplot2)
library(npregfast)
p <- ggplot(children, aes(x = age, y = height, color = sex)) +
  geom_point(alpha = 0.25) + theme_minimal() +
  labs(x = "Age (years)", y = "Height (cm)", color = "Gender") +
  theme(legend.position = c(0.9,0.2))
plot(p)
```



The “bent cable” regression model can be used as kind of crude growth model for these data. It can be viewed as a generalization of the segmented regression model where rather than having two lines meet at a sharp angle, one line gradually transitions into the other by attaching them by what looks like a bent cable. The figure below shows a bent cable model.



The grey lines show a segmented regression model while the solid curve shows a bent cable model. Essentially there are two lines: one line to the left of $\delta - \gamma$ and one line to the right of $\delta + \gamma$. And between the two lines (i.e., between $\delta - \gamma$ and $\delta + \gamma$) is a quadratic polynomial that joins the two lines in such a way that the whole piece-wise function is smooth. The parameter δ represents the point at which the two lines would meet if there was no bend, and γ is the half of the distance between the points $\delta - \gamma$ and $\delta + \gamma$. As γ gets closer to zero this function approaches a segmented regression model (as shown by the grey lines).

The bent cable regression model can be written as

$$E(Y) = \beta_0 + \beta_1 x + \beta_2 q(x, \delta, \gamma),$$

where $q(x, \delta, \gamma)$ is a function defined as

$$q(x, \delta, \gamma) = \frac{(x - \delta + \gamma)^2}{4\gamma} \mathbf{1}(\delta - \gamma \leq x \leq \delta + \gamma) + \mathbf{1}(x > \delta + \gamma)(x - \delta).$$

This can be written case-wise as

$$E(Y) = \begin{cases} \beta_0 + \beta_1 x, & \text{if } x < \delta - \gamma, \\ \beta_0 + \beta_1 x + \beta_2 \frac{(x - \delta + \gamma)^2}{4\gamma}, & \text{if } \delta - \gamma \leq x \leq \delta + \gamma, \\ \beta_0 - \delta\beta_2 + (\beta_1 + \beta_2)x, & \text{if } x > \delta + \gamma. \end{cases}$$

So when $x < \delta - \gamma$ we have a line with intercept β_0 and slope β_1 , and after $x > \delta + \gamma$ we have another line with intercept $\beta_0 - \delta\beta_2$ and slope $\beta_1 + \beta_2$. Between $\delta - \gamma$ and $\delta + \gamma$ is what is basically a quadratic regression model. And all three functions are constrained so that they form one smooth and continuous function.

Given the complexity of the function $q(x, \delta, \gamma)$, it is useful to program it.

```
q <- function(x, delta, gamma) {
  (x - delta + gamma)^2 / (4 * gamma) *
  (delta - gamma <= x & x <= delta + gamma) +
  (x > (delta + gamma)) * (x - delta)
}
```

First I will estimate a *linear* model with crude guesses of δ and γ .

```
m <- nls(height ~ b0 + b1 * age + b2 * q(age, 15, 1), data = children,
  start = list(b0 = 0, b1 = 0, b2 = 0))
summary(m)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t)
b0	84.886	0.80646	105.26	0.00e+00
b1	5.320	0.06612	80.46	0.00e+00
b2	-4.172	0.21769	-19.16	1.78e-76

Next we can use the estimates of β_0 , β_1 , and β_2 as starting values in a nonlinear model.

```
m <- nls(height ~ b0 + b1 * age + b2 * q(age, delta, gamma), data = children,
  start = list(b0 = 85, b1 = 5.3, b2 = -5, delta = 15, gamma = 1))
summary(m)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t)
b0	85.898	0.95916	89.555	0.000e+00
b1	5.217	0.08468	61.613	0.000e+00
b2	-5.239	0.68653	-7.631	3.297e-14
delta	15.662	0.27560	56.828	0.000e+00
gamma	1.483	0.51344	2.889	3.897e-03

The slope after the bend is $\beta_1 + \beta_2$, but if $\beta_2 = -\beta_1$ then the slope after the bend would be zero. This model would then be

$$E(Y) = \beta_0 + \beta_1 x - \beta_1 q(x, \delta, \gamma).$$

Let's consider using this model but now with a separate growth curve for males and females.

```
m <- nls(height ~ case_when(
  sex == "male" ~ b0m + b1m*age - b1m*q(age, deltam, gammam),
  sex == "female" ~ b0f + b1f*age - b1f*q(age, deltaf, gammaf)),
  data = children, start = list(b0m = 86, b0f = 86, b1m = 5, b1f = 5,
  deltam = 15, deltaf = 15, gammam = 1.5, gammaf = 1.5))
summary(m)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t)
b0m	79.5271	1.04815	75.874	0.000e+00
b0f	86.2213	1.65345	52.146	0.000e+00
b1m	5.6137	0.08511	65.959	0.000e+00
b1f	5.4542	0.16443	33.171	3.665e-200
deltam	16.3983	0.12218	134.209	0.000e+00
deltaf	14.1533	0.14833	95.416	0.000e+00
gammam	0.8673	0.49692	1.745	8.105e-02
gammaf	1.9069	0.43727	4.361	1.348e-05

```
d <- expand.grid(sex = c("male", "female"), age = seq(5, 20, length = 200))
d$yhat <- predict(m, newdata = d)
```

```
p <- ggplot(children, aes(x = age, y = height, color = sex)) +
  geom_point(alpha = 0.125) + theme_minimal() +
```

```
geom_line(aes(y = yhat), data = d) +
  labs(x = "Age (years)", y = "Height (cm)", color = "Gender") +
  theme(legend.position = c(0.9,0.2))
plot(p)
```

