In this section we'll explore basic hypothesis testing in R, along with learning a bit about some elements that make a well-coded function. After adding our trusty auto.dta dataset to the package we made last week, we'll work through calculating t and F-statistics.

Last section

Hopefully you're now comfortable using a package to store your functions nicely. One thing I think I got wrong last week was what the LazyData field in the DESCRIPTION file does. If we specify LazyData: TRUE, R will load any package specific datasets when the library() function is called. If we specify LazyData: FALSE, we would have to manually load any datasets using the data() function.

Because we're going to use it again, let's add the auto.dta dataset to our respective packages. To start, open your package project in RStudio and add a folder called data to the package folder. Next, call the following from the package directory.

```
library(foreign)
auto <- read.dta("<path to>/auto.dta")
names(auto) <- c("price", "mpg", "weight")
save(auto, file = "data/auto.rda")</pre>
```

Now, make sure you have the LazyData: TRUE field specified in your DESCRIPTION file, and rebuild your package. You've now added the auto dataset to your package! It will be loaded each time you call your package with library().

Calculating *t*-tests and *F*-tests

First, a basic overview in conducting t and F-tests. We've got a lot of what we need already in our package. Let's start by calling it into the R-environment.

```
library(misc212)
```

Remember, this contains our OLS() function and the auto data.frame, which we'll use soon. For reference, consider the regression output from lm():

```
results <- lm(price ~ 1 + mpg + weight, data = auto)
coef(summary(results))
##
                  Estimate
                             Std. Error
                                                       Pr(>|t|)
                                           t value
## (Intercept) 1946.068668 3597.0495988 0.5410180 0.590188628
## mpg
                -49.512221
                             86.1560389 -0.5746808 0.567323727
## weight
                  1.746559
                              0.6413538 2.7232382 0.008129813
summary(results)$fstatistic
##
      value
               numdf
                        dendf
## 14.73982 2.00000 71.00000
```

Now we'll run OLS and define some useful elements for hypothesis testing using the definitions in lecture notes:

```
X <- cbind(1, auto$mpg, auto$weight)
y <- auto$price
n <- NROW(X)
k <- NCOL(X)
b <- OLS(y, X)
e <- y - X %*% b
s2 <- t(e) %*% e/(n - k)
XpXinv <- solve(t(X) %*% X)
se <- sqrt(s2 * diag(XpXinv))</pre>
```

By the way, it's good practice to define intermediate variables like XpXinv, and s2. This can be useful for debugging and making your code more readable. For example, I could have defined se as

```
sqrt((t(y - X %*% b) %*% (y - X %*% b) / (n-k)) * diag(solve(t(X) %*% X)))
```

(or worse!), which would have been a nightmare to debug or understand.

There's a cool trick I recently learned in RStudio to turn code like this into functions. Ultimately, we'd like to turn this into a function of y and X, just like the OLS() function. Let's highlight the rows from n <- ... to se <- ... and hit Ctrl/Command + Alt + X. Name the function something appropriate. I named mine se. Cool huh?! The only modification I had to make was to add a return line.

We can now use the vector of standard errors to calculate our t and p values for the individual t-tests:

```
seResults <- se(y, X)
b <- OLS(y, X)
n <- NROW(X)
k <- NCOL(X)
t <- (b - 0) / seResults
p <- apply(t, 1, function(t) {2 * pt(-abs(t), df = (n - k))})</pre>
```

Great! We have replicated the t value and Pr(>|t|) columns of the canned output. Now let's try to replicate the full regression F-statistic.

This is a joint test of coefficient significance; are the coefficients jointly different from a zero vector? Note well that the "regression F-statistic" almost always refers to a test of joint significance of the coefficients on everything but the intercept. Max has a great description as to why the F test is different from two separate tests of significance. Going from the notation in the notes, we are testing joint significance by setting:

$$\mathbf{R} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad \mathbf{r} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$
 (1)

We will work from equation (2.81), which is fairly daunting, but, because r = 0, we can omit it:

$$F = \frac{(\mathbf{R}\mathbf{b})'[\mathbf{R}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{R}']^{-1}(\mathbf{R}\mathbf{b})/J}{s^2}$$
(2)

Let's start calculating:

```
R <- rbind(c(0, 1, 0), c(0, 0, 1))

J <- 2

RXXInvR <- solve(R %*% solve(t(X) %*% X) %*% t(R))

F <- t(R %*% b) %*% RXXInvR %*% (R %*% b) / (s2 * J)
```

It worked! This is, of course, one of the simplest possible F-tests we could conduct, but you can see how it would be easy to construct your own F-tests using this framework.

Let's turn this into a function. A good start might be:

```
FCalc <- function(R, J, b, s2, X) {
   RXXInvR <- solve(R %*% solve(t(X) %*% X) %*% t(R))
   F <- t(R %*% b) %*% RXXInvR %*% (R %*% b) / (s2 * J)
   F
}</pre>
```

which we could call with:

```
R <- rbind(c(0, 1, 0), c(0, 0, 1))
J <- 2
FCalc(R, J, b, s2, X)
## [,1]
## [1,] 14.73982</pre>
```

This gets the job done. But, it seems like it could be better. For a moment, let's just think about what I got right here. The first line has the right spacing between all the elements; I start the first piece of calculation on a new line and the last line is a lone '}'. The body of the function is indented with 2 spaces. All of this is consistent with normal R style. The only functions that don't need to conform to this style are short one line functions where the function body can also be put on the first line:

```
xSq <- function(x) x^2
xSq(3)
## [1] 9</pre>
```

Good practice is to use the minimum inputs to a function, to make its use easier. Let's do this with the FCalc() function:

¹See Google's style guide for more.

```
FCalc <- function(R, y, X) {
    n <- NROW(X)
    k <- NCOL(X)
    b <- OLS(y, X)
    e <- y - X %*% b
    s2 <- t(e) %*% e / (n - k)
    J <- NROW(R)
    RXXInvR <- solve(R %*% solve(t(X) %*% X) %*% t(R))
    F <- t(R %*% b) %*% RXXInvR %*% (R %*% b) / (s2 * J)
    F
}</pre>
```

We could also add a p-value and return the results as a list or data.frame. One thing we should add is a check that our R matrix is the correct size:

```
FCalc <- function(R, y, X) {
   if (NCOL(R) != NCOL(X)) {
      stop("Dimensions of R and X do not match")
   }
   n <- NROW(X)
   k <- NCOL(X)
   b <- OLS(y, X)
   e <- y - X %*% b
   s2 <- t(e) %*% e / (n - k)
   J <- NROW(R)
   RXXInvR <- solve(R %*% solve(t(X) %*% X) %*% t(R))
   F <- t(R %*% b) %*% RXXInvR %*% (R %*% b) / (s2 * J)
   F
}</pre>
```

This still isn't perfect, especially if we're worried about computational time.² We would likely use these functions something like this:

```
OLSResults <- OLS(y, X)
seResults <- se(y, X)
FResults <- FCalc(R, y, X)</pre>
```

Here, OLS() is called three times, once in each function, which is inefficient. A simple modification could be to give the results of the OLS() function as argument to the other functions. Nonetheless, many other lines of code are repeated in the se() and FCalc() functions. I'll leave it to you to work out a nice solution to this. As another exercise, you can extend the function to include the case where $r \neq 0$.

²This can be an issue if you are performing many simulations, or using very large data sets.

Puzzle

• Partitioned regression: Generate a 100×4 matrix X including a column of ones for the intercept. Additionally, generate a vector y according to the generating process:

$$y_i = 1 + x_{1i} + 2x_{2i} + 3x_{3i} + \varepsilon_i,$$

where $\varepsilon_i \sim N(0,1)$. Let Q be the first three columns of X and let N be the final column. In addition, let

$$\hat{\gamma}_1 = (Q'Q)^{-1}Q'y$$
 and $f = y - Q\hat{\gamma}_1$
 $\hat{\gamma}_2 = (Q'Q)^{-1}Q'N$ and $g = N - Q\hat{\gamma}_2$
 $\hat{\gamma}_3 = f \cdot g/||g||^2$ and $e = f - g\hat{\gamma}_3$

Show that $\hat{\beta} = [(\hat{\gamma}_1 - \hat{\gamma}_2 \hat{\gamma}_3) \quad \hat{\gamma}_3]$. Note that the total dimension of $\hat{\beta}$ is 4.