

Introduction to Data Analysis in R

Module 3: Programming, joining data, and more

Andrew Proctor

andrew.proctor@phdstudent.hhs.se

January 28, 2019



- 1 Intro
- 2 Revisiting basics
- 3 Iteration
- 4 Conditionals
- 5 Functions
- 6 Joins
- 7 Manipulating text



Intro



Goals for Module

- ① Basics of programming in R—learn how to write and use:
 - Iterations (loops and map functions)
 - Conditional statements
 - Basic functions
- ② Learn how to perform different types of dataset joins.
- ③ Learn how to manipulate strings and use “regular expressions”
- ④ Learn basic web scraping



Revisiting basics



Assignment Operator

So far, when changing a data object, we have always been a bit repetitive:

```
mydataframe <- mydataframe %>%  
  rename(NewVarName = OldVarName)
```

Along with the standard pipe (`%>%`), by loading the [magrittr](#) package, you can also use the so-called “assignment pipe” (`%<>%`).

- The above rename with the assignment pipe appears as:

```
mydataframe %<>% rename(NewVarName = OldVarName)
```



Lists

Another subtlety glossed over so far are *lists*.

- As mentioned in module 1, vectors come in two forms: atomic vectors (with a single data type) and lists (with heterogeneous data types).
- Lists can take as inputs not only single-valued elements, but also vectors or data frames.
- Creating a list from other objects is done with the **list()** function.



List Creation Example

```
wages_df; date_df; description
```

```
##           wage schooling    sex exper
## 1 134.23058         13 female      8
## 2 249.67744         13 female     11
## 3  53.56478         10 female     11
```

```
##   month year
## 1   Jan 2017
## 2   Feb 2018
## 3 March 2019
```

```
## [1] "Data on wages and date information."
```

```
mylist <- list(wages_df, date_df, description)
```



List Creation Example ctd

mylist x

Show Attributes

Name	Type	Value
mylist	list [3]	List of length 3
[[1]]	list [3 x 4] (S3: data.frame)	A data.frame with 3 rows and 4 columns
wage	double [3]	134.2 249.7 53.6
schooling	integer [3]	13 13 10
sex	factor	Factor with 3 levels: "female", "female", "female"
exper	integer [3]	8 11 11
[[2]]	list [3 x 2] (S3: tbl_df, tbl, dat)	A tibble with 3 rows and 2 columns
month	character [3]	'Jan' 'Feb' 'March'
year	double [3]	2017 2018 2019
[[3]]	character [1]	'Data on wages and date information.'



Subsetting a list

- To subset a vector/matrix/data frame, one uses single brackets, eg `mydf[,]`.
- To refer to an object of a list, use double brackets.

```
mylist[[3]]
```

```
## [1] "Data on wages and date information."
```

Note: The function `list()` does not take transfer the names of the data frames, so you will need to either subset by position or assign names to the list objects.



Extracting a list

An easy way of extracting an object from a list is with the **extract2()** function from [magrittr](#). This allows you to extract a given list object by name or position.

```
wage_data <- mylist %>% extract2(1)
wage_data
```

```
##           wage schooling      sex exper
## 1 134.23058           13 female      8
## 2 249.67744           13 female     11
## 3  53.56478           10 female     11
```



The unlist function

Instead of creating more complicated data objects, **unlist()** takes a list and turns it into a simple (atomic) vector.

Example:

```
str(simple_list)
```

```
## List of 4
## $ : num 1
## $ : num 2
## $ : num 3
## $ : num 4
```

```
simple_list %<>% unlist() %>% str()
```

```
## num [1:4] 1 2 3 4
```



Iteration



For loops

For tasks that you want to iterate over multiple data frames/variables/elements, you may want to think about creating a **loop**.

- A loop performs a function/functions multiple times, across either a list of objects or a set of index values.

Syntax:

```
for(indexname in range) {  
  do stuff  
}
```



For loop across numeric values

```
for (i in 1:4){  
  print(i^2)  
}
```

```
## [1] 1  
## [1] 4  
## [1] 9  
## [1] 16
```



For loop across named elements

You can also loop over elements instead of values.

- In the last module exercises, you had to convert the type of many variables. Here's one way you could do that with a loop:

```
nlsy97 <- import("nlsy97.rds")
factor.vars <- c("personid", "year", "sex", "race",
                 "region", "schooltype")
for (i in factor.vars){
  nlsy97[,i] %<>% unlist() %>% as.factor()
}
```



The map() function

For iterations over vectors and dataframes, the `map()` function is a great alternative to the for loop.

Map functions take a user-supplied function and iterate it over:

- Elements for a vector
- Objects of a list
- Columns of a data frame

Map functions are much simpler to write than loops and are also generally a good bit faster.

- **Sidenote:** Map is a part of the tidyverse collection of packages. In base R, the `apply()` family of functions does roughly the same thing, but `map()` simplifies and improves this task.



Using the map() function

Syntax:

```
map(data, fxn, option1, option2...)
```

Example:

```
nlsy97[,factor.vars] %<>% map(as.numeric)
```



Using class-specific map variants

There are multiple map variants that enforce a given data type on results. You should use these whenever you want output of a certain class.

- **map_lgl** for logical vector
- **map_dbl** for numeric vector
- **map_chr** for character vector
- **map_df** for a data frame



Example of difference with class-specific map variants

```
nlsy.sub <- nlsy97 %>% select(parentincome,
                             motheredyrs, gpa)
nlsy.sub %>% map_dbl(IQR, na.rm=TRUE)
```

```
## parentincome motheredyrs      gpa
##           55000           2      226
```

```
nlsy.sub %>% map(IQR, na.rm=TRUE)
```

```
## $parentincome
## [1] 55000
##
## $motheredyrs
## [1] 2
##
```



Using `map()` with anonymous functions

`map()` works with not only predefined functions, but also “anonymous functions”—unnamed functions defined inside of `map()`.

- Suppose I want the z-standardized values of the variables from the previous example:

```
# Create Z Transform  
ztransform <- map_df(nlsy.sub, function(x)  
  (x - mean(x, na.rm=TRUE)) / sd(x, na.rm=TRUE)  
)
```



Using map() with anonymous functions ctd

Did my anonymous function work?

```
# Means
```

```
map_dbl(ztransform, function(x)
  round(mean(x, na.rm=TRUE), 10))
```

```
## parentincome motheredysr      gpa
##              0              0      0
```

```
# Standard deviations
```

```
map_dbl(ztransform, function(x)
  round(sd(x, na.rm=TRUE), 10))
```

```
## parentincome motheredysr      gpa
##              1              1      1
```



Conditionals



If statements

“If statements” are also a useful part of programming, either in conjunction with iteration or seperately.

- An if statement performs operations only if a specified condition is met.
 - An important thing to know, however, is that if statements evaluate conditions of length one (ie non-vector arguments).
 - We will cover a vector equivalent to the if statement shortly.

Syntax

```
if(condition){  
  do stuff  
}
```



Example of an if statement

- In the for loop example, the loop was indexed over only the columns of indicator codes.
- Equally, the loop could be done over all columns with an if-statement to change only the indicator codes.

```
for (j in colnames(nlsy97)){  
  
  if(j %in% factor.vars){  
    nlsy97[,j] %<>% unlist() %>% as.numeric()  
  }  
  
}
```



Multiple conditions

You can encompass several conditions using the **else if** and catch-all **else** control statements.

```
if (condition1) {  
  do stuff  
} else if (condition2) {  
  do other stuff  
} else {  
  do other other stuff  
}
```



Vectorized if statements

- As alluded to earlier, if statements can't test-and-do for vectors, but only single-valued objects.
- Most of the time, you probably want to use conditional statements on vectors. The vector equivalent to the if statement is `ifelse()`

Syntax:

```
ifelse(condition, true_statement, false_statement)
```

The statements returned can be simple values, but they can also be functions or even further conditions. You can easily nest multiple `ifelses` if desired.



An ifelse example

```
numbers <- sample(1:30, 7); numbers
```

```
## [1] 29 11 13 22 27 12 30
```

```
ifelse(numbers %% 2 == 0, "even", "odd")
```

```
## [1] "odd" "odd" "odd" "even" "odd" "even" "even"
```

Note: What if we tried a normal if statement instead?

```
if(numbers %% 2 == 0){  
  print("even")} else{  
  print("odd")}
```

```
## [1] "odd"
```



Multiple vectorized if statements

A better alternative to multiple nested `ifelse` statements is the tidyverse **`case_when`** function.

Syntax:

```
case_when(  
  condition1 ~ statement1,  
  condition2 ~ statement2,  
  condition3 ~ statement3,  
)
```



A case_when example

```
nums_df <- numbers %>% as.tibble() %>%  
  mutate(interval = case_when(  
    (numbers > 0 & numbers <= 10) ~ "1-10",  
    (numbers > 10 & numbers <= 20) ~ "10-20",  
    (numbers > 20 & numbers <= 30) ~ "20-30"))  
nums_df[1:4,]
```

```
## # A tibble: 4 x 2  
##   value interval  
##   <int> <chr>  
## 1     29 20-30  
## 2     11 10-20  
## 3     13 10-20  
## 4     22 20-30
```



Functions



When you should write a function

If you find yourself performing the same specific steps more than a couple of times (perhaps with slight variations), then you should consider writing a function.

A function can serve essentially as a wrapper for a series of steps, where you define generalized inputs/arguments.



Writing a function

Ingredients:

- Function name
- Arguments
- Function body

Syntax:

```
function_name <- function(arg1, arg2, ...){  
  do stuff  
}
```



Function example

Let's turn the calculation of even or odd that was completed earlier into a function:

```
# Make odd function
odd <- function(obj){
  ifelse(obj %% 2 == 0, "even", "odd")
}
```

Notice that *obj* here is a descriptive placeholder name for the data object to be supplied as an argument for the function.

```
odd(numbers)
```

```
## [1] "odd" "odd" "odd" "even" "odd" "even" "even"
```



RStudio's "Extract Function"

A useful way of writing simple functions when you've already written the code for a specific instance is to use RStudio's *Extract Function* option, which is available from the code menu.

- *Extract function* will take the code chunk and treat any data objects referenced but not created within the chunk as function arguments.



Joins



Merging data

Shifting gears from programming. . .

Another staple task in applied work is combining data from multiple data sets. The tidyverse set of packages includes several useful types of merges (or “joins”):

- **left_join()** Appends columns from dataset B to dataset A, keeping all observations in dataset A.
- **inner_join()** Appends columns together, keeping only observations that appear in both dataset A and B.
- **semi_join()** Keeps only columns of dataset A for observations that appear in both dataset A and B.
- **anti_join()** Keeps only columns of dataset A for observations that *do not* appear in both dataset A and B.



Joining using keys

The starting point for any merge is to enumerate the column or columns that uniquely identify observations in the dataset.

- For cross-sectional data, this might be a personal identifier or (for aggregate data) something like municipality, state, country, etc.
- For panel data, this will typically be both the personal/group identifier and a timing variable, for example Sweden in 2015 in a cross-country analysis.



Mismatched key names across datasets

Sometimes the names of the key variables are different across datasets.

- You could of course rename the key variables to be consistent.
- But mismatched key names are easily handled by the tidyverse join functions.

Syntax:

```
join_function(x, y, by = c("x_name" = "y_name"))
```



left_join

The `left_join()` is the most frequent type of join, corresponding to a standard **merge** in Stata.

- `left_join` simply appends additional variables from a second dataset to a main dataset, keeping all the observations (rows) of the first dataset.

Syntax:

```
left_join(x, y, by = "key")
```

If the key is multiple columns, use `c()` to list them.



left_join example

```
# Look at the datasets  
earnings
```

```
##    person_id wage  
## 1         001  150  
## 2         002   90  
## 3         003  270
```

```
educ
```

```
##    person_id schooling  
## 1         001        12  
## 2         003         8  
## 3         004        16
```



left_join example ctd

```
# Combine data
combined_data <- left_join(earnings, educ,
                           by="person_id")
```

```
## Warning: Column `person_id` joining factors with different
## to character vector
```

```
# Print data
combined_data
```

```
##   person_id wage schooling
## 1      001  150         12
## 2      002   90         NA
## 3      003  270          8
```



inner_join

If you want to combine the variables of two data sets, but only keep the observations present in both datasets, use the `inner_join()` function.

```
combined_data <- inner_join(earnings, educ,  
                             by="person_id")  
combined_data
```

```
##   person_id wage schooling  
## 1         001   150        12  
## 2         003   270         8
```



semi_join

To keep using only the variables in the first dataset, but where observations in the first dataset are matched in the second dataset, use `semi_join()`.

- `semi_join` is an example of a *filtering join*. Filtering joins don't add new columns, but instead just filter observations for matches in a second dataset.
- `left_join` and `inner_join` are instead known as *mutating joins*, because new variables are added to the dataset.



semi_join example

```
filtered_data <- semi_join(earnings, educ,  
                           by="person_id")  
filtered_data
```

```
##   person_id wage  
## 1         001  150  
## 2         003  270
```



anti_join

Another *filtering join* is `anti_join()`, which filters for observations that are *not matched* in a second dataset.

```
filtered_data <- anti_join(earnings, educ,  
                           by="person_id")  
filtered_data
```

```
##   person_id wage  
## 1         002   90
```

There are still other join types, which you can read about [here](#).



Appending data

Finally, instead of joining different datasets for the same individuals, sometimes you want to join together files that are for different individuals within the same dataset.

- When join data where the variables for each dataset are the same, but the observations are different, this is called *appending* data.

The function for appending data in the tidyverse is:

```
bind_rows(list(dataframe1,dataframe2,...))
```



Manipulating text



Concatenating strings

The last type of data preparation that we will cover in this course is manipulating string data.

- The simplest string manipulation may be concatenating (ie combining) strings.
 - A great function for combining string in R is the **glue()** function, part of the Tidyverse [glue package](#).
- The glue function lets you reference variable values inside of text strings by writing the variable in curly brackets `{ }` inside of the string.



Glue Example

```
date_df %<>% mutate(  
  say.month = glue("The month is {month}"),  
  mo.yr = glue("{month} {year}")  
)  
date_df
```

##	month	year	say.month	mo.yr
## 1	Jan	2017	The month is Jan	Jan 2017
## 2	Feb	2018	The month is Feb	Feb 2018
## 3	March	2019	The month is March	March 2019



Glue Example 2

```
numbers <- c(1,2,3)
for (i in numbers){
  print(glue("The magic number is {i}"))
}
```

```
## The magic number is 1
## The magic number is 2
## The magic number is 3
```



Extracting and replacing parts of a string

Other common string manipulating tasks include extracting or replacing parts of a string.

- These tasks can be done via the **str_extract()** and **str_replace()** in the Tidyverse [stringr](#) package.
- We saw examples of these two functions in the last seminar exercise:



Extracting and replacing parts of a string

The syntax for each function is:

```
str_extract(string_object, "pattern_to_match")  
str_replace(string_object, "pattern_to_match",  
             "replacement_text")
```

By default, both function operate on the first match of the specified pattern. To operate on *all* matches, add “_all” to the function name, as in:

```
str_extract_all(string_object, "pattern_to_match")
```



Extract and replace example

In the last seminar, we created a “year” column from years indicated in the “variable” column text via the expression:

```
nlsy97$year <- str_extract(nlsy97$variable, "[0-9]+")
```

After creating the “year” column, we then removed the year values from the values of the “variable” column by replacing these numbers with an empty string.

```
nlsy97$variable <- str_replace(nlsy97$variable,  
                                "[0-9]+", "")
```



Trimming a string

When working with formatted text, a third common task is to remove extra spaces before or after the string text.

- This is done with the **str_trim()** function. The syntax is:

```
str_trim(string, side = "left"/"right"/"both")
```

Note, when printing a string, any formatting characters are shown. To view how the string looks formatted, use the **ViewLines()** function.



Using regular expressions with strings

Often we want to modify strings based on a pattern rather than an exact expression, as seen with the **str_extract()** and **str_replace()** examples.

- Patterns are specified in R (as in many other languages) using a syntax known as “regular expressions” or *regex*.
- Today, we will very briefly introduce some regular expressions.



Common Expressions

- To match “one of” several elements, refer to them in square brackets, eg: `[abc]`
- To match one of a range of values, use a hyphen to indicate the range: e.g. `[a-z],[0-9]`
- To match either of a couple of patterns/expressions, use the OR operator, eg: `“2017|2018”`
- There are also abbreviation for one of specific types of characters
 - eg: `[:digit:]` for numbers, `[:alpha:]` for letters, `[:punct:]` for punctuation, and `.` for every character.
 - See the RStudio cheat sheet on `stringr` for more examples (and in general, as a brilliant reference to *regex*)



How many times to match?

Aside from specifying the characters to match, such as “[0-9]”, another important component of regular expressions is how many time should the characters appear.

- “[0-9]” will match any part of a string composed of exactly *1* number.
- “[0-9]+” will match any part of a string composed of *1 or more* numbers.
- “[0-9]{4}” will match any part of a string composed of exactly *4* numbers.
- “[0-9]*” will match any part of a string composed of zero or more numbers.



Examples with repetition

Suppose we want to extract year data that is mixed in with other data as well.

```
messy_var <- c(1,1987,2006,2010,307,2018)
str_extract(messy_var, "[0-9]*")
```

```
## [1] "1" "1" "2" "2" "3" "2"
```

```
str_extract(messy_var, "[0-9]+")
```

```
## [1] "1"      "1987" "2006" "2010" "307" "2018"
```

```
str_extract(messy_var, "[0-9]{4}")
```

```
## [1] NA      "1987" "2006" "2010" NA      "2018"
```



Escaping special characters

Often, special characters can cause problems when working with strings. For example, trying to add a quote can result in R thinking you are trying to close the string.

For most characters, you can “escape” (cause R to read as part of the string) special characters by prepending them with a backslash.

Example:

```
quote <- "\"Without data, you're just another person  
with an opinion.\" - W. Edwards Deming."  
writeLines(quote)
```

```
## "Without data, you're just another person  
## with an opinion." - W. Edwards Deming.
```



Matching strings that precede or follow specific patterns

To match part of a string that occurs before or after a specific other pattern, you can also specify “lookarounds”, the pattern the match should precede or follow:

To match a string pattern x , preceded or followed by y :

- **y precedes x :** “ $(?<=y)x$ ”
- **y follows x :** “ $x(?=y)$ ”



Look around example

```
price_info <-c("The price is 5 dollars")  
str_extract(price_info, "(?<=(The price is )).+")
```

```
## [1] "5 dollars"
```

```
str_extract(price_info, ".+(?=( dollars))")
```

```
## [1] "The price is 5"
```



Web Scraping



Web scraping with Rvest

“Scraping” data from the web - that is, automating the retrieval of data displayed online (other than through API) is an increasingly common data analysis task.

- Today, we will briefly explore very rudimentary web scraping, using the **rvest** package.
- The specific focus today is only on scraping data structured as a table on a webpage. The basic method highlighted will work much of the time - but does not work for every table.



Using rvest to scrape a table

- The starting point for scraping a web table with rvest is the **read_html()** function, where the URL to the page with data should go.
- After reading the webpage, the table should be parsed. For many tables, the **read_html** can be piped directly into the **html_table()** function.
 - If this works, the data should then be converted from a list into a dataframe/tibble.
- If **html_table()** does not work, a more robust option is to first pipe **read_html** into **html_nodes(xpath = "//table")** and then into **html_table(fill=TRUE)**
 - **html_nodes(xpath = "//table")** looks for all HTML objects coded as a table, hence tends to produce lists with several objects.



Web scraping example

```
tech_stock_names <- c("MSFT", "AMZN", "GOOGL", "AAPL",  
                      "FB", "INTC", "CSCO")  
  
tech_stocks <- list()  
for(j in 1:length(tech_stock_names)){  
  tech_stocks[[j]] <- read_html(  
    glue("https://finance.yahoo.com/quote/{tech_stock_  
      names[j]}/history")) %>%  
    html_table() %>% as.data.frame() %>%  
    mutate(stock = tech_stock_names[j])  
}
```



Web scraping example ctd

tech_stocks x

Show Attributes

Name	Type	Value
tech_stocks	list [7]	List of length 7
[[1]]	list [101 x 8] (S3: data.frame)	A data.frame with 101 rows and 8 columns
Date	character [101]	'Jan 25, 2019' 'Jan 24, 2019' 'Jan 23, 2019' 'Jan 2...
Open	character [101]	'107.24' '106.86' '106.12' '106.75' '107.46' '105....
High	character [101]	'107.88' '107.00' '107.04' '107.10' '107.90' '106....
Low	character [101]	'106.20' '105.34' '105.34' '104.86' '105.91' '104....
Close.	character [101]	'107.17' '106.20' '106.71' '105.68' '107.71' '106....
Adj.Close..	character [101]	'107.17' '106.20' '106.71' '105.68' '107.71' '106....
Volume	character [101]	'31,225,600' '23,164,800' '25,874,300' '32,371,3...
stock	character [101]	'MSFT' 'MSFT' 'MSFT' 'MSFT' 'MSFT' 'MSFT' ...
[[2]]	list [101 x 8] (S3: data.frame)	A data.frame with 101 rows and 8 columns
Date	character [101]	'Jan 25, 2019' 'Jan 24, 2019' 'Jan 23, 2019' 'Jan 2...
Open	character [101]	'1,670.50' '1,641.07' '1,656.00' '1,681.00' '1,712...
High	character [101]	'1,683.48' '1,657.26' '1,657.43' '1,681.87' '1,716...
Low	character [101]	'1,661.61' '1,631.78' '1,612.00' '1,610.20' '1,691...
Close.	character [101]	'1,670.57' '1,654.93' '1,640.02' '1,632.17' '1,696...
Adj.Close..	character [101]	'1,670.57' '1,654.93' '1,640.02' '1,632.17' '1,696...



Web scraping example

```
tech_stocks %<>% bind_rows()  
tech_stocks[1:5,c(1,6:8)]
```

##	Date	Adj.Close..	Volume	stock
## 1	Feb 01, 2019	102.78	35,264,100	MSFT
## 2	Jan 31, 2019	104.43	55,636,400	MSFT
## 3	Jan 30, 2019	106.38	49,471,900	MSFT
## 4	Jan 29, 2019	102.94	31,490,500	MSFT
## 5	Jan 28, 2019	105.08	29,476,700	MSFT



Another webscraping example

```
gini_list <- read_html(
  "http://wdi.worldbank.org/table/1.3") %>%
  html_nodes(xpath = "//table") %>%
  html_table(fill=TRUE)
gini_data <- gini_list %>% extract2(3) %>%
  as.data.frame() %>% select(1:3)
gini_data[1:3,]
```

```
##           X1      X2      X3
## 1 Afghanistan  ..      ..
## 2      Albania 2012 29.0
## 3      Algeria 2011 27.6
```

