# Unit Test

**Thanks to Professor Gerard**

## Learning Objectives

- Assertions
- Unit Tests
- Chapter 12 from R Packages

## A Working Example

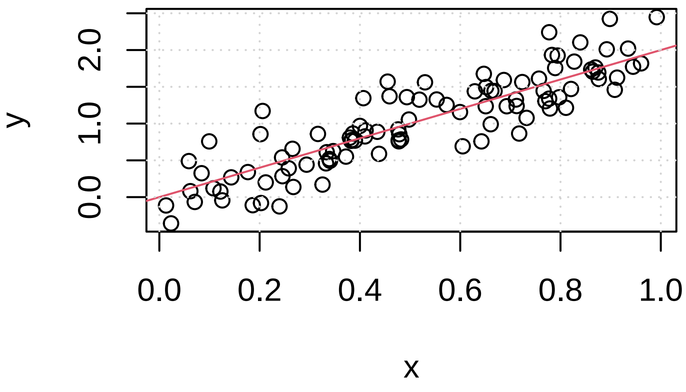
- For this lecture, let's suppose that we want to create a package to simulate data from the normal simple linear regression model.
- Recall that the normal simple linear regression model is of the form

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \tag{1}$$
$$\epsilon_i \sim N(0, \sigma^2) \tag{2}$$

- Here,
  - $Y_i$ is the value of the response variable for observation $i$.
  - $X_i$ is the value of the predictor variable for observation $i$.
  - $\beta_0$ is the $y$-intercept,
  - $\beta_1$ is the slope (values that are 1 $x$ larger tend to be $\beta_1$ $y$ larger, on average).
  - $\epsilon_i$ is the error for observation $i$. Assumed to be a random variable with a normal distribution with mean 0 and variance $\sigma^2$.
- If we had the $X_i$'s, $\beta_0$, $\beta_1$, $\sigma^2$, and the sample size $n$, then it would be easy to simulate under this model.

```r
n <- 100
sigma2 <- 0.1
beta0 <- 0
beta1 <- 2
x <- runif(n)
eps <- rnorm(n, mean = 0, sd = sqrt(sigma2))
y <- beta0 + beta1 * x + eps

plot(x, y)
abline(a = beta0, b = beta1, col = 2)
grid()
```



- There are many design considerations for simulating under this model:

  1. Do we simulate the $X$'s or do we obtain these values from the user? If we simulate them, how do we do this? Should we allow the user to do both?
  2. Do we simulate $\beta_0$ and $\beta_1$? Do we allow the user to input a distribution for these effect sizes?
  3. Do we simulate $\sigma^2$? This is often difficult for the user to choose, so maybe there is a more intuitive specification for it?

- Let's start with a basic function where we assume the user has provided everything. We'll expand on this later.

```r
#' @title Simulate SLR
#'
#' @description Simulate response values from the normal simple
#'     linear regression model.
#'
#' @param n The sample size
#' @param x The values of the predictor variable for the \code{n}
#'    individuals.
#' @param beta0 The y-intercept.
#' @param beta1 The slope.
#' @param sigma2 The error variance.
#'
#' @return A vector of length n. The values of the response variable.
#'
#' @author David Gerard
#'
#' @examples
#' n <- 100
#' x <- runif(n)
#' beta0 <- 0
#' beta1 <- 2
#' sigma2 <- 0.5
#' y <- simreg(n = n, x = x, beta0 = beta0, beta1 = beta1, sigma2 = sigma2)
#' plot(x, y)
#' abline(a = beta0, b = beta1)
simreg <- function(n, x, beta0, beta1, sigma2) {
  eps <- stats::rnorm(n = n, mean = 0, sd = sqrt(sigma2))
  y <- beta0 + beta1 * x + eps
  return(y)
}
```

## Assertions

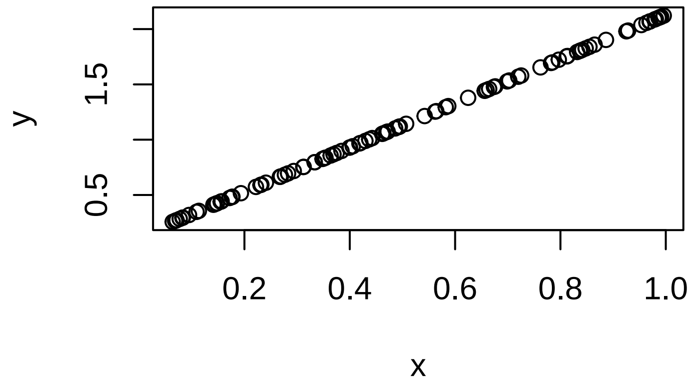
- One hallmark of good programming is to return an error as early as possible.
- For example, what if the user provided an incorrect input

```r
n <- 100
sigma2 <- 0.1
beta0 <- 0
```

```r
beta1 <- 2
x <- runif(n)
y <- simreg(n = 1, x = x, beta0 = beta0, beta1 = beta1, sigma2 = sigma2)
```

It ran OK, but there was no error even though `n = 100`. What gives? Let's look at a plot.

```r
plot(x, y)
```



So R is recycling the one error term that it simulated. It would be nice to catch this so tha

- An **assertion** is a statement during your code that should always evaluation to `TRUE`. If an assertion evaluates to `FALSE` then this throws an error.
- In R, the base assertion is `stopifnot()`.

```r
x <- 10
stopifnot(x == 10)
stopifnot(x > 20)
```

```
Error: x > 20 is not TRUE
```

- If you want to be more explicit about your errors, you can put `stop()` inside an if-then statement.

```r
if (x != 10) {
  stop("x is not 10")
}
```

- For user-facing functions, I like to check user arguments for validity in R.
  - Other languages force argument validity, but R, e.g., allows users to insert characters for numeric arguments!
- Let's try this out for `simreg()`.

```r
simreg <- function(n, x, beta0, beta1, sigma2) {
  ## Check input
  stopifnot(length(x) == n)

  ## Simulate y
  eps <- stats::rnorm(n = n, mean = 0, sd = sqrt(sigma2))
  y <- beta0 + beta1 * x + eps
  return(y)
}
```

- Then we get an error that tells us we made a mistake. This could save a user a huge amount of debugging time down the road.

```r
y <- simreg(n = 1, x = x, beta0 = beta0, beta1 = beta1, sigma2 = sigma2)
```

- If you just don't like the behavior, but don't want to kill the program, use `warning()`.

```r
simreg <- function(n, x, beta0, beta1, sigma2) {
  ## Check input
  if (length(x) != n) {
    warning("n not equal to length(x). Recycling error terms.")
  }

  ## Simulate y
  eps <- stats::rnorm(n = n, mean = 0, sd = sqrt(sigma2))
  y <- beta0 + beta1 * x + eps
  return(y)
}
y <- simreg(n = 1, x = x, beta0 = beta0, beta1 = beta1, sigma2 = sigma2)
```

- **Exercise**: Add assertions to check:

1. That `n`, `beta0`, `beta1`, and `sigma2` are all length 1.
2. That all of the variables are numerics.
3. That `sigma2` is non-negative.

- You should also place assertions in the middle of code (not just checking user inputs) in cases where you want to be doubly sure that your code is working.
- E.g. I often place an assertion during optimization scripts to make sure that the objective function is not decreasing each iteration.

## Unit Tests

- So far your work flow has been to iteratively:

1. Write a function.
2. Load the package into memory with `devtools::load_all()`
3. Play around with it, testing it on your own.

- This is great, but informal. If your code changes, those informal checks you ran might no longer work, and you wouldn't know.
- A **unit test** is a stored test that you can rerun automatically.
- Your workflow when coding using unit tests is to:

1. Modify code or tests.
2. Test package with `devtools::test()`. This will run all unit tests.
3. Repeat until all tests pass.

- Writing unit tests is a fair amount of work but it is worth it because:

1. If your code changes in a breaking way, your unit tests will alert you. This makes you more confident to make robust changes to your code.
2. I often find bugs while I create unit tests. Describing what I expect and testing out corner cases formally lowers the chance of a bug ending up in your final product.

- `{testthat}` is one of the R package that implements unit tests in R. The other popular ones are probably `{RUnit}` and `{tinytest}`.

```r
library(testthat)
local_edition(3)
```

- To use `{testthat}`, run

```r
usethis::use_testthat()
```

- This will have created a new folder "tests". Inside this folder is an R script "testthat.R" and another folder "testthat".

```
.
DESCRIPTION
NAMESPACE
R
tests
    testthat
    testthat.R
```

- "testthat.R" contains a few lines of code telling R to run all of your unit tests during package checking.
- Unit tests will be in R scripts inside the "testthat" folder.
- **Expectation**: Describes expected result of a computation.
  - Correct value?
  - Correct type (character/numeric/factor/logical)?
  - Correctly produces an error when expected?
  - All expectations are functions like `expect_*()`
- **Test**: A group of related expectations. Usually, a test tests only one function, or a couple tightly related functions. A test is created with `test_that()`.
- **Testthat File**: A collection of related tests.

## Expectation

- An expectation returns an error if a function or result is not what you expect.
- In `{testthat}` all expectations begin with `expect_`.
- The first argument is the actual result of a function in your package. The second argument is the expected result.
- The most common expectation is to test for equality with `expect_equal()`.

```r
x <- 10
y <- 10
expect_equal(x, y)
```

```
You can specify the tolerance level so for items that are only approximately equal
```

```r
expect_equal(10, 10 + 10^-8)
expect_equal(10, 10 + 10^-5)
```

```
Error: 10 (`actual`) not equal to 10 + 10^-5 (`expected`).

  `actual`: 10.00000
`expected`: 10.00001
```

```r
expect_equal(10, 10 + 10^-5, tolerance = 10^-4)
```

- Make sure to **only** check for equality between two things. If you provide three unnamed arguments, the third one is interpreted as the tolerance. This is a common error that I have done many times.

```r
## Bad
expect_equal(10, 10, 10)
```

```
Warning: Unused arguments (10)
```

```r
## Because this will also run OK (tolerance = 10)
expect_equal(10, 2, 10)
```

```
Warning: Unused arguments (10)
```

```
Error: 10 (`actual`) not equal to 2 (`expected`).

  `actual`: 10
`expected`:  2
```

- Use `ignore_attr = TRUE` if your objects have different attributes and you just care about the numeric values (default `expect_equal()` will throw an error):

```r
local_edition(3) ## not necessary for package
names(x) <- "hello"
expect_equal(x, y)
```

```
Error: `x` (`actual`) not equal to `y` (`expected`).

`names(actual)` is a character vector ('hello')
`names(expected)` is absent
```

```r
expect_equal(x, y, ignore_attr = TRUE)
```

- The `local_edition(3)` code makes it so my code chunks use the most recent `{testthat}` functions. You don't need to worry about that in your package. `{usethis}` will automatically assume the third edition. You can explicitly use the third edition by adding the following to your DESCRIPTION file:

```
Config/testthat/edition: 3
```

- `expect_match()` checks for a regular expression match.

```r
expect_match("hello", "ll")
expect_match("helo", "ll")
```

```
Error: "helo" does not match "ll".
Actual value: "helo"
```

- You can use `expect_warning()` and `expect_error()` to check that your functions error correctly.

```r
simreg <- function(n, x, beta0, beta1, sigma2) {
  ## Check input
  stopifnot(length(x) == n)

  ## Simulate y
  eps <- stats::rnorm(n = n, mean = 0, sd = sqrt(sigma2))
  y <- beta0 + beta1 * x + eps
  return(y)
}

x <- runif(100)
beta0 <- 0
beta1 <- 2
sigma2 <- 0.5
expect_error(simreg(n = 1,
                    x = x,
                    beta0 = beta0,
                    beta1 = beta1,
                    sigma2 = sigma2))
```

- It is recommended that you think harder about your unit tests, but you can just test for a non-error by using `expect_error()` and setting `regexp = NA`

```r
expect_error(simreg(n = length(x),
                    x = x,
                    beta0 = beta0,
                    beta1 = beta1,
                    sigma2 = sigma2),
             regexp = NA)
```

- `expect_type()` is tests for the type of the output (`"double"`, `"integer"`, `"character"`, `"logical"`, or `"list"`).

```r
local_edition(3)
expect_type(1, "double")
expect_type(1L, "integer")
expect_type("1", "character")
expect_type(TRUE, "logical")
```

- `expect_s3_class()` is used to test for the class of the object (e.g. `"data.frame"`, `"matrix"`, `"tibble"`, `"lm"`, etc..)

```r
y <- simreg(n = length(x), x = x, beta0 = beta0, beta1 = beta1, sigma2 = sigma2)
lmout <- lm(y ~ x)
expect_s3_class(object = lmout, class = "lm")
```

- `expect_true()` acts like `stopifnot()` except for unit tests instead of assertions.

```r
expect_true(3 == 3)
```

- **Example**: A common test for a simulation script is to see if estimators that we expect to work well on average do, indeed, work well on average. In the case of the simple linear regression model, we will check that, for large $n$, the OLS estimates are reasonably close to the true value of $\beta_1$

```r
x <- runif(1000000)
beta0 <- 0
beta1 <- 2
sigma2 <- 0.5
y <- simreg(n = length(x), x = x, beta0 = beta0, beta1 = beta1, sigma2 = sigma2)
lmout <- lm(y ~ x)
expect_equal(coef(lmout)[[2]], beta1, tolerance = 0.01)
```

- **Exercise**: Write an expectation that the output is a numeric vector.

### Test

- Expectations go inside tests.
- All `{testthat}` tests are of the form

```r
test_that("Human Readable Description", {
  ## Code running test
})
```

- The first argument is a human-readable and informative description of what the test is accomplishing.
- The second argument is is an expression where you put code.
  - An expression is a multi-lined block of R code surrounded by curly braces `{}`.
- Let's put out a couple expectations in our test for `simreg()`.

```r
test_that("simreg() output is consistent", {
  set.seed(991)
  x <- runif(1000000)
  beta0 <- 0
  beta1 <- 2
  sigma2 <- 0.5
  y <- simreg(n = length(x), x = x, beta0 = beta0, beta1 = beta1, sigma2 = sigma2)
  lmout <- lm(y ~ x)
  expect_equal(coef(lmout)[[2]], beta1, tolerance = 0.001)

  expect_equal(length(x), length(y))
})
```

```
Test passed
```

- Notice that I put two expectations in the same test. This is all connected to the output of `simreg()`, so it makes sense to put them in the same test.
- Whenever a test generates something randomly, I like to set a seed for reproducibility.
  - A random seed initializes the pseudorandom process. So any "random draws" in R will be the same if you set the same seed via `set.seed()`.
- If you find yourself printing stuff in the console when writing code, try writing a test instead.
- I usually have a unit test open at the same time that I am coding a function.
- Try to test a function in only one file. If you do change something and need to update your tests, that will make it easier to update.

## Testthat File

- A testthat file is just an R script that holds a few related tests.
- You can create an R script for unit testing by typing

```r
usethis::use_test()
```

specifying the `name` of the R script.

- You should choose a one or two-word name (separated by dashes `-`) that describes the collection of tests. E.g.

```r
usethis::use_test("sim-code")
```

- **Exercise**: Edit `regsim()` so that `x` is either a vector or `NULL`. If `NULL`, then your function should simulate `x` from a standard normal distribution. You can check if a value is `NULL` via `is.null()`. The function should then return a list of length two with the simulated `x` and `y` values. Create a new unit test for this new behavior.
- **Exercise**: In `simreg()`, if `x` is provided, then `n` is not really needed since it can be inferred from `x`. Set the default of `n` to be `NULL` and only require it if `x` is not provided. Give a warning if both `x` and `n` are provided, and throw an error if both `x` and `n` are `NULL`. Write a unit test to check all of these new behaviors. *Note*: It is typical (and good practice) to put all arguments with defaults after all arguments without defaults.

## Test Coverage

- There are various ways to estimate what proportion of lines of your code are covered by unit tests.
- The `{covr}` package will do this for you with

```r
covr::package_coverage()
```

- Running this is as far as we'll go in this class.
- If you have an open-source repo on GitHub, then you can use different some websites to automatically check your test coverage each time you push.

```r
usethis::use_coverage(type = "codecov")
```

```
- You would then set up your repo on <https://codecov.io/>.
- But using codecov for private repos costs money, so we won't do this in our class.
```