Wednesday, Jan 18

Example: The *data frame* trees comes with R. We can see it if we just type trees at the prompt in the R console.

trees

	Girth	Height	Volume
1	8.3	70	10.3
2	8.6	65	10.3
3	8.8	63	10.2
4	10.5	72	16.4
5	10.7	81	18.8
6	10.8	83	19.7
7	11.0	66	15.6
8	11.0	75	18.2
9	11.1	80	22.6
10	11.2	75	19.9
11	11.3	79	24.2
12	11.4	76	21.0
13	11.4	76	21.4
14	11.7	69	21.3
15	12.0	75	19.1
16	12.9	74	22.2
17	12.9	85	33.8
18	13.3	86	27.4
19	13.7	71	25.7
20	13.8	64	24.9
21	14.0	78	34.5
22	14.2	80	31.7
23	14.5	74	36.3
24	16.0	72	38.3
25	16.3	77	42.6
26	17.3	81	55.4
27	17.5	82	55.7
28	17.9	80	58.3
29	18.0	80	51.5
30	18.0	80	51.0
31	20.6	87	77.0

Let's specify the model

$$E(V_i) = \beta_0 + \beta_1 g_i + \beta_2 h_i,$$

where V_i , g_i , and h_i are the volume, girth, and height from the *i*-th observation.

```
m <- lm(formula = Volume ~ Girth + Height, data = trees)
```

There's a lot to say here.

1. lm is a function to which we have provided two arguments: formula and data. Other arguments can be found using args(lm), some of which we will use later.

```
args(lm)
```

```
function (formula, data, subset, weights, na.action, method = "qr",
    model = TRUE, x = FALSE, y = FALSE, qr = TRUE, singular.ok = TRUE,
    contrasts = NULL, offset, ...)
```

We do not need to name the arguments if we provide them in the same order as they are expected. For example, this would also work:

```
m <- lm(Volume ~ Girth + Height, trees)
```

Just about all functions that estimate a regression model expect formula to be the first argument. A common convention (and one that I use) is to name all arguments except the first:

```
m <- lm(Volume ~ Girth + Height, data = trees)
```

- 2. The formula argument is *symbolic*, not literal. It is a system for communicating with R the regression model you want to specify. The model formula Volume ~ Girth + Height implies the statistical model $E(V_i) = \beta_0 + \beta_1 g_i + \beta_2 h_i$.
- 3. We have assigned the output of this function to an object called m (R is an object-oriented programming language). Note that you can also use = instead of <-. We can apply other functions to this object. For example, print(m).

```
print(m)
```

Call:

```
lm(formula = Volume ~ Girth + Height, data = trees)
```

Coefficients:

```
(Intercept) Girth Height
-57.9877 4.7082 0.3393
```

But if you just have m it will interpret that as print(m).

m

Call:

```
lm(formula = Volume ~ Girth + Height, data = trees)
```

Coefficients:

```
(Intercept) Girth Height -57.9877 4.7082 0.3393
```

A bit more information can be extracted by using the summary function.

```
summary(m)
```

Call:

```
lm(formula = Volume ~ Girth + Height, data = trees)
```

Residuals:

```
Min 1Q Median 3Q Max
-6.4065 -2.6493 -0.2876 2.2003 8.4847
```

Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) -57.9877
                        8.6382 -6.713 2.75e-07 ***
Girth
              4.7082
                        0.2643 17.816 < 2e-16 ***
Height
              0.3393
                        0.1302
                                 2.607
                                         0.0145 *
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 3.882 on 28 degrees of freedom
Multiple R-squared: 0.948,
                             Adjusted R-squared: 0.9442
F-statistic:
              255 on 2 and 28 DF, p-value: < 2.2e-16
```

In lecture I will often trim the output from summary using something like the following.

summary(m)\$coefficients

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) -57.9876589 8.6382259 -6.712913 2.749507e-07
Girth 4.7081605 0.2642646 17.816084 8.223304e-17
Height 0.3392512 0.1301512 2.606594 1.449097e-02
```

This shows estimates of the parameters β_0 , β_1 , and β_2 , and some other information concerning inferences for those parameters (more on that later).

Example: Here are the data and a specified linear model for the study on dopamine activity in schizophrenics. The data are available in the **BSDA** package.

```
library(BSDA) # install with install.packages("BSDA")
Dopamine
```

```
# A tibble: 25 \times 2
     dbh group
   <int> <chr>
     104 nonpsychotic
 1
     105 nonpsychotic
 3
     112 nonpsychotic
 4
     116 nonpsychotic
 5
     130 nonpsychotic
 6
     145 nonpsychotic
 7
     154 nonpsychotic
8
     156 nonpsychotic
9
     170 nonpsychotic
     180 nonpsychotic
10
# ... with 15 more rows
```

head(Dopamine)

```
# A tibble: 6 x 2
    dbh group
    <int> <chr>
1    104 nonpsychotic
2    105 nonpsychotic
3    112 nonpsychotic
4    116 nonpsychotic
5    130 nonpsychotic
6    145 nonpsychotic
```

tail(Dopamine)

```
# A tibble: 6 x 2
    dbh group
    <int> <chr>
1    226 psychotic
2    245 psychotic
3    270 psychotic
4    275 psychotic
5    306 psychotic
6    320 psychotic
```

Also you can try ?Dopamine or help(Dopamine) to see the help file (you can also do this for functions like lm). A tibble is another way that data are stored in R that is mostly interchangeable with data frames (they are effectively "enhanced" data frames).

Let's specify a linear model using the 1m function.

```
m <- lm(dbh ~ group, data = Dopamine)
summary(m)$coefficients</pre>
```

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) 164.26667 12.58563 13.051923 4.058662e-12
grouppsychotic 78.33333 19.89963 3.936422 6.586761e-04
```

Note: The grouppsychotic tells us that an indicator variable was created for the level/category psychotic for the categorical variable group. How would we write this model mathematically?

Example: Here are the data from the anorexia study.

```
library(MASS) # install with install.packages("MASS")
head(anorexia)
```

```
Treat Prewt Postwt
1 Cont 80.7 80.2
2 Cont 89.4 80.1
3 Cont 91.8 86.4
4 Cont 74.0 86.3
5 Cont 78.1 76.1
```

6 Cont 88.3 78.1

summary(anorexia)

```
Treat
                              Postwt
              Prewt
CBT : 29
          Min.
                 :70.00
                          Min. : 71.30
          1st Qu.:79.60
Cont:26
                          1st Qu.: 79.33
FT :17
          Median :82.30
                          Median: 84.05
          Mean
                 :82.41
                          Mean
                                 : 85.17
                          3rd Qu.: 91.55
          3rd Qu.:86.00
          Max.
                 :94.90
                          Max.
                                 :103.60
```

Here we are going to create another variable change which is the change in weight. (Note: I redefined change from the original lecture as the post-weight minus the pre-weight so that a positive value indicates weight gain and a negative value indicates weight loss.)

```
anorexia$change <- anorexia$Postwt - anorexia$Prewt
head(anorexia)</pre>
```

```
Treat Prewt Postwt change
1 Cont 80.7
               80.2
                     -0.5
2 Cont 89.4
               80.1
                     -9.3
3 Cont 91.8
               86.4
                     -5.4
4 Cont 74.0
               86.3
                     12.3
5 Cont 78.1
               76.1
                     -2.0
6 Cont 88.3
               78.1 -10.2
```

Let's specify a linear model.

```
m <- lm(change ~ Treat, data = anorexia)
summary(m)$coefficients</pre>
```

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.006897 1.397996 2.150861 0.03499197
TreatCont -3.456897 2.033297 -1.700144 0.09360765
TreatFT 4.257809 2.299644 1.851508 0.06837576
```

What are the indicator variables? How would we write this model mathematically?

We can change the parameterization using relevel.

```
anorexia$Treat <- relevel(anorexia$Treat, ref = "Cont")
m <- lm(change ~ Treat, data = anorexia)
summary(m)$coefficients</pre>
```

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.450000 1.476449 -0.3047854 0.761447048
```

```
TreatCBT 3.456897 2.033297 1.7001438 0.093607652
TreatFT 7.714706 2.348163 3.2854224 0.001602338
```

What are the indicator variables? How would we write this model mathematically?

Note: We can change the parameterization for the model for the previous example, but we need to make group a *factor* because the relevel function will only work on variables that are factors (although the function 1m automatically converts a character variable to a factor). We can see that it is not a factor (yet) from summary and also from the is.factor function.

summary(Dopamine)

```
dbh group
Min. :104.0 Length:25
1st Qu.:150.0 Class :character
Median :200.0 Mode :character
Mean :195.6
3rd Qu.:230.0
Max. :320.0
is.factor(Dopamine$group)
```

[1] FALSE

Here's what happens if you try to use relevel with the group variable.

```
Dopamine$group <- relevel(Dopamine$group, ref = "psychotic")</pre>
```

Error in relevel.default(Dopamine\$group, ref = "psychotic"): 'relevel' only for (unordered) factors Let's make group a factor and then change the parameterization.

```
Dopamine$group <- factor(Dopamine$group)
Dopamine$group <- relevel(Dopamine$group, ref = "psychotic")</pre>
```

Note that we could also have done this with one line of code.

```
Dopamine$group <- relevel(factor(Dopamine$group), ref = "psychotic")</pre>
```

Here's the reparameterized model.

```
m <- lm(dbh ~ group, data = Dopamine)
summary(m)$coefficients</pre>
```

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) 242.60000 15.41419 15.738750 8.320341e-14
groupnonpsychotic -78.33333 19.89963 -3.936422 6.586761e-04
```

What is this model?

Here's another parameterization. Including the term -1 in the model formula argument suppresses the inclusion of the β_0 parameter (again, it is symbolic, not literal).¹

```
m <- lm(dbh ~ -1 + group, data = Dopamine)
summary(m)$coefficients</pre>
```

```
Estimate Std. Error t value Pr(>|t|) grouppsychotic 242.6000 15.41419 15.73875 8.320341e-14 groupnonpsychotic 164.2667 12.58563 13.05192 4.058662e-12
```

Let's try that with the anorexia data.

```
m <- lm(change ~ -1 + Treat, data = anorexia)
summary(m)$coefficients</pre>
```

```
Estimate Std. Error t value Pr(>|t|)
TreatCont -0.450000 1.476449 -0.3047854 0.7614470484
TreatCBT 3.006897 1.397996 2.1508614 0.0349919664
TreatFT 7.264706 1.825915 3.9786656 0.0001687833
```

What are these models?

Example: Sometimes we may also want so basic descriptive statistics. There are *many* ways to do this in R. One flexible approach is to use the **dplyr** package.

```
library(dplyr) # install with install.packages("dplyr") or install.packages("tidyverse")

Dopamine %>% group_by(group) %>% summarize(dbh = mean(dbh))
```

A tibble: 3 x 4

Treat meanchange sdchange samplesize <dbl> <dbl> <int> <fct> 0.450 7.99 26 1 Cont 2 CBT -3.0129 7.31 17 3 FT -7.267.16

¹When we say something like dbh ~ group this is actually translated as dbh ~ 1 + group where the "explanatory variable" of 1 effectively becomes the term β_0 . Including this term is the default even if we do not mention it explicitly. But if we do not want it then we "add" -1 to the model formula to remove it.

The **dplyr** and **tidyr** packages are very useful for manipulating and summarizing data. They have a bit of a learning curve, but they are well worth learning. I will provide many examples of how they can be used.