Friday, Jan 12

Linear Models

The regression model
$$E(Y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k,$$
is a *linear model* because it is a *linear function*. But a linear model is *linear in the parameters* (i.e., $\beta_0, \beta_1, \ldots, \beta_k$) but not necessarily *linear in the explanatory variables* (i.e., $x_1, x_2, \ldots, x_k$). For example, the following are all *linear models* even though $E(Y)$ is not a linear function of the explanatory variable(s):
$$E(Y) = \beta_0 + \beta_1 \log(x), \quad E(Y) = \beta_0 + \beta_1 x + \beta_2 x^2, \quad E(Y) = \beta_1 x_1 x_2.$$
Note that in some cases β_0 can be omitted (or, equivalently, fixed as $\beta_0 = 0$).

Why is there so much focus on *linear* models in statistics?

1. Easier to interpret.
2. Can sometimes approximate more complex functions.
3. Sufficient for categorical explanatory variables.
4. Inferential theory is simpler.
5. Computational tractability.
6. Didactic value.

So, we will start with linear models, but will certainly cover a variety of non-linear models.

Parameter Interpretation (Quantitative Explanatory Variables)

In the linear model
$$E(Y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k,$$
the parameter β_j (for $j > 0$) represents the *rate of change* in $E(Y)$ with respect to x_j *assuming all other x_j are held constant*.

Example: Assume that
$$E(Y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2.$$
If x_1 is increased to $x_1 + 1$, then
$$\beta_0 + \beta_1(x_1 + 1) + \beta_2 x_2 = \underbrace{\beta_0 + \beta_1 x_1 + \beta_2 x_2}_{E(Y)} + \beta_1 = E(Y) + \beta_1,$$
meaning that $E(Y)$ changes by β_1 if x_1 increases one unit. Note that in this interpretation it is assumed that x_2 *does not change* when x_1 changes, so β_1 does not have the same interpretation in $E(Y) = \beta_0 + \beta_1 x_1$ unless x_1 and x_2 are not correlated (e.g., if x_1 represents a randomized treatment). Also we are not necessarily assuming that this is a *causal* relationship in the sense that changing x_1 *causes* a change in $E(Y)$.

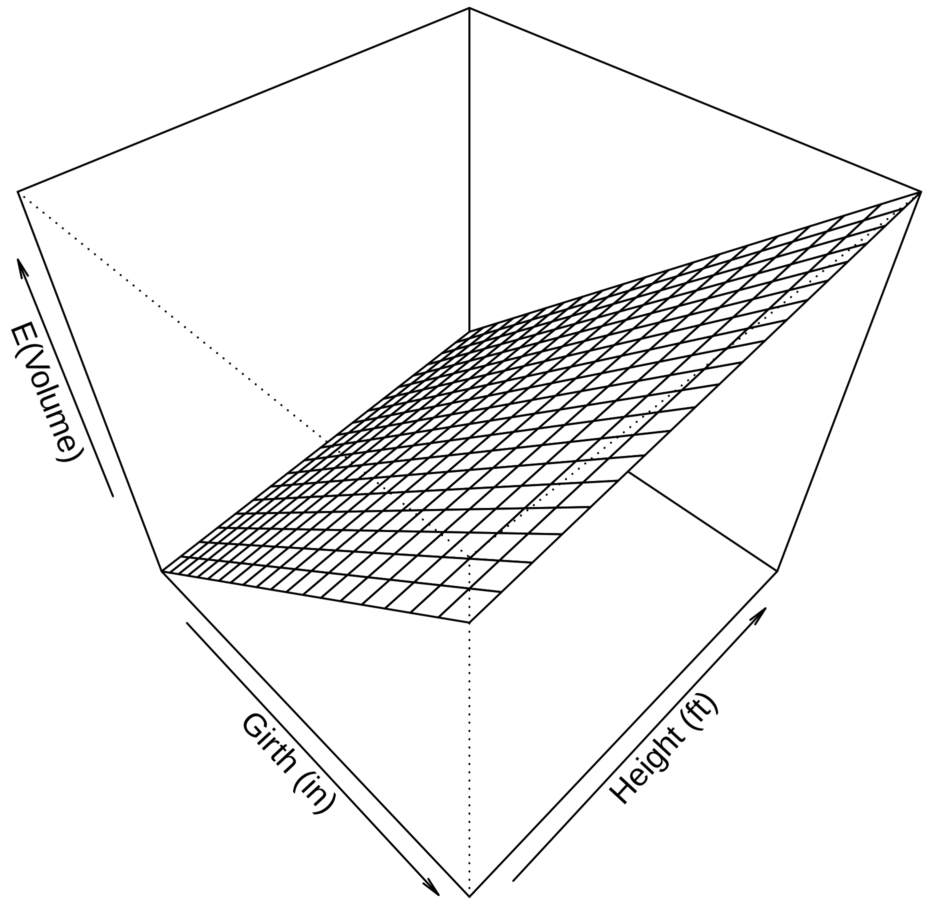
Note: From calculus we note that β_j is the partial derivative of $E(Y)$ with respect to x_j,
$$\frac{\partial E(Y)}{\partial x_j} = \beta_j,$$

which shows that the rate of change of $E(Y)$ with respect to x_j is *constant*.

Example: Suppose we have the model

$$E(V) = -57.99 + 0.34h + 4.71g,$$

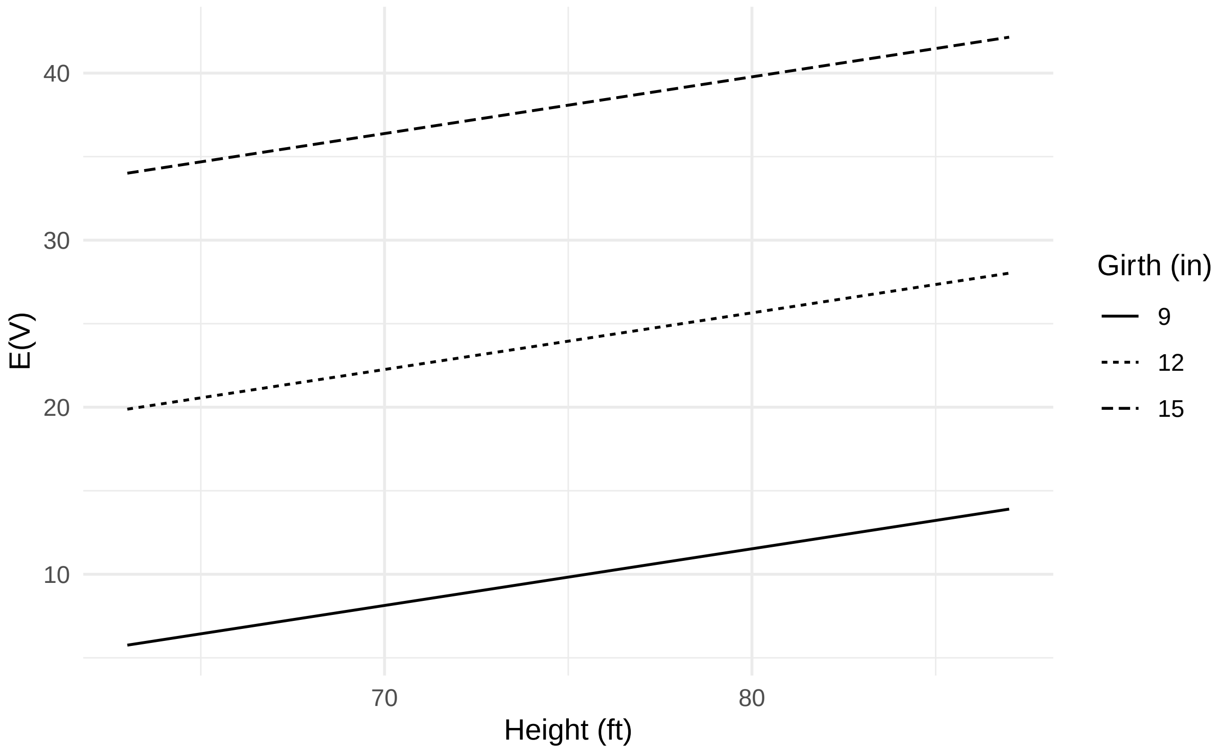
where V represents tree volume (in cubic feet), and g and h denote tree girth (in) and height (ft), respectively. If we were to plot $E(V)$ as a function of both h and g then it would form a *plane*.



But three-dimensional plots can be difficult to read, and higher-dimensional plots are not practical. But consider that we can still make a two-dimensional plot of we express $E(V)$ as a function of one explanatory variable *while holding the other explanatory variable(s) constant*. For example, we can write $E(V)$ as a function of only h *for some chosen value of* g as

$$E(V) = \underbrace{(-57.99 + 4.71g)}_{\text{constant}} + 0.34h.$$

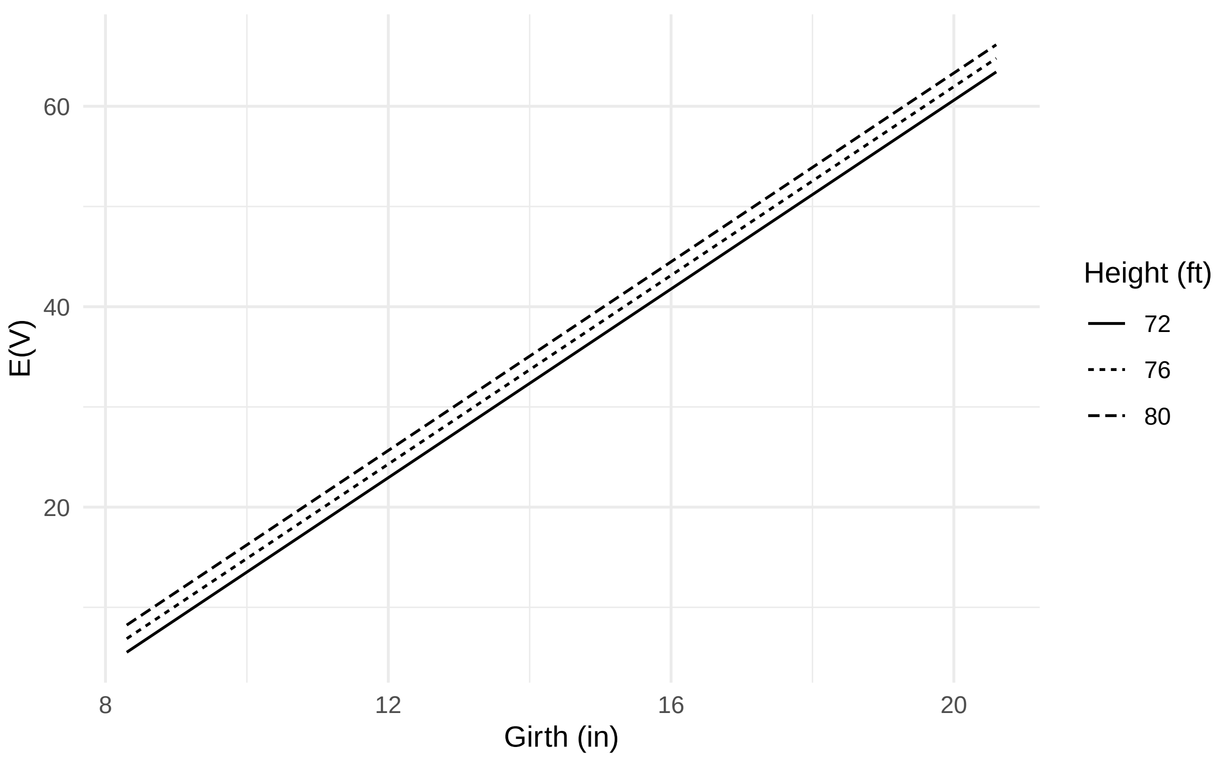
Here I have set g equal to 9, 12, and 15 to plot $E(V)$ as a function of h.



Similarly we can write $E(V)$ as a function of only g *for some chosen value of* h as

$$E(V) = \underbrace{(-57.99 + 0.34h)}_{\text{constant}} + 4.71g.$$

Here I have set h equal to 72, 76, and 80 to plot $E(V)$ as a function of g.



Note that in both cases the *rate of change* of $E(V)$ with respect to one explanatory variable *does not depend on the value of itself or another variable.*

Example: Suppose we have

$$E(Y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2,$$

where $x_1 = x$ and $x_2 = x^2$ so that we can also write the model as

$$E(Y) = \beta_0 + \beta_1 x + \beta x^2.$$

Then if we increase x by one unit to $x + 1$ we have the change in the expected response of

$$\beta_0 + \beta_1(x + 1) + \beta_2(x + 1)^2 - [\beta_0 + \beta_1 x + \beta_2 x^2] = \beta_1 + \beta_2(2x + 1),$$

so the change depends on x. So the change in the expected response *depends on the value of* x.

Example: Suppose we have

$$E(Y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3,$$

where $x_3 = x_1 x_2$. Then if we increase x_1 by one unit we have a change in the expected response of

$$\beta_0 + \beta_1(x_1 + 1) + \beta_2 x_2 + \beta_3(x_1 + 1)x_2 - [\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2] = \beta_1 + \beta_3 x_2.$$

So the change in the expected response if we increase x_1 *depends on the value of* x_2.

Example: Suppose we have

$$E(Y) = \beta_0 + \beta_1 \log_2(x),$$

where $\log_2$ is the base-2 logarithm. Here β_1 is the change in $E(Y)$ if we increase $\log_2(x)$ by one unit, not x. If we increase x by one unit we have a change in the expected response of

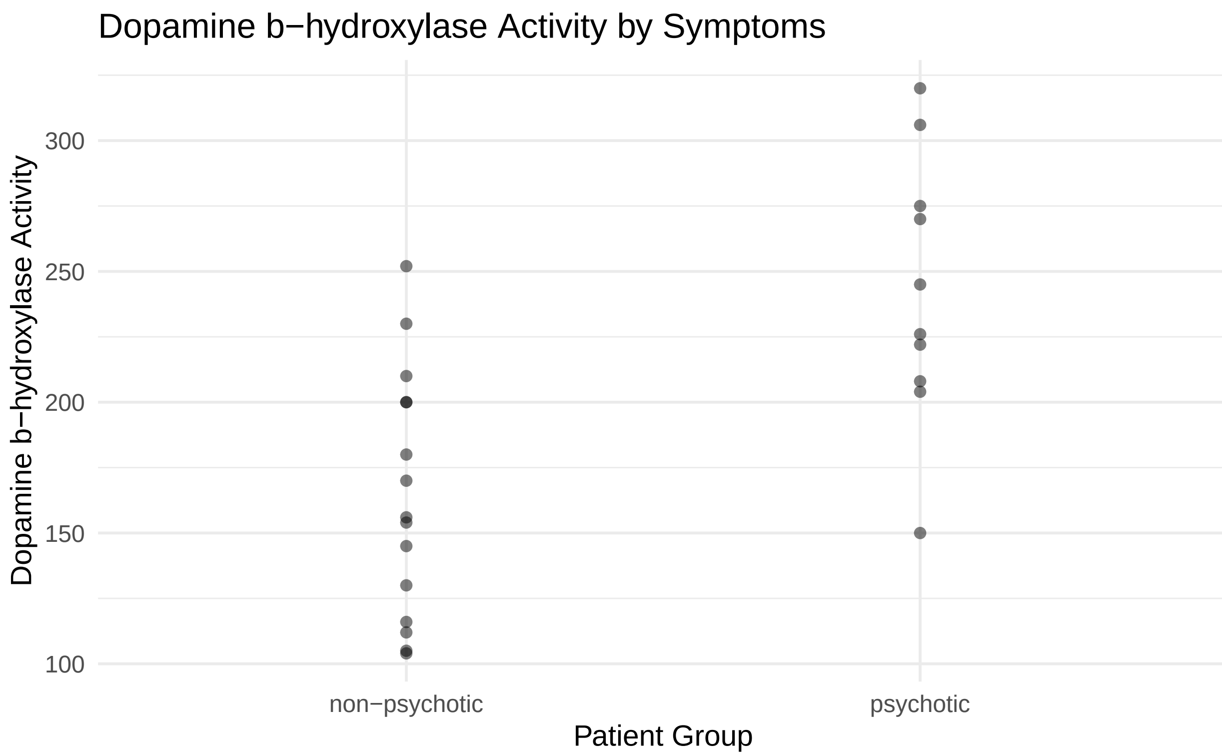
$$\beta_0 + \beta_1 \log_2(x + 1) - [\beta_0 + \beta_1 \log_2(x)] = \log_2(x + 1) - \log_2(x),$$

or $\log_2(1 - 1/x)$ if $x > 0$. So the change in the expected response if we increase x by one unit *depends on the value of* x. But it can be shown that β_1 is the change in $E(Y)$ if we *double* x. We'll discuss log transformations later in the course.

Indicator Variables and Parameter Interpretation

Indicator (or "dummy") variables can be used when an explanatory variable is *categorical*.

Example: Consider the following data from an observational study comparing the dopamine b-hydroxylase activity of schizophrenic patients that had been classified as non-psychotic or psychotic after treatment.



Note: In an introductory statistics course, a so-called "population mean" (μ) is what we would call an expected value so that $E(Y) = \mu$.

Consider two hypothetical population means:

$$\mu_p = \text{expected activity of psychotic patients}$$
$$\mu_n = \text{expected activity of non-psychotic patients}$$

Inferences might consider three quantities:

1. μ_p (expected activity for a psychotic patient)
2. μ_n (expected activity for a non-psychotic patient)
3. $\mu_p - \mu_n$ (difference in expected activity between psychotic and non-psychotic patients)

Let x_i be an *indicator variable* for *psychotic* schizophrenics such that

$$x_i = \begin{cases} 1, & \text{if the } i\text{-th subject is psychotic,} \\ 0, & \text{otherwise.} \end{cases}$$

Then if we specify the model $E(Y_i) = \beta_0 + \beta_1 x_i$, where Y_i is the dopamine activity of the i-th subject, we can also write the model *case-wise* as

$$E(Y_i) = \begin{cases} \beta_0 + \beta_1, & \text{if the } i\text{-th subject is psychotic,} \\ \beta_0, & \text{if the } i\text{-th subject is non-psychotic.} \end{cases}$$

Thus the quantities of interest are *functions* of β_0 and β_1:

1. $\mu_p = \beta_0 + \beta_1$
2. $\mu_n = \beta_0$
3. $\mu_p - \mu_n = \beta_1$

The interpretion of the model parameters depends on how we define our indicator variable (i.e., the *parameterization* of the model). If instead we defined x_i as

$$x_i = \begin{cases} 1, & \text{if the } i\text{-th subject is non-psychotic,} \\ 0, & \text{otherwise,} \end{cases}$$

then

$$E(Y_i) = \begin{cases} \beta_0 + \beta_1, & \text{if the } i\text{-th subject is non-psychotic,} \\ \beta_0, & \text{if the } i\text{-th subject is psychotic.} \end{cases}$$

and the quantities of interest become

1. $\mu_p = \beta_0$
2. $\mu_n = \beta_0 + \beta_1$
3. $\mu_p - \mu_n = -\beta_1$

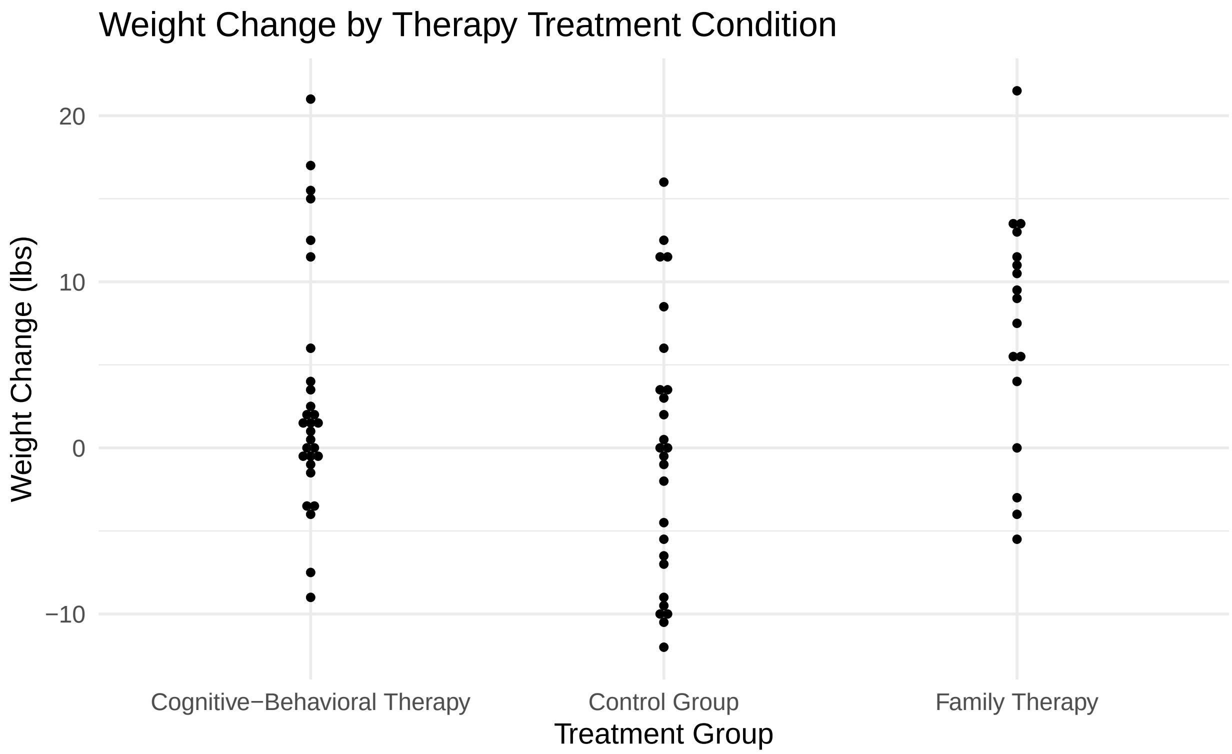
Note: Usually, if we have a categorical explanatory variable with k levels, we need $k - 1$ indicator variables. This is true if β_0 is in the model. But suppose we define

$$x_{i1} = \begin{cases} 1, & \text{if the } i\text{-th subject is psychotic,} \\ 0, & \text{otherwise,} \end{cases}$$

$$x_{i2} = \begin{cases} 1, & \text{if the } i\text{-th subject is non-psychotic,} \\ 0, & \text{otherwise,} \end{cases}$$

and we use the model $E(Y_i) = \beta_1 x_{i1} + \beta_2 x_{i2}$. How are β_1 and β_2 related to μ_p, μ_n, and $\mu_p - \mu_n$?

Example: Consider the following data from a randomized experiment that examined the weight change between before and after therapy for subjects with anorexia.



Let Y_i denote weight change in the i-th subject. Each subject was assigned at random to one of three therapies for anorexia: *control*, *cognitive-behavioral*, or *family therapy*. Suppose we define x_{i1} and x_{i2} as

$$x_{i1} = \begin{cases} 1, & \text{if } i\text{-th subject received cognitive-behavioral therapy,} \\ 0, & \text{otherwise,} \end{cases}$$

and

$$x_{i2} = \begin{cases} 1, & \text{if } i\text{-th subject received family therapy,} \\ 0, & \text{otherwise.} \end{cases}$$

Then if we specify the model

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

we we can also write the model *case-wise* as

$$E(Y_i) = \begin{cases} \beta_0, & \text{if the } i\text{-th subject is in the control group,} \\ \beta_0 + \beta_1, & \text{if the } i\text{-th subject received CBT,} \\ \beta_0 + \beta_2, & \text{if the } i\text{-th subject received FT.} \end{cases}$$

What then might be some quantities of interest (in terms of $\beta_0, \beta_1, \beta_2$)?