

Accelerated Lecture 7: Writing Functions

Harris Coding Camp

Summer 2022

Functions

```
# example of a function  
circle_area <- function(r) {  
  pi * r ^ 2  
}
```

- ▶ Why do we want to write our own functions?
- ▶ What is function?
- ▶ How do we write functions in practice?

What is the code doing?

```
data |>
  mutate(a = (a - min(a)) / (max(a) - min(a)),
         b = (b - min(b)) / (max(b) - min(b)),
         c = (c - min(c)) / (max(c) - min(c)),
         d = (d - min(d)) / (max(d) - min(a)))
```

```
## # A tibble: 100 x 4
##       a      b      c      d
##   <dbl> <dbl> <dbl> <dbl>
## 1 0.539 0.977 0.449 1.21
## 2 0.580 0.308 0.425 0.905
## 3 0.755 0.479 0.732 0.489
## 4 0.501 0.510 0.632 1.60
## 5 0.867 0.494 0.610 1.15
## 6 0.574 0.778 0.327 1.23
## 7 0.240 0.711 0.934 0.557
## 8 0.807 0.541 0      0.789
## 9 0.869 0.481 0.489 0.530
## 10 0.596 0.436 0.242 1.18
## # ... with 90 more rows
```

What is the code doing?

```
rescale_01 <- function(x) {  
  (x - min(x)) / (max(x) - min(x))  
}
```

```
data |>  
  mutate(a = rescale_01(a),  
         b = rescale_01(b),  
         c = rescale_01(c),  
         d = rescale_01(d))
```

```
## # A tibble: 100 x 4  
##       a      b      c      d  
##   <dbl> <dbl> <dbl> <dbl>  
## 1 0.539 0.977 0.449 0.582  
## 2 0.580 0.308 0.425 0.434  
## 3 0.755 0.479 0.732 0.234  
## 4 0.501 0.510 0.632 0.765  
## 5 0.867 0.494 0.610 0.553  
## 6 0.574 0.778 0.327 0.588  
## 7 0.240 0.711 0.934 0.267  
## 8 0.807 0.541 0      0.378  
## 9 0.869 0.481 0.489 0.254
```

Why write functions?

Functions

- ▶ encapsulate logic
- ▶ communicate what a chunk of code does

and help us

- ▶ re-use code we've put effort into
- ▶ avoid copy-paste headaches

Coder folk wisdom: **D**o not **R**epeat **Y**ourself

“You should consider writing a function whenever you’ve copied and pasted a block of code more than twice (i.e. you now have three copies of the same code).”

- ▶ Grolemond and Wickham (chapter 26)

Function anatomy: name, arguments and body

```
# function anatomy
function_name <- function(argument_1, argument_2) {
  do_this(argument_1, argument_2)
}

# function call
function_name(x, y)
```

1. function name

- ▶ specify function name with <-

2. function arguments (sometimes called “inputs”)

- ▶ can be any R object: vectors, data frames, lists, functions, etc.

3. function body

- ▶ code that does stuff (typically with the inputs)

In “function call”, we set `argument_1 = x` and `argument_2 = y`

- ▶ The function returns `do_this(x, y)`

Function anatomy: example

- ▶ assign to **name**: `rescale_01`
- ▶ **arguments**: `x`
- ▶ **body**: `(x - min(x)) / (max(x) - min(x))`

```
rescale_01 <- function(x) {  
  (x - min(x)) / (max(x) - min(x))  
}
```

```
rescale_01(c(.1, 1.1, .6))
```

```
## [1] 0.0 1.0 0.5
```

The last line of the code will be the value returned by the function!

- ▶ We do not explicitly call `return()`

You start writing code to say Hello to all of your friends

```
print("Hello Jasmin!")
```

```
## [1] "Hello Jasmin!"
```

```
print("Hello Joan!")
```

```
## [1] "Hello Joan!"
```

```
print("Hello Andrew!")
```

```
## [1] "Hello Andrew!"
```

```
# and so on...
```

- ▶ You notice it's getting repetitive. ... time for a function!

What part of the code is changing?

Or what aspects of the code do you want to change?

```
print("Hello Jasmin!")  
print("Hello Joan!")  
print("Hello Andrew!")  
# and so on...
```

- ▶ Make this an **argument**

Writing a function: parameterize the code

```
# print("Hello Jasmin!") becomes ...
```

```
name <- "Jasmin"
```

```
print(paste0("Hello ", name, "!"))
```

```
## [1] "Hello Jasmin!"
```

- ▶ Check several potential inputs to avoid future headaches

Writing a function: add the structure

Now let's add the **structure** to formally define the new function:

```
# name <- "Jasmin"
# print(paste0("Hello ", name, "!"))

function(name) {
  print(paste0("Hello ", name, "!"))
}
```

- ▶ **arguments:** name
- ▶ **body:** print(paste0("Hello ", name, "!"))
- ▶ assign to **name**: not yet...

Writing a function: assign to a name

Use **names** that actively tell the user what the code does

- ▶ We recommend `verb()` or `verb_thing()`
 - ▶ **good**: `filter()`, `rescale_01()` or `compare_prices()`
 - ▶ **bad**: `prices()`, `calc()`, or `fun1()`

```
say_hello_to <- function(name) {  
  print(paste0("Hello ", name, "!"))  
}
```

- ▶ **arguments**: `name`
- ▶ **body**: `print(paste0("Hello ", name, "!"))`
- ▶ assign to **name**: `say_hello_to`

First example: printing output

Test out different inputs!

```
say_hello_to("Jasmin")
```

```
## [1] "Hello Jasmin!"
```

```
say_hello_to("Joan")
```

```
## [1] "Hello Joan!"
```

```
say_hello_to("Andrew")
```

```
## [1] "Hello Andrew!"
```

```
# Cool this function is vectorized!
```

```
say_hello_to(c("Jasmin", "Joan", "Andrew"))
```

```
## [1] "Hello Jasmin!" "Hello Joan!"   "Hello Andrew!"
```

Second example: calculating the mean of a sample

You hear there's something called the law of large numbers.¹

You're curious to see if it works through simulations.

So you start calculating the mean of i.i.d. samples with increasing sample sizes.

¹You will learn about this in Stats I

Recall `rnorm(n)` generates a random sample of size `n`

```
rnorm(1, mean = 5, sd = 10)
```

```
## [1] 3.024819
```

```
rnorm(3, mean = 5, sd = 10)
```

```
## [1] 0.9497615 -3.1374033 6.0598231
```

```
rnorm(6, mean = 5, sd = 10)
```

```
## [1] 4.4095936 -0.2806806 -18.9663948 -13.4286629 5.1492043 -20.
```


You calculate the *mean* of i.i.d. samples with increasing sample sizes.

```
mean(rnorm(1, mean = 5, sd = 10))
```

```
## [1] 16.59023
```

```
mean(rnorm(3, mean = 5, sd = 10))
```

```
## [1] 5.065391
```

```
mean(rnorm(6, mean = 5, sd = 10))
```

```
## [1] 7.211749
```

```
# et cetera
```

Second example: calculating the mean of a sample

The sample size is changing, so it becomes the **argument**:

- ▶ Call it `n`.
 - ▶ You could call it anything ... `sample_size`, `jerry` etc.

The **body** is almost identical to the code you already wrote.

```
calc_sample_mean <- function(n) {  
  mean(rnorm(n, mean = 5, sd = 10))  
}
```

Commenting functions with clear names

For added clarity, you can unnest your code and assign the intermediate results to meaningful names:

```
calc_sample_mean <- function(sample_size) {  
  
  our_sample <- rnorm(sample_size, mean = 5, sd = 10)  
  sample_mean <- mean(our_sample)  # probably overkill  
  
  sample_mean  
  
}
```

The last line of code run is returned by default.

```
calc_sample_mean <- function(n) {  
  our_sample <- rnorm(n, mean = 5, sd = 10)  
  mean(our_sample)  
}
```

```
set.seed(1)  
calc_sample_mean(4)
```

```
## [1] 5.792104
```

You can specify what to return()

`return()` explicitly tells R what the function will return.

```
calc_sample_mean <- function(n) {  
  our_sample <- rnorm(n, mean = 5, sd = 10)  
  return(mean(our_sample))  
}
```

```
set.seed(1)  
calc_sample_mean(4)
```

```
## [1] 5.792104
```

- Style guide says only use `return()` to break out of a function early.

If the last line is an *assignment* ... no **visible** output

► Avoid this.

```
calc_sample_mean <- function(n) {  
  # last line of code is an assignment!  
  sample_mean <- mean(rnorm(n, mean = 5, sd = 10))  
}
```

```
# looks like nothing happened  
calc_sample_mean(10)  
# but we can capture the output with an assignment  
x <- calc_sample_mean(10)  
x
```

```
## [1] 8.209093
```

One-liners and anonymous functions

If the function can be fit on one line, you can write it without the curly brackets:

```
calc_sample_mean <- function(n) mean(rnorm(n))
```

Some settings call for *anonymous functions*, where the function has no name.

```
function(n) mean(rnorm(n, mean = 5, sd = 10))
```

Always test your code

We want to: calculate the *mean* of i.i.d. samples with increasing sample sizes.

```
calc_sample_mean(1)
```

```
## [1] 0.6198257
```

```
calc_sample_mean(3)
```

```
## [1] -0.5608922
```

```
calc_sample_mean(30)
```

```
## [1] 0.1162788
```

```
# what is the output if we plug in 0?
```

```
calc_sample_mean(0)
```

```
## [1] NaN
```


Try to foresee the kind of input you expect to use

```
calc_sample_mean(c(1, 3, 30))
```

```
## [1] 0.9454276
```

Hmmm ... We hoped to get 3 sample means out but only got 1

Debug tool: Add temporary print() statements

```
calc_sample_mean <- function(n) {  
  
  our_sample <- rnorm(n, mean = 5, sd = 10)  
  print("our_sample:")  
  print(our_sample)  
  
  mean(our_sample)  
}
```

```
set.seed(1)  
calc_sample_mean(c(1, 3, 30))
```

```
## [1] "our_sample:"  
## [1] -1.264538  6.836433 -3.356286  
  
## [1] 0.7385363
```

Debug tool: Put suspicious code into the console

```
rmnorm(c(1, 3, 30))
```

```
## [1] 1.5952808 0.3295078 -0.8204684
```

```
rmnorm(c(-1, 0, 3, 12))
```

```
## [1] 0.4874291 0.7383247 0.5757814 -0.3053884
```

Uh-oh. `rmnorm()` is not vectorized!

- ▶ “If `length(n) > 1`, the length is taken to be the number required.” see `?rmnorm()`

How to deal with unvectorized functions

If we want to vector input with length > 1

- ▶ Use loops (tomorrow)
- ▶ Use `purrr::map()` or `apply()` family of functions
- ▶ In a data context use `group_by(row_number())`

```
# create a tibble to test our function
sample_tibble <- tibble(sample_sizes = c(1, 3, 6))

# split the data by row
# apply the function to each row
# combine
sample_tibble |>
  group_by(row_number()) |>
  mutate(sample_means = calc_sample_mean(sample_sizes))
```

rowwise() is short-hand for group_by(row_number())

```
tibble(sample_sizes = c(1, 3, 6)) |>  
  rowwise() |>  
  mutate(sample_means = calc_sample_mean(sample_sizes))
```

```
## [1] "our_sample:"  
## [1] 20.11781  
## [1] "our_sample:"  
## [1] 8.898432 -1.212406 -17.146999  
## [1] "our_sample:"  
## [1] 16.249309 4.550664 4.838097 14.438362 13.212212 10.939013
```

```
## # A tibble: 3 x 2  
## # Rowwise:  
##   sample_sizes sample_means  
##       <dbl>         <dbl>  
## 1           1          20.1  
## 2           3          -3.15  
## 3           6          10.7
```

Review: Conditional execution

`if` statements allow you to conditionally execute certain blocks of code depending on whether a condition is satisfied

```
if (condition) {  
    # code executed when condition is TRUE  
} else {  
    # code executed when condition is FALSE  
}
```

Help a user out.

We may want to warn the user that they did something funny.

```
calc_sample_mean <- function(n) {  
  
  if (length(n) > 1) {  
    print("Warning: n should be length == 1")  
  }  
  
  our_sample <- rnorm(n, mean = 5, sd = 10)  
  mean(our_sample)  
}  
  
calc_sample_mean(c(2,3,1))
```

```
## [1] "Warning: n should be length == 1"
```

```
## [1] 10.91893
```

- ▶ NB: warning() makes warnings and stop() throws errors.

Helping a user out.

We may want to warn the user that they did something funny.

```
calc_sample_mean <- function(n) {  
  
  if (length(n) > 1) {  
    stop("n must be length == 1")  
  }  
  
  our_sample <- rnorm(n, mean = 5, sd = 10)  
  mean(our_sample)  
}  
  
calc_sample_mean(c(2,3,1))
```

Error in calc_sample_mean(c(2, 3, 1)) : n must be length == 1

- Can replace if with stopifnot(length(n) == 1)

Making functions work for you

1. Use clear names, even for objects inside the functions
 2. Anticipate inputs and test them
 3. Debug using `print()` statements and the console
 4. Functions return the last line of code
- ▶ `return()` unnecessary
 - ▶ avoid assignment `<-` in last line

Some data use -99 or -98 to represent missing-ness

1. Write a function that takes a vector and replaces negative values with NA.

```
replace_neg(c(-98, 1, 2, 1))
```

```
## [1] NA  1  2  1
```

2. Write examples where you use `replace_neg()` with columns in a tibble.
3. Does your function work on non-numeric inputs?

What if we don't always want `mean=5` and
`sd=10`?

We can add additional arguments!

- ▶ typically, put “data” arguments first
- ▶ and then “detail” arguments after

```
calc_sample_mean <- function(sample_size,  
                               our_mean,  
                               our_sd) {  
  
  sample <- rnorm(sample_size,  
                  mean = our_mean,  
                  sd = our_sd)  
  
  mean(sample)  
}
```

Setting defaults

If there's a “natural” default, we can set default values for “detail” arguments

```
calc_sample_mean <- function(sample_size,  
                               our_mean = 0, our_sd = 1) {  
  
  sample <- rnorm(sample_size, mean = our_mean, sd = our_sd)  
  
  mean(sample)  
}
```

```
# uses the defaults  
calc_sample_mean(sample_size = 10)
```

```
## [1] -0.1468848
```

Setting defaults

```
# we can change one or two defaults.  
# You can refer by name, or use position  
calc_sample_mean(10, our_sd = 2)
```

```
## [1] -0.03143666
```

```
calc_sample_mean(10, our_mean = 6)
```

```
## [1] 6.118949
```

```
calc_sample_mean(10, 6, 2)
```

```
## [1] 6.871897
```

Setting defaults

This won't work though:

- ▶ the most important argument is missing!

```
calc_sample_mean(our_mean = 5)
```

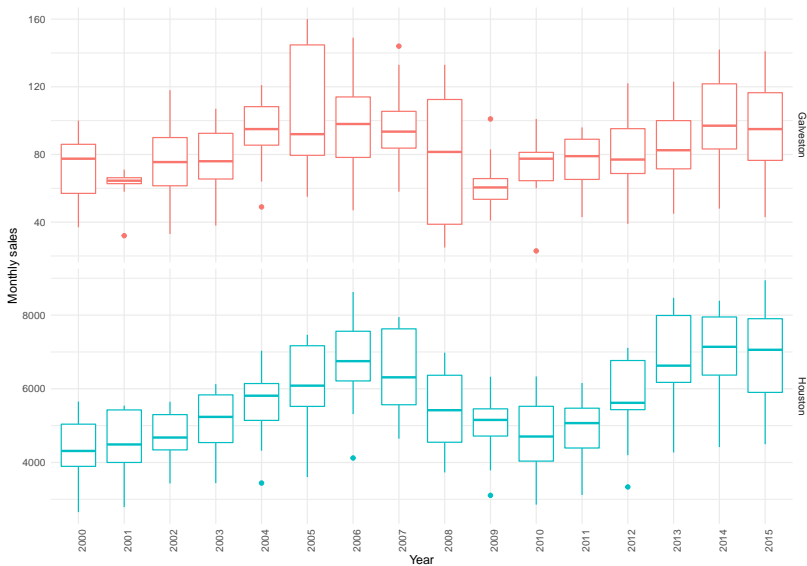
```
Error in rnorm(sample_size, mean = our_mean, sd = our_sd) :  
  argument "sample_size" is missing, with no default
```

What will happen if we execute the code below? Explain?

```
new.function <- function(a, b) {  
  print(a)  
  print(b)  
}  
  
new.function(6)
```


Using functions for data visualization

You're exploring data and want to make this plot for a variety of city pairings.



Suppose we want another set of plots with Austin and San Antonio.

- Copy-paste adjust and then ... you decide you want to tinker with the plot more! Now you have to do it twice.

```
txhousing |>
  filter(city == "Houston" | city == "Galveston")) |>
  ggplot(aes(x = as_factor(year),
             y = sales,
             color = city)) +
  geom_boxplot(show.legend = FALSE) +
  labs(color = NULL, y = "Monthly sales", x = "Year") +
  theme_minimal() +
  facet_grid(vars(city), scales = "free_y") +
  theme(axis.text.x = element_text(angle = 90))
```

How would you parameterize this to take arbitrary cities?

```
# zooming in  
txhousing |>  
  filter(city == "Houston" | city == "Galveston") ...
```

How would you parameterize this to take arbitrary cities?

This code

```
# zooming in  
txhousing |>  
  filter(city == "Houston" | city == "Galveston") ...
```

becomes ...

```
sales_box_plot <- function(city1, city2) {  
  txhousing |>  
    filter(city == city1 | city == city2) ...
```

OR

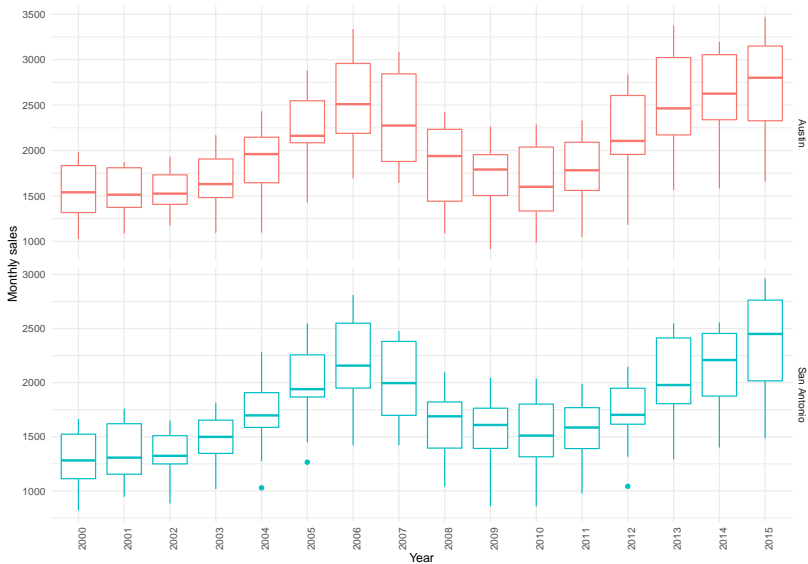
```
sales_box_plot <- function(cities) {  
  txhousing |>  
    filter(city %in% cities) |> ...
```

A function for our plot

```
sales_box_plot <- function(cities) {  
  txhousing |>  
    filter(city %in% cities) |>  
    ggplot(aes(x = as_factor(year),  
              y = sales,  
              color = city)) +  
    geom_boxplot(show.legend = FALSE) +  
    labs(color = NULL, y = "Monthly sales", x = "Year") +  
    theme_minimal() +  
    facet_grid(vars(city), scales = "free_y") +  
    theme(axis.text.x = element_text(angle = 90))  
}
```

Function magic!

```
sales_box_plot(c("Austin", "San Antonio"))
```



Suppose you want `y` to change as well ...

```
housing_box_plot <- function(cities, y, ylab) {  
  txhousing |>  
    filter(city %in% cities) |>  
    ggplot(aes(x = as_factor(year),  
              y = y,  
              color = city)) +  
    geom_boxplot(show.legend = FALSE) +  
    labs(color = NULL, y = ylab, x = "Year") +  
    theme_minimal() +  
    facet_grid(vars(city), scales = "free_y") +  
    theme(axis.text.x = element_text(angle = 90))  
}  
  
housing_box_plot(c("Austin"), sales, "Monthly sales")
```

Error in FUN(X[[i]], ...) : object 'sales' not found

The function doesn't know to look for sales in the data

Need to help R distinguish between an object in the global environment

```
sales <- some_object
```

and sales column in data

```
txhousing$sales
```

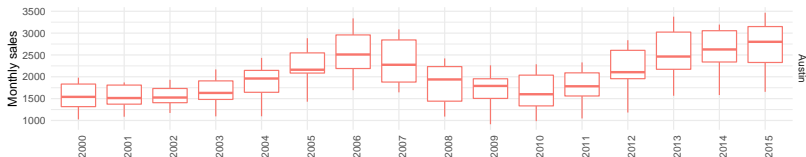
Use `{{...}}` to refer to columns names passed as function argument

- ▶ This is “sugar” that tells R to look within the data for the variable.

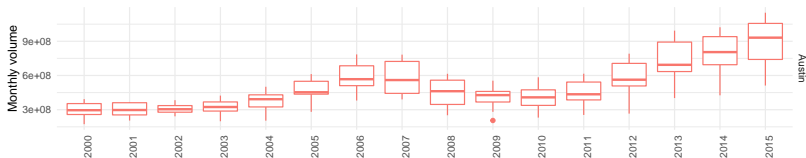
```
housing_box_plot <- function(cities, y, ylab) {  
  txhousing |>  
    filter(city %in% cities) |>  
    ggplot(aes(x = as_factor(year),  
              y = {{ y }},  
              color = city)) +  
    geom_boxplot(show.legend = FALSE) +  
    labs(color = NULL, y = ylab, x = NULL) +  
    theme_minimal() +  
    facet_grid(vars(city), scales = "free_y") +  
    theme(axis.text.x = element_text(angle = 90))  
}
```

With `{}`, R knows `sales` and `volume` are column names

```
housing_box_plot(c("Austin"), sales, "Monthly sales")
```



```
housing_box_plot(c("Austin"), volume, "Monthly volume")
```



Advanced: ... (dot-dot-dot) passes arbitrary inputs

- ▶ You've seen ... as an argument in the help documents.

Advanced: ... (dot-dot-dot) passes arbitrary inputs to a function

...

```
calc_sample_mean <-  
  function(sample_size, ...) {  
    sample <- rnorm(sample_size, ...)  
    mean(sample)  
  }
```

```
calc_sample_mean(3, mean = 1)
```

```
## [1] 0.8245071
```

```
calc_sample_mean(3, 1)
```

```
## [1] 0.9379499
```

```
calc_sample_mean(3, mean = 1, sd = 3)
```

Compare the code

```
# explicit --  
# users know immediately know what your function takes  
# and what the defaults are  
calc_sample_mean <-  
  function(n, mean = 0, sd = 1) {  
  
    sample <- rnorm(n, mean = mean, sd = sd)  
  
    mean(sample)  
  }  
  
# implicit --  
# user has to dig into rnorm  
calc_sample_mean <-  
  function(sample_size, ...) {  
    sample <- rnorm(sample_size, ...)  
    mean(sample)  
  }
```

We can recreate `count()` with ...

```
my_count <- function(data, ...) {  
  
  # ... Variables to group by  
  
  data |>  
    group_by(...) |>  
    summarize(n = n()) |>  
    ungroup()  
}  
  
my_count(midwest, inmetro)
```

```
## # A tibble: 2 x 2  
##   inmetro     n  
##   <int> <int>  
## 1      0  287  
## 2      1  150
```

Real code, more sophisticated but same idea!

Recap

- ▶ Write functions when you are using a set of operations repeatedly
- ▶ Functions consist of arguments and a body and usually a name
- ▶ Functions are for humans
 - ▶ pick names for the function and arguments that are clear and consistent
- ▶ Debug your code as much as you can as you write it.
 - ▶ if you want to use your code with `mutate()`, test the code with vectors
- ▶ Introduced a few sophisticated ways to work with function arguments!
 - ▶ `{{col_name}}` to refer to column names in dplyr context
 - ▶ ... to pass arbitrary arguments to functions.

For more: See Functions Chapter in R for Data Science

Next steps:

Lab:

Today: Writing functions (challenging lab!)

I can encapsulate code into functions, and debug and apply them!

Lecture:

Tomorrow: Loops and iteration.

Appendix

More on working with distributions

Probability distributions

R has built-in functions for working with distributions.

	example	what it does?
r	<code>rnorm(n)</code>	generates a random sample of size n
p	<code>pnorm(q)</code>	returns CDF value at q
q	<code>qnorm(p)</code>	returns inverse CDF (the quantile) for a given probability
d	<code>dnorm(x)</code>	returns pdf value at x

Probability distributions you are familiar with are likely built-in to R.

For example, the binomial distribution has `dbinom()`, `pbinom()`, `qbinom()`, `rbinom()`. The t distribution has `dt()`, `pt()`, `qt()`, `rt()`, etc.

Read this tutorial for more examples.

We should be familiar with `r` functions

- `rnorm()`: random sampling

```
rnorm(1)
```

```
## [1] 0.6107264
```

```
rnorm(5)
```

```
## [1] -0.934097632 -1.253633400  0.291446236 -0.443291873  0.001105352
```

```
rnorm(30)
```

```
## [1]  0.07434132 -0.58952095 -0.56866873 -0.13517862  1.17808700 -1.
```

```
## [7]  0.59394619  0.33295037  1.06309984 -0.30418392  0.37001881  0.
```

```
## [13] -0.54252003  1.20786781  1.16040262  0.70021365  1.58683345  0.
```

```
## [19] -1.27659221 -0.57326541 -1.22461261 -0.47340064 -0.62036668  0.
```

```
## [25] -0.91092165  0.15802877 -0.65458464  1.76728727  0.71670748  0.
```

What are p and q?

`pnorm` returns the probability we observe a value less than or equal to some value q .

```
pnorm(1.96)
```

```
## [1] 0.9750021
```

```
pnorm(0)
```

```
## [1] 0.5
```

`qnorm` returns the inverse of `pnorm`. Plug in the probability and get the cutoff.

```
qnorm(.975)
```

```
## [1] 1.959964
```

```
qnorm(.5)
```

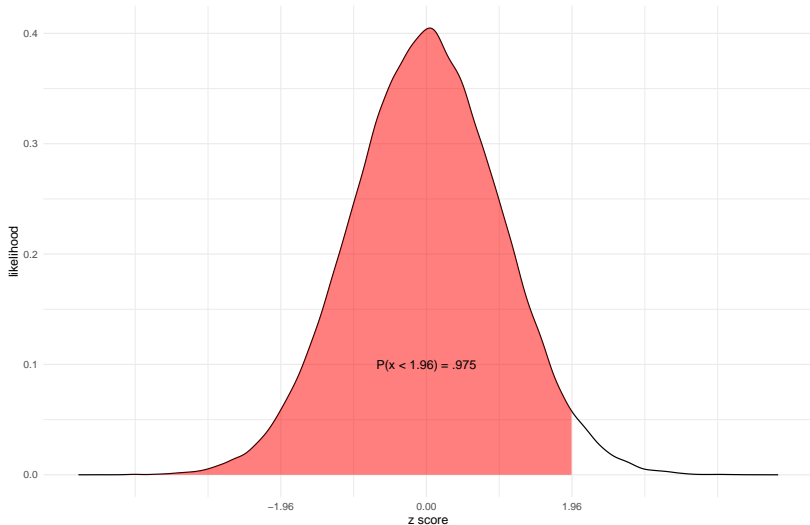
```
## [1] 0
```

This might be easier understood with pictures!

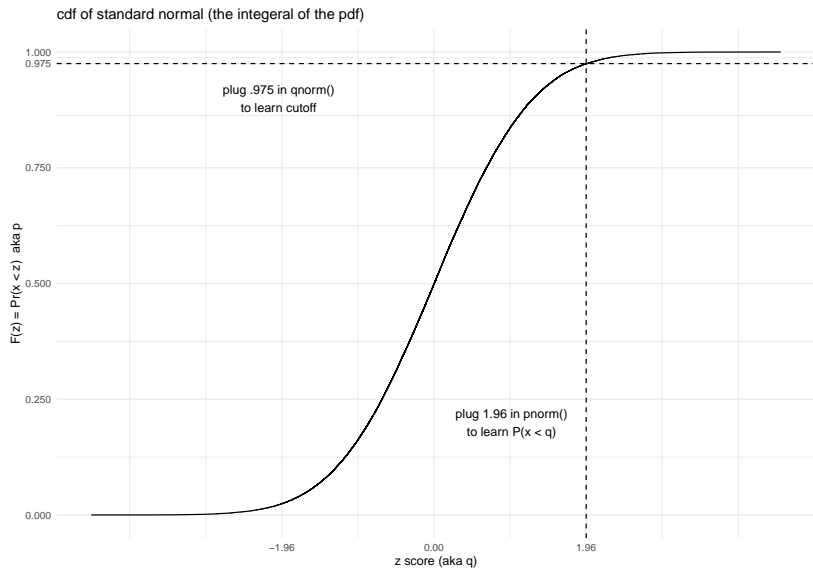
What are p and q?

pdf of standard normal

area under curve is the probability of being less than a cutoff



What are p and q?



What is d?

- ▶ `dnorm()`: density function, the PDF evaluated at X .

```
dnorm(0)
```

```
## [1] 0.3989423
```

```
dnorm(1)
```

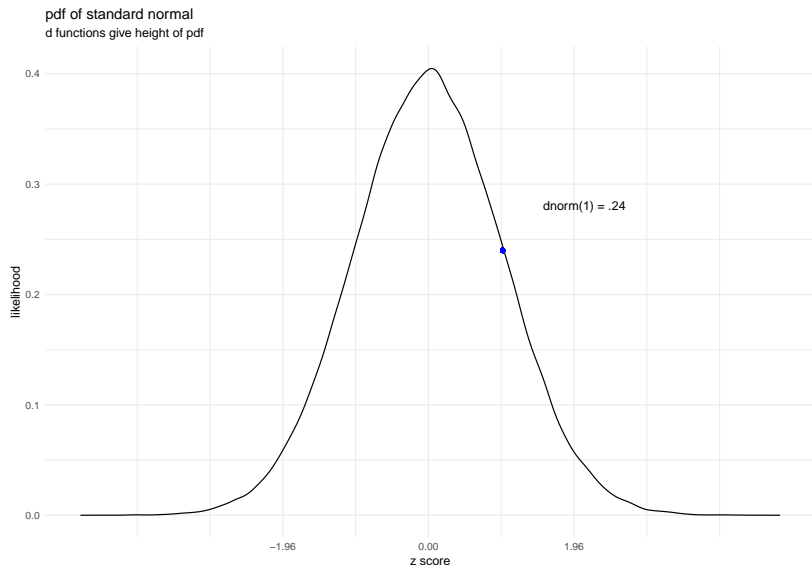
```
## [1] 0.2419707
```

```
dnorm(-1)
```

```
## [1] 0.2419707
```

What is d?

`dnorm` gives the height of the distribution function. Sometimes this is called a likelihood.



passing functions to functions

Revisiting calc_sample_mean

Now you're getting really curious and want to see if these ideas hold with different distributions!

Recall:

```
calc_sample_mean
```

```
## function(sample_size, our_mean, our_sd) {  
##  
##   sample <- rnorm(sample_size,  
##                   mean = our_mean,  
##                   sd = our_sd)  
##  
##   mean(sample)  
## }
```

One approach – make new functions for each distribution

```
calc_sample_mean_t <- function(sample_size, our_df) {  
  sample <- rt(sample_size, our_df)  
  mean(sample)  
}  
  
calc_sample_mean_chisq <- function(sample_size, our_df) {  
  sample <- rchisq(sample_size, our_df)  
  mean(sample)  
}  
  
# Fun fact: 2^31 -1 is the largest seed in R  
set.seed(2147483647)  
calc_sample_mean_t(10, our_df = 5)
```

```
## [1] -0.3284298
```

```
calc_sample_mean_chisq(10, our_df = 5)
```

```
## [1] 6.111243
```

Nothing is stopping you from passing a function as an argument

`rdist` can be any distribution!

```
calc_sample_mean <-  
  function(sample_size, rdist, our_mean = 0, our_sd = 1) {  
  
    sample <- rdist(sample_size, mean = our_mean, sd = our_sd)  
  
    mean(sample)  
  }  
  
set.seed(1)  
calc_sample_mean(4, rnorm)
```

```
## [1] 0.07921043
```

rdist can be any distribution ... not yet!

- The complication here is each distribution has it's own parameters. df, mean etc.

```
calc_sample_mean <-  
  function(sample_size, rdist, our_mean = 0, our_sd = 1) {  
  
    sample <- rdist(sample_size, mean = our_mean, sd = our_sd)  
  
    mean(sample)  
  }  
  
calc_sample_mean(4, rf)
```

Error in rdist(sample_size, mean = our_mean, sd = our_sd) : unused arguments (mean = our_mean, sd = our_sd)

A sophisticated approach - parameterize the distribution!

- ▶ ... takes arbitrary arguments which you can pass to another function
- ▶ Warning ... (dot-dot-dot) is a challenge to use

```
calc_sample_mean <-  
  function(sample_size, rdist = rnorm, ...) {  
  
    sample <- rdist(sample_size, ...)  
  
    mean(sample)  
  }
```

```
set.seed(2147483647)  
calc_sample_mean(10, rt, df = 5)
```

```
## [1] -0.3284298
```

```
calc_sample_mean(10, rchisq, df = 5)
```

```
## [1] 6.111243
```


More examples

... takes arbitrary named arguments which you can pass to another function

```
# function(sample_size, fn = rnorm, ...)
# sample <- rnorm(10)
calc_sample_mean(10)
```

```
## [1] 0.125801
```

```
# sample <- rf(4, df1 = 2, df2 = 3)
calc_sample_mean(4, rf, df1 = 2, df2 = 3)
```

```
## [1] 2.897411
```

```
# sample <- rbeta(9, shape1 = .3, shape2 = 5)
calc_sample_mean(9, rbeta, shape1 = .3, shape2 = 5)
```

```
## [1] 0.02183321
```

in a data context

```
tibble(x = c(1, 10, 100, 1000, 1e5)) |>  
  rowwise() |>  
  mutate(normal = calc_sample_mean(x, mean = 4, sd = 6),  
         uniform = calc_sample_mean(x, runif, min = 2, max = 6),  
         poisson = calc_sample_mean(x, rpois, lambda = 4))
```

```
## # A tibble: 5 x 4
```

```
## # Rowwise:
```

```
##       x normal uniform poisson  
##   <dbl> <dbl>   <dbl>   <dbl>  
## 1      1  6.33    5.90     2  
## 2     10  4.17    3.63    4.4  
## 3    100  3.86    4.16    4.44  
## 4   1000  4.09    4.01    3.98  
## 5 100000  4.01    4.00    4.00
```