Creating Models for Research

Last time we saw there were two questions in evluating our model

- 1. Is there evidence of at least one non-zero (0) coefficient?
- 2. Is there also evidence that each individual coefficient is non-zero?

With the advertising data we saw the answer to the first question was yes, but the second was not a yes for every variable.

Let's revisit this data. Recall, we have data from a hypothetical company's advertising spending and sales for the last three years. The variables are TV, Radio, and Newspaper which are the amount spent on the respective ads in thousands of dollars. The final variable is Sales which is that month's sales in units.

Download the data and import it to RStudio. ($https://raw.githubusercontent.com/moravian-mspa/MGMT555/master/m5_Tutorial_FitandEffect/Advertising.csv)$

```
library(tidyverse)
Advertising <- read_csv("Advertising.csv");
Parsed with column specification:
cols(
  Month = col_double(),
  TV = col_double(),
  Radio = col double(),
  Newspaper = col_double(),
  Sales = col_double()
attach(Advertising)
head(Advertising)
# A tibble: 6 x 5
  Month
            TV Radio Newspaper Sales
  <dbl> <dbl> <dbl>
                          <dbl> <dbl>
      1 230.
                37.8
                           69.2
                                   663
1
2
      2 44.5 39.3
                           45.1
                                   312
3
      3 17.2 45.9
                           69.3
                                   279
      4 152.
4
                41.3
                           58.5
                                   555
5
      5 181.
                10.8
                           58.4
                                   387
          8.7 48.9
                           75
                                   216
We create a model of the form:
\mathtt{Sales} = b_0 + b_1 \mathtt{TV} + b_2 \mathtt{Newspaper} + b_3 \mathtt{Radio}
summary(lm(Sales ~ TV + Newspaper + Radio))
Call:
lm(formula = Sales ~ TV + Newspaper + Radio)
Residuals:
    Min
              1Q Median
                                3Q
-147.90 -27.41
                   16.41
                            37.81
                                     74.63
Coefficients:
```

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) 104.9599
                        24.7455
                                 4.242 0.000177 ***
                         0.1038 12.390 9.39e-14 ***
TV
             1.2859
            -0.3562
                         0.4958
                                -0.718 0.477686
Newspaper
Radio
             5.6130
                         0.8516
                                 6.591 1.98e-07 ***
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
Residual standard error: 55.14 on 32 degrees of freedom
Multiple R-squared: 0.8687,
                               Adjusted R-squared: 0.8564
F-statistic: 70.56 on 3 and 32 DF, p-value: 3.38e-14
```

At this point we saw that the model was significant, but the variable Newspaper was not significant. Let's try another model without that variable.

```
summary(lm(Sales ~ TV + Radio))
```

```
Call:
lm(formula = Sales ~ TV + Radio)
```

Residuals:

```
Min 1Q Median 3Q Max
-149.53 -28.00 13.35 41.02 69.98
```

Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) 99.2844 23.2781 4.265 0.000158 ***

TV 1.3002 0.1011 12.859 2.11e-14 ***

Radio 5.2133 0.6401 8.145 2.11e-09 ***
---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 54.73 on 33 degrees of freedom
Multiple R-squared: 0.8666, Adjusted R-squared: 0.8585
F-statistic: 107.2 on 2 and 33 DF, p-value: 3.689e-15
```

Notice our adjusted- R^2 decreased slightly, but the overall p-value is smaller and the coefficients on each of the other variables changed slightly. We are more confident in these numbers.

Backward Elimination

The process we just used is called backward elimination. Here's how it works.

- 1. Create a model with all the predictor variables that could reasonably be included.
- 2. Find the variable with the largest p-value. If it is larger than our threshold (we will use 0.05) then that variable is eliminated from our model.
- 3. Create a new model with the remaining variables and repeat until all remaining variables have p-values less than the threshold.

In fact there are several techniques that could be used to decide on which predictors are most appropriate to keep, but we will focus on using backward elimination.

Another example

Imagine an antique clock dealer has collected data on recent auctions of grandfather clocks. The variables are Price: final selling price, Bidders: the number of bidders, Age: the age of the clock, Temp: the outside temperature the day of the auction.

```
clocks <- read_csv("auction.csv");</pre>
Parsed with column specification:
cols(
  Age = col_double(),
  Bidders = col_double(),
  Price = col_double(),
  Temp = col_double()
Let's check the correlations of these variables.
cor(clocks)
                         Bidders
                Age
                                       Price
                                                     Temp
         1.00000000 -0.25374910
                                  0.73023321 -0.02776564
Age
Bidders -0.25374910 1.00000000
                                  0.39464036 -0.03929614
         0.73023321  0.39464036  1.00000000  -0.09977079
Price
Temp
        -0.02776564 -0.03929614 -0.09977079 1.00000000
We are most interested in what correlates well with Price. It looks like Temp has the least correlation.
We can create a model with all these variables.
summary(lm(clocks$Price ~ clocks$Bidders + clocks$Age + clocks$Temp))
Call:
lm(formula = clocks$Price ~ clocks$Bidders + clocks$Age + clocks$Temp)
Residuals:
     Min
               10
                    Median
                                  30
-177.585 -119.716
                    -0.102
                              91.672 232.665
Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)
               -1245.7241
                             205.7941 -6.053 1.59e-06 ***
clocks$Bidders
                  85.4659
                               8.7625
                                        9.754 1.66e-10 ***
clocks$Age
                  12.7067
                               0.9079 13.996 3.64e-14 ***
clocks$Temp
                  -1.2855
                               1.5459 -0.832
                                                  0.413
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Residual standard error: 133.9 on 28 degrees of freedom
Multiple R-squared: 0.8953,
                                 Adjusted R-squared: 0.8841
F-statistic: 79.81 on 3 and 28 DF, p-value: 7.833e-14
As we suspected, the outside temperature is the least significant, so we will remove it.
summary(lm(clocks$Price ~ clocks$Bidders + clocks$Age ))
```

Call:

lm(formula = clocks\$Price ~ clocks\$Bidders + clocks\$Age)

Residuals:

Min 1Q Median 3Q Max -207.2 -117.8 16.5 102.7 213.5

Coefficients:

clocks\$Age

Estimate Std. Error t value Pr(>|t|)
(Intercept) -1336.7221 173.3561 -7.711 1.67e-08 ***
clocks\$Bidders 85.8151 8.7058 9.857 9.14e-11 ***

Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1

0.9024 14.114 1.60e-14 ***

Residual standard error: 133.1 on 29 degrees of freedom Multiple R-squared: 0.8927, Adjusted R-squared: 0.8853 F-statistic: 120.7 on 2 and 29 DF, p-value: 8.769e-15

Every variable is significant, so we are done.

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