Data Cleaning

Introduction to R for Public Health Researchers

Data Cleaning

In general, data cleaning is a process of investigating your data for inaccuracies, or recoding it in a way that makes it more manageable.

MOST IMPORTANT RULE - LOOK AT YOUR DATA!

Useful checking functions

- is.na is TRUE if the data is FALSE otherwise
- · ! negation (NOT)
 - if is.na(x) is TRUE, then !is.na(x) is FALSE
- · all takes in a logical and will be TRUE if ALL are TRUE
 - all(!is.na(x)) are all values of x NOT NA
- any will be TRUE if ANY are true
 - any (is.na(x)) do we have any NA's in x?
- · complete.cases returns TRUE if EVERY value of a row is NOT NA
 - very stringent condition
 - FALSE missing one value (even if not important)

Dealing with Missing Data

Missing data types

One of the most important aspects of data cleaning is missing values.

Types of "missing" data:

- · NA general missing data
- NaN stands for "Not a Number", happens when you do 0/0.
- Inf and -Inf Infinity, happens when you take a positive number (or negative number) by 0.

Finding Missing data

Each missing data type has a function that returns TRUE if the data is missing:

- NA is.na
- · NaN is.nan
- Inf and -Inf is.infinite
- · is.finite returns FALSE for all missing data and TRUE for non-missing

Missing Data with Logicals

One important aspect (esp with subsetting) is that logical operations return NA for NA values. Think about it, the data could be > 2 or not we don't know, so R says there is no TRUE or FALSE, so that is missing:

```
x = c(0, NA, 2, 3, 4)

x > 2

[1] FALSE NA FALSE TRUE TRUE
```

Missing Data with Logicals

What to do? What if we want if x > 2 and x isn't NA? Don't do x != NA, do x > 2 and x is NOT NA:

```
x != NA
[1] NA NA NA NA NA
x > 2 & !is.na(x)
[1] FALSE FALSE TRUE TRUE
```

Missing Data with Logicals

What about seeing if a value is equal to multiple values? You can do (x == 1 | x == 2) & !is.na(x), but that is not efficient.

```
(x == 0 \mid x == 2) \# has NA
[1] TRUE NA TRUE FALSE FALSE
(x == 0 \mid x == 2) \& !is.na(x) \# No NA
[1] TRUE FALSE TRUE FALSE FALSE
```

what to do?

Missing Data with Logicals: %in%

NEVER has NA, even if you put it there (BUT DON'T DO THIS):

```
x %in% c(0, 2, NA) # NEVER has NA and returns logical

[1] TRUE TRUE TRUE FALSE FALSE

x %in% c(0, 2) | is.na(x)

[1] TRUE TRUE TRUE FALSE FALSE
```

Missing Data with Operations

Similarly with logicals, operations/arithmetic with NA will result in NAS:

```
      x + 2

      [1] 2 NA 4 5 6

      x * 2

      [1] 0 NA 4 6 8
```

Lab Part 1

Website

Tables and Tabulations

Useful checking functions

- · unique gives you the unique values of a variable
- table (x) will give a one-way table of x
 - table(x, useNA = "ifany") will have row NA
- table (x, y) will give a cross-tab of x and y

Creating One-way Tables

Here we will use table to make tabulations of the data. Look at ?table to see options for missing data.

```
unique(x)
[1] 0 NA 2 3 4
table(x)
X
0 2 3 4
1 1 1 1
table(x, useNA = "ifany") # will not
X
     2 3 4 <NA> 1 1 1
```

Creating One-way Tables

1 1 4 4

useNA = "ifany" will not have NA in table heading if no NA:

Creating One-way Tables

You can set useNA = "always" to have it always have a column for NA

```
table(c(0, 1, 2, 3, 2, 3, 3, 2,2, 3), useNA = "always")

0  1  2  3 <NA>
1  1  4  4  0
```

Tables with Factors

If you use a factor, all levels will be given even if no exist! - (May be wanted or not):

Creating Two-way Tables

A two-way table. If you pass in 2 vectors, table creates a 2-dimensional table.

```
tab <- table(c(0, 1, 2, 3, 2, 3, 3, 2,2, 3),

c(0, 1, 2, 3, 2, 3, 3, 4, 4, 3),

useNA = "always")
tab
```

```
0 1 2 3 4 <NA>
0 1 0 0 0 0 0 0
1 0 1 0 0 0 0
2 0 0 2 0 2 0
3 0 0 0 4 0 0
<NA> 0 0 0 0 0 0
```

Finding Row or Column Totals

margin.table finds the marginal sums of the table. margin is 1 for rows, 2 for columns in general in R. Here is the column sums of the table:

margin.table(tab, 2)

0 1 2 3 4 <NA>
1 1 2 4 2 0

Proportion Tables

<NA>

prop.table finds the marginal proportions of the table. Think of it dividing the table by it's respective marginal totals. If margin not set, divides by overall total.

```
prop.table(tab)
          1 2 3 4 <NA>
   0.1 0.0 0.0 0.0 0.0 0.0
   0.0 0.1 0.0 0.0 0.0 0.0
   0.0 0.0 0.2 0.0 0.2 0.0
   0.0 0.0 0.0 0.4 0.0 0.0
 <NA> 0.0 0.0 0.0 0.0 0.0 0.0
prop.table(tab, 1) * 100
     0 100
```

Lab Part 2

Website

Download Salary FY2014 Data

From https://data.baltimorecity.gov/City-Government/Baltimore-City-Employee-Salaries-FY2015/nsfe-bg53 https://data.baltimorecity.gov/api/views/nsfe-bg53/rows.csv

Read the CSV into R Sal:

```
Sal = read_csv("http://data.baltimorecity.gov/api/views/nsfe-bg53/rows.csv")
Sal = rename(Sal, Name = name)
```

Checking for logical conditions

- any() checks if there are any TRUES
- all() checks if ALL are true

```
head (Sal, 2)
```

[1] FALSE

```
Name
JobTitle AgencyID

1 Aaron, Patricia G Facilities/Office Services II A03031

2 Aaron, Petra L ASSISTANT STATE'S ATTORNEY A29045
Agency HireDate AnnualSalary GrossPay

1 OED-Employment Dev (031) 10/24/1979 $55314.00 $53626.04

2 States Attorneys Office (045) 09/25/2006 $74000.00 $73000.08

any(is.na(Sal$Name)) # are there any NAs?
```

Recoding Variables

Example of Recoding

For example, let's say gender was coded as Male, M, m, Female, F, f. Using Excel to find all of these would be a matter of filtering and changing all by hand or using if statements.

In R, you can simply do something like:

```
data$gender[data$gender %in%
    c("Male", "M", "m")] <- "Male"</pre>
```

or use ifelse

Example of Cleaning: more complicated

Sometimes though, it's not so simple. That's where functions that find patterns come in very useful.

```
table (gender)
gender
     F
       FeMAle FEMALE
                           Fm
                                   \mathbb{M}
                                                mAle
                                                        Male
                                                               MaLe
                                                                       MALE
                                          Ma
    75
            82
                           89
                                   89
                                           79
                                                  87
                                                          89
                                                                  88
                   74
                                                                          95
   Man Woman
    73
            80
```

String functions

Pasting strings with paste and paste0

Paste can be very useful for joining vectors together:

```
paste("Visit", 1:5, sep = " ")
[1] "Visit 1" "Visit 2" "Visit 3" "Visit 4" "Visit 5"
paste("Visit", 1:5, sep = " ", collapse = " ")
[1] "Visit 1 Visit 2 Visit 3 Visit 4 Visit 5"
paste ("To", "is going be the ", "we go to the store!", sep = "day ")
[1] "Today is going be the day we go to the store!"
# and paste0 can be even simpler see ?paste0
paste0("Visit",1:5)
[1] "Visit1" "Visit2" "Visit3" "Visit4" "Visit5"
```

Paste Depicting How Collapse Works

```
paste(1:5)

[1] "1" "2" "3" "4" "5"

paste(1:5, collapse = " ")

[1] "1 2 3 4 5"
```

Useful String Functions

Useful String functions

- toupper(), tolower() uppercase or lowercase your data:
- str_trim() (in the stringr package) or trimws in base
 - will trim whitespace
- nchar get the number of characters in a string

The stringr package

Like dplyr, the stringr package:

- Makes some things more intuitive
- · Is different than base R
- Is used on forums for answers
- Has a standard format for most functions
 - the first argument is a string like first argument is a data.frame in dplyr

Splitting/Find/Replace and Regular Expressions

- · R can do much more than find exact matches for a whole string
- · Like Perl and other languages, it can use regular expressions.
- What are regular expressions?
 - Ways to search for specific strings
 - Can be very complicated or simple
 - Highly Useful think "Find" on steroids

A bit on Regular Expressions

- http://www.regular-expressions.info/reference.html
- They can use to match a large number of strings in one statement
- · . matches any single character
- * means repeat as many (even if 0) more times the last character
- · ? makes the last thing optional
- ^ matches start of vector ^a starts with "a"
- \$ matches end of vector b\$ ends with "b"

Splitting Strings

Substringing

Very similar:

Base R

- substr(x, start, stop) substrings from position start to position stop
- strsplit(x, split) splits strings up returns list!

stringr

- str_sub(x, start, end) substrings from position start to position end
- str_split(string, pattern) splits strings up returns list!

Splitting String: base R

In base R, strsplit splits a vector on a string into a list

Splitting String: stringr

stringr::str_split does the same thing:

Using a fixed expression

One example case is when you want to split on a period ".". In regular expressions . means **ANY** character, so

```
str_split("I.like.strings", ".")

[[1]]
  [1] "" "" "" "" "" "" "" "" "" "" ""

str_split("I.like.strings", fixed("."))

[[1]]
  [1] "I" "like" "strings"
```

Let's extract from y

```
suppressPackageStartupMessages(library(dplyr)) # must be loaded AFTER plyr
y[[2]]
[1] "like" "writing"
sapply(y, dplyr::first) # on the fly
[1] "I" "like" "R"
sapply(y, nth, 2) # on the fly
[1] "really" "writing" "code"
sapply(y, last) # on the fly
[1] "really" "writing" "programs"
```

'Find' functions: stringr

str_detect, str_subset, str_replace, and str_replace_all search for matches to argument pattern within each element of a character vector: they differ in the format of and amount of detail in the results.

- str_detect returns TRUE if pattern is found
- str_subset returns only the strings which pattern were detected
 - convenient wrapper around x[str detect(x, pattern)]
- str_extract returns only strings which pattern were detected, but ONLY the pattern
- str replace replaces pattern with replacement the first time
- str_replace_all replaces pattern with replacement as many times matched

Let's look at modifier for stringr

?modifiers

- fixed match everything exactly
- regexp default uses regular expressions
- ignore_case is an option to not have to use tolower

'Find' functions: finding values, stringr and dplyr

Replacing and subbing: stringr

We can do the same thing (with 2 piping operations!) in dplyr

```
dplyr_sal = Sal
dplyr_sal = dplyr_sal %>% mutate(
  AnnualSalary = AnnualSalary %>%
    str_replace(fixed("$"), "") %>%
    as.numeric) %>%
    arrange(desc(AnnualSalary))
```

Showing differnce in str_extract and str_extract_all

str_extract_all extracts all the matched strings - \\d searches for
DIGITS/numbers

```
head(str_extract(Sal$AgencyID, "\\d"))

[1] "0" "2" "6" "9" "4" "9"

head(str_extract_all(Sal$AgencyID, "\\d"), 2)

[[1]]
[1] "0" "3" "0" "3" "1"

[[2]]
[1] "2" "9" "0" "4" "5"
```

Sorting characters

- sort reorders the data characters work, but not
- rank gives the rank of the data ties are split
- order gives the indices, if subset, would give the data sorted
 - x[order(x)] is the same as sorting

```
sort(c("1", "2", "10")) # not sort correctly (order simply ranks the data)
[1] "1" "10" "2"

order(c("1", "2", "10"))
[1] 1 3 2

x = rnorm(10)
x[1] = x[2] # create a tie
rank(x)

[1] 3.5 3.5 1.0 8.0 5.0 7.0 6.0 9.0 2.0 10.0
```

Lab Part 3

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'Find' functions: base R

grep: grep, grep1, regexpr and gregexpr search for matches to argument pattern within each element of a character vector: they differ in the format of and amount of detail in the results.

grep(pattern, x, fixed=FALSE), where:

- pattern = character string containing a regular expression to be matched in the given character vector.
- x = a character vector where matches are sought, or an object which can be coerced by as.character to a character vector.
- If fixed=TRUE, it will do exact matching for the phrase anywhere in the vector (regular find)

'Find' functions: stringr compared to base R

Base R does not use these functions. Here is a "translator" of the stringr function to base R functions

- str_detect similar to grep1 (return logical)
- grep(value = FALSE) is similar to which(str_detect())
- str subset similar to grep (value = TRUE) return value of matched
- str_replace similar to sub replace one time
- str_replace_all similar to gsub replace many times

Important Comparisons

Base R:

- Argument order is (pattern, x)
- Uses option (fixed = TRUE)

stringr

- Argument order is (string, pattern) aka (x, pattern)
- Uses function fixed (pattern)

'Find' functions: Finding Indices

These are the indices where the pattern match occurs:

```
grep("Rawlings", Sal$Name)

[1] 10256 10257 10258

which(grepl("Rawlings", Sal$Name))

[1] 10256 10257 10258

which(str_detect(Sal$Name, "Rawlings"))

[1] 10256 10257 10258
```

'Find' functions: Finding Logicals

These are the indices where the pattern match occurs:

```
head(grepl("Rawlings", Sal$Name))

[1] FALSE FALSE FALSE FALSE FALSE
head(str_detect(Sal$Name, "Rawlings"))

[1] FALSE FALSE FALSE FALSE FALSE FALSE
```

'Find' functions: finding values, base R

Showing differnce in str_extract

str_extract extracts just the matched string

```
ss = str_extract(Sal$Name, "Rawling")
head(ss)

[1] NA NA NA NA NA NA
ss[!is.na(ss)]

[1] "Rawling" "Rawling" "Rawling"
```

Showing differnce in str_extract and str_extract_all

str_extract_all extracts all the matched strings

```
head(str_extract(Sal$AgencyID, "\\d"))

[1] "0" "2" "6" "9" "4" "9"

head(str_extract_all(Sal$AgencyID, "\\d"), 2)

[[1]] "0" "3" "0" "3" "1"

[[2]] [1] "2" "9" "0" "4" "5"
```

Using Regular Expressions

- Look for any name that starts with:
 - Payne at the beginning,
 - Leonard and then an S
 - Spence then capital C

Using Regular Expressions: stringr

```
head(str_subset( Sal$Name, "^Payne.*"), 3)

[1] "Payne El,Boaz L" "Payne El,Jackie"
[3] "Payne Johnson,Nickole A"

head(str_subset( Sal$Name, "Leonard.?S"))

[1] "Payne,Leonard S" "Szumlanski,Leonard S"

head(str_subset( Sal$Name, "Spence.*C.*"))

[1] "Spencer,Charles A" "Spencer,Clarence W" "Spencer,Michael C"
```

Replace

Let's say we wanted to sort the data set by Annual Salary:

```
class(Sal$AnnualSalary)
[1] "factor"
sort(c("1", "2", "10")) # not sort correctly (order simply ranks the data)
[1] "1" "10" "2"
order(c("1", "2", "10"))
[1] 1 3 2
```

Replace

So we must change the annual pay into a numeric:

```
head(Sal$AnnualSalary, 4)

[1] $55314.00 $74000.00 $64500.00 $46309.00
1654 Levels: $10000.00 $100000.00 $100013.00 $100200.00 ... $99994.00

head(as.numeric(Sal$AnnualSalary), 4)

[1] 908 1302 1094 722
```

R didn't like the \$ so it thought turned them all to NA.

sub() and gsub() can do the replacing part in base R.

Replacing and subbing

Now we can replace the \$ with nothing (used fixed=TRUE because \$ means ending):

Replacing and subbing: stringr

We can do the same thing (with 2 piping operations!) in dplyr

```
dplyr_sal = Sal
dplyr_sal = dplyr_sal %>% mutate(
  AnnualSalary = AnnualSalary %>%
    str_replace(
      fixed("$"),
      "") %>%
    as.numeric) %>%
    arrange(desc(AnnualSalary))
check_Sal = Sal
rownames(check_Sal) = NULL
all.equal(check_Sal, dplyr_sal)
```

[1] TRUE

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