Introduction to Data Analysis in R

Module 2: Data Preparation using the Tidyverse

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Intro

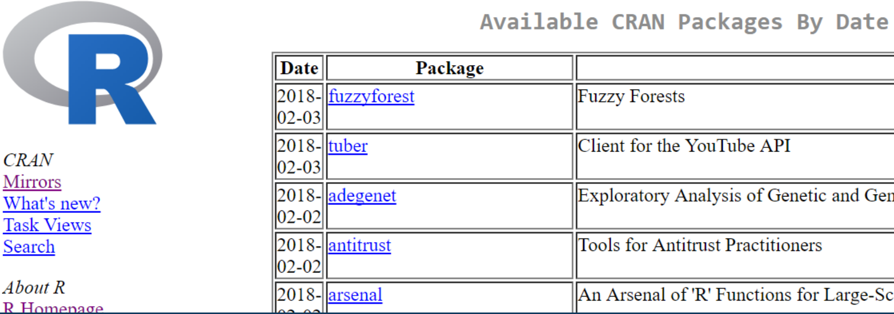
Goals for Today

1. Learn how to use packages in R
2. Learn how to import and export data.
3. Learn how to perform common data prep functions from the tidyverse collection of packages.
4. Learn how to clean and “tidy” data.

Packages in R

Role of Packages in R

- Packages in R are similar to user-written commands (think *ssc install*) in Stata.
- But *most* things you do in Stata probably use core Stata commands.
- In R, most of your analysis will probably be done using packages.



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Available CRAN Packages By Date

Date	Package	
2018-02-03	fuzzyforest	Fuzzy Forests
2018-02-03	tuber	Client for the YouTube API
2018-02-02	adegenet	Exploratory Analysis of Genetic and Gen
2018-02-02	antitrust	Tools for Antitrust Practitioners
2018-	arsenal	An Arsenal of 'R' Functions for Large-Sc

Installing and using a package

- To install a package, use the function (preferably in the console) install.packages()
- To begin with, let's install 2 packages:
  - tidyverse: the umbrella package for common data preparation and visualization in R.
  - rio: a package for easy data import, export (saving), and conversion.

```
install.packages("tidyverse")     # Install tidyverse
install.packages("rio")     # Install rio
```

Loading a package during analysis

Unlike Stata, in R you need to declare what packages you will be using at the beginning of each R document.

- To do this, use the library() function.
  - require() also works, but its use is discouraged for this purpose.

```
library("tidyverse")     # Install tidyverse
library("rio")    # Install rio
```

Data Prep Preliminaries

Import and export using rio

Previously, importing and exporting data was a mess, with a lot of different functions for different file formats:

- Stata DTA files alone required two functions: read.dta (for Stata 6-12 DTA files), read.dta13 (for Stata 13 and later files), etc.

The rio package simplifies this by reducing all of this to just one function, import()

- Automatically determines the file format of the file and uses the appropriate function from other packages to load in a file.

Import and export using rio II

```
PISA_2015 <- import("PISA2015.sas7bdat")
PISA_2015[1:5,1:6]
```

```
##   CNTRYID CNT CNTSCHID  CYC NatCen Region
## 1       8 ALB   800001 06MS 000800    800
## 2       8 ALB   800002 06MS 000800    800
## 3       8 ALB   800003 06MS 000800    800
## 4       8 ALB   800004 06MS 000800    800
## 5       8 ALB   800005 06MS 000800    800
```

```
export(PISA_2015, "PISA_2015.rds")
```

Tibbles: an update to the data frame

Last class, we covered data frames—the most basic data object class for data sets with a mix of data class.

Today, we introduce one final data object: the **tibble**!

- The tibble can be thought of as an update to the data frame—and it's the first part of the *tidyverse* package that we'll look at.

Tibble vs data frames

There are three main benefits to the tibble:

1. Displaying data frames:
   - If you display a data frame, it will print as much as much output as allowed by the "max.print" option in the R environment. With large data sets, that's far too much. Tibbles by default print the first 10 rows and as many columns as will fit in the window.
2. Partial matching in data frames:
   - When using the **$** method to reference columns of a data frame, partial names will be matched if the reference isn't exact. This might sound good, but the only real reason for there to be a partial match is a typo, in which case the match might be wrong.
3. Tibbles are required for some functions.

Creating or converting to tibbles

The syntax for creating tibbles exactly parallels the syntax for data frames:

- tibble() creates a tibble from underlying data or vectors.
- as_tibble() coerces an existing data object into a tibble.

```
PISA_2015 <- as_tibble(PISA_2015); PISA_2015[1:5,1:5]
```

```
## # A tibble: 5 x 5
##   CNTRYID CNT   CNTSCHID CYC   NatCen
##     <dbl> <chr>    <dbl> <chr> <chr>
## 1       8 ALB     800001 06MS  000800
## 2       8 ALB     800002 06MS  000800
## 3       8 ALB     800003 06MS  000800
## 4       8 ALB     800004 06MS  000800
## 5       8 ALB     800005 06MS  000800
```

Glimpse

Another tidyverse function that's very useful is glimpse(), a function very similar to str().

- Both functions display information about the structure of a data object.
- str() provides more information, such as column (variable) attributes embedded from external data formats, but consequently is much less readable for complex data objects.
- glimpse() provides only column names, classes, and some data values (much more readable)
- I will often use str() when I want more detailed information about data structure, but use glimpse() for quicker glances at the data.

Pipes

Another major convenience enhancement from the tidyverse is ***pipes***, denoted **%>%**,

- Pipes allow you to combine multiple steps into a single piece of code.
- Specifically, after performing a function in one step, a pipe takes the data generated from the first step and uses it as the data input to a second step.

Pipes Example

```r
barro.lee.data <- import("BL2013_MF1599_v2.1.dta") %>%
  as_tibble() %>% glimpse(width = 50)
```

```
## Observations: 1,898
## Variables: 20
## $ BLcode      <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1...
## $ country     <chr> "Algeria", "Algeria", "Al...
## $ year        <dbl> 1950, 1955, 1960, 1965, 1...
## $ sex         <chr> "MF", "MF", "MF", "MF", "...
## $ agefrom     <dbl> 15, 15, 15, 15, 15, 15, 1...
## $ ageto       <dbl> 999, 999, 999, 999, 999, ...
## $ lu          <dbl> 80.68459, 81.05096, 82.61...
## $ lp          <dbl> 17.563400, 17.018442, 14....
## $ lpc         <dbl> 3.745905, 3.464397, 3.069...
## $ ls          <dbl> 1.454129, 1.639253, 2.752...
```

Data Preparation

Tidyverse and the verbs of data manipulation

A motivating principle behind the creation of the tidyverse was the language of programming should really behave like a language.

Data manipulation in the tidyverse is oriented around a few key "verbs" that perform common types of data manipulation.

1. filter() subsets the rows of a data frame based on their values.
2. select() selects variables (columns) based on their names.
3. mutate() adds new variables that are functions of existing variables.
4. summarize() creates a number of summary statistics out of many values.
5. arrange() changes the ordering of the rows.

Note: the first argument for each these functions is the data object (so pipe!).

Filtering data

Filtering keeps observations (rows) based on conditions.

- Just like using use subset conditions in the row arguments of a bracketed subset

```
# Using brackets
wages[(wages$schooling > 10) & (wages$exper > 10),]
```

```
##        wage schooling    sex exper
## 2 249.6774        13 female    11
```

```
# Using filter
wages  %>% filter(schooling > 10,exper > 10)
```

```
##        wage schooling    sex exper
## 1 249.6774        13 female    11
```

Filtering data ctd

Notice a couple of things about the output:

1. It doesn't look like we told filter() what data set we would be filtering.

- That's because the data set has already been supplied by the pipe. We could have also written the filter as:

```
filter(wages, schooling > 10,exper > 10)
```

```
##         wage schooling    sex exper
## 1 249.6774        13 female    11
```

2. We didn't need to use the logical **&**. Though multiple conditions can still be written in this way with filter(), the default is just to separate them with a comma.

Selecting data

Just like filter is in many ways a more convenient form of writing out bracketed row subset conditions, the verb select() is largely a more convenient method for writing column arguments.

```
# Using brackets
wages_row1[,c("wage","schooling","exper")]
```

```
##          wage schooling exper
## 1 134.2306        13     8
```

```
# Using select
wages_row1  %>% select(wage,schooling,exper)
```

```
##          wage schooling exper
## 1 134.2306        13     8
```

An example of dropping a column

One option we have not covered so far in creating subsets is dropping rows or columns.

R has a specific notation for this, easily used with select():

```
wages_row1 # What wages_row1 looks like:
```

```
##        wage schooling    sex exper
## 1 134.2306        13 female     8
```

```
wages_row1  %>% select(-exper) #drop exper
```

```
##        wage schooling    sex
## 1 134.2306        13 female
```

An example of dropping a column

Dropping columns (or rows) using the - notation also works with brackets, but only when using the number location of the row or column to be dropped.

```
wages_row1[,-4] # works
```

```
##        wage schooling    sex
## 1 134.2306        13 female
```

```
# wages_row1[,-"exper"] does not work
wages_row1[,"exper"] <- NULL # works (NULL is R delete)
```

Because of select()'s ability to use named arguments when dropping, it is generally easier (except when quotes are required due to improper names).

"Mutating" data

Creating new variables that are functions of existing variables in a data set can be done with mutate().

mutate() takes as its first argument the data set to be used and the equation for the new variable:

```
wages <- wages %>%
  mutate(expsq = exper^2) # Create expersq
wages # Display wages
```

```
##          wage schooling    sex exper expsq
## 1 134.23058        13 female     8    64
## 2 249.67744        13 female    11   121
## 3  53.56478        10 female    11   121
```

Summarizing data

Summary statistics can also be easily created using the tidyverse function summarize()

The summarize() functions uses summary statistic functions in R to create a new summary tibble, with syntax largely identical to mutate().

Let's try summarizing with the mean() summary statistic.

```
wages %>%
  summarize(avg_wage = mean(wage))
```

```
##   avg_wage
## 1 145.8243
```

Summary Statistics functions in R

There are a number of summary statistics available in R, which can be used either with the summarize() command or outside of it:

Measures of central tendency and spread:

- mean(), median() sd(), var(), quantile(), IQR()

Position:

- first(), last(), nth(),

Count:

- n(), n_distinct(),

Multiple summary variables

Let's look at an example of using multiple summary variables with a larger 50-observation sample for the wages data set.

```
wages %>%
  summarize(avg.wage = mean(wage), sd.wage = sd(wage),
        avg.exper = mean(exper), sd.exper = sd(exper))
```

```
## # A tibble: 1 x 4
##   avg.wage sd.wage avg.exper sd.exper
##      <dbl>   <dbl>     <dbl>    <dbl>
## 1    5942.  17526.      7.47     2.08
```

Grouping data

Creating summary statistics by group is another routine task. This is accommodated in the tidyverse using the group_by().

- The arguments of group_by(), in addition to the data set, are simply the grouping variables separated by commas.

```
wages %>% group_by(sex) %>%
  summarize(avg.wage = mean(wage), sd.wage = sd(wage))
```

```
## # A tibble: 2 x 3
##   sex    avg.wage sd.wage
##   <fct>     <dbl>   <dbl>
## 1 female    5473.  18883.
## 2 male      6410.  16711.
```

Arranging (sorting) data

If you want to sort your data by the values of a particular variable, you can easily do so as well with the arrange() function.

```
wages[1:3,] %>% arrange(exper)
```

```
## # A tibble: 3 x 4
##    wage schooling sex    exper
##   <dbl>     <int> <fct>  <int>
## 1  175.        12 female     5
## 2  103.        11 male       7
## 3 1411.        14 female     8
```

Not: arrange() sorts values in ascending order by default. If you want to sort in descending order, wrap the variable name inside **desc()** in the function.

Sampling from data

Creating a sample from a data set in R is made easy by two main function in R: sample_n and sample_frac.

Syntax:

```
sample_n(data, size, replace = FALSE/TRUE)
sample_frac(data, size = 1, replace = FALSE/TRUE)
```

A data prep example with fuel economy data

Let's use tidyverse data manipulation verbs to work through a practical data prep problem from start to finish.

For the problem, Let's use fuel economy data again, but with half of the data set. The data comes from the `vehicles` data set in the fueleconomy package.

```
# install.packages("fueleconomy") # Run only once
library(fueleconomy)
```

Now let's look at how fuel efficiency has changed over time in the data set. Specifically, let's create descriptive statistics of fuel efficiency by year for "normal" passenger vehicles (4-8 cylinders).

What's in the data set?

```
glimpse(vehicles[2:12], width=50)
```

```
## Observations: 33,442
## Variables: 11
## $ make  <chr> "AM General", "AM General", "AM...
## $ model <chr> "DJ Po Vehicle 2WD", "DJ Po Veh...
## $ year  <int> 1984, 1984, 1984, 1984, 1985, 1...
## $ class <chr> "Special Purpose Vehicle 2WD", ...
## $ trans <chr> "Automatic 3-spd", "Automatic 3...
## $ drive <chr> "2-Wheel Drive", "2-Wheel Drive...
## $ cyl   <int> 4, 4, 6, 6, 4, 6, 6, 4, 4, 6, 4...
## $ displ <dbl> 2.5, 2.5, 4.2, 4.2, 2.5, 4.2, 3...
## $ fuel  <chr> "Regular", "Regular", "Regular"...
## $ hwy   <int> 17, 17, 13, 13, 17, 13, 21, 26,...
## $ cty   <int> 18, 18, 13, 13, 16, 13, 14, 20,...
```

Create summary tibble

```
annual.mpg <- vehicles %>% sample_frac(0.5) %>%
  filter(cyl %in% 4:8) %>% group_by(year) %>%
  summarize(hwy.avg = mean(hwy), hwy.sd = sd(hwy),
            city.avg = mean(cty), city.sd = sd(cty)) %>%
  arrange(desc(city.avg))
```

Note: Here I used **%in%**, which works like **inrange** in Stata. You could alternately write two inequalities to achieve the same thing.

View summary tibble

```
# Print annual.mpg
annual.mpg
```

```
## # A tibble: 32 x 5
##      year hwy.avg hwy.sd city.avg city.sd
##     <int>   <dbl>  <dbl>    <dbl>   <dbl>
##  1  2015    28.6   5.42     20.6    4.78
##  2  2014    27.8   6.44     20.4    5.76
##  3  2013    27.3   6.02     20.0    5.78
##  4  2012    26.3   5.83     19.2    5.21
##  5  2011    25.7   5.36     18.8    4.86
##  6  2010    25.3   4.90     18.4    4.38
##  7  1985    22.8   6.21     17.7    4.70
##  8  2009    24.2   4.54     17.6    3.92
##  9  1986    22.4   5.82     17.5    4.48
```

Summarizing a data set with the summary() function

Although the tidyverse summarize() function is more powerful, often you just a want a quick look at summary statistics for the whole data set.

- You can easily do this with the base R summary() function, which produces summaries not just for data sets, but also for other R output like the results of a regression.

```
summary(wages)
```

```
##        wage            schooling         sex            exper
##  Min.   :   1.69   Min.   : 8    female:15   Min.   : 3.
##  1st Qu.:  44.07   1st Qu.:11    male  :15   1st Qu.: 6.
##  Median : 160.96   Median :12                Median : 7.
##  Mean   : 5941.66  Mean   :12                Mean   : 7.
##  3rd Qu.: 1519.01  3rd Qu.:13                3rd Qu.: 8.
```

Cleaning data

Common data cleaning tasks

There are a few data cleaning tasks that are pervasive in empirical work:

1. Ensure columns have useful names
2. Recoding variable values
3. Addressing missing values

Renaming columns

Renaming columns is easily accommodated with the tidyverse rename() command.

Syntax:

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

To see rename() in action, let's go back to the `barro.lee.data` educational data set we imported earlier:

Renaming columns example

Let's look at columns 1 and 7 through 9:

```
glimpse(barro.lee.data[,c(1,7:9)], width = 50)
```

```
## Observations: 1,898
## Variables: 4
## $ BLcode <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ...
## $ lu     <dbl> 80.68459, 81.05096, 82.61115, ...
## $ lp     <dbl> 17.563400, 17.018442, 14.31374...
## $ lpc    <dbl> 3.745905, 3.464397, 3.069391, ...
```

See how these variable names are uninformative?

Renaming columns example ctd

```r
str(barro.lee.data[,c(1,7:9)])
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    1898 obs. o
##  $ BLcode: atomic  1 1 1 1 1 1 1 1 1 1 ...
##   ..- attr(*, "label")= chr "Country Code"
##   ..- attr(*, "format.stata")= chr "%8.0g"
##  $ lu    : atomic  80.7 81.1 82.6 80.9 73.6 ...
##   ..- attr(*, "label")= chr "Percentage of No Schooling"
##   ..- attr(*, "format.stata")= chr "%7.2f"
##  $ lp    : atomic  17.6 17 14.3 14.4 19.2 ...
##   ..- attr(*, "label")= chr "Percentage of Primary"
##   ..- attr(*, "format.stata")= chr "%7.2f"
##  $ lpc   : atomic  3.75 3.46 3.07 4.01 5.23 ...
##   ..- attr(*, "label")= chr "Percentage of Primary Compl
##   ..- attr(*, "format.stata")= chr "%7.2f"
```

Renaming columns example ctd

```
barro.lee.data <- barro.lee.data %>%
  rename(countrycode = BLcode,
    perc.noschool = lu,
    perc.primary = lp,
    perc.primary.complete = lpc)
```

Renaming columns example ctd

Now let's look at the variable names again:

```
glimpse(barro.lee.data[,c(1,7:9)], width = 50)
```

```
## Observations: 1,898
## Variables: 4
## $ countrycode            <dbl> 1, 1, 1, 1, 1, ...
## $ perc.noschool          <dbl> 80.68459, 81.05...
## $ perc.primary           <dbl> 17.563400, 17.0...
## $ perc.primary.complete <dbl> 3.745905, 3.464...
```

Recoding variables

Along with renaming variables, recoding variables is another integral part of data wrangling.

```r
wages[1:4,"sex"] # Look at sex column
```

```
## # A tibble: 4 x 1
##   sex
##   <fct>
## 1 female
## 2 female
## 3 male
## 4 male
```

Recoding variables ctd

```
wages$sex <- wages$sex %>% recode("male"=0,
                                  "female"=1) # recode
wages[1:4,"sex"] # Look at sex column
```

```
## # A tibble: 4 x 1
##     sex
##   <dbl>
## 1     1
## 2     1
## 3     0
## 4     0
```

Missing Values

Another problem characteristic of observational data is missing data. In R, the way to represent missing data is with the value **NA**.

- You can recode missing value that *should be* NA but are code using a different schema either by using brackets, or the tidyverse na_if() function.

```
## Replace 99-denoted missing data with NA
# bracket method
wages[wages$schooling==99,] <- NA
# tidyverse method
wages$schooling <- wages$schooling %>% na_if(99)
```

Missing values continued

You can check for (correctly-coded) missing-values using the is.na() function.

```
## Missing
wages[is.na(wages$wage),]
```

```
## # A tibble: 3 x 4
##     wage schooling   sex exper
##    <dbl>     <int> <dbl> <int>
## 1     NA        14     1     8
## 2     NA        11     0     8
## 3     NA        10     0     8
```

Note: R does not naturally support multiple types of missingness like other languages, although it's possible to use the sjmisc package to do this.

Tidy data

Principles of tidy data

Rules for tidy data (from *R for Data Science*):

1. Each variable must have its own column.
2. Each observation must have its own row.
3. Each value must have its own cell.

Tidy data tools in the tidyverse

There two main tidyverse verbs for making data tidy are:

gather(): reduces variable values are spread over multiples columns into a single column.

spread(): when multiple variables values are stored in the same columns, moves each variable into it's own column.

Gathering data

If values for a single variable are spread across multiple columns (e.g. income for different years), gather() moves this into single "values" column with a "key" column to identify what the different columns differentiated.

Syntax:

```
gather(data, key, value, columnstocombine)
```

Gather example

```
earnings.panel
```

```
## # A tibble: 7 x 3
##   person  y1999 y2000
##   <chr>   <dbl> <dbl>
## 1 Elsa       10    15
## 2 Mickey     20    28
## 3 Ariel      17    21
## 4 Gaston     19    19
## 5 Jasmine    32    35
## 6 Peter      22    29
## 7 Alice      11    15
```

Gather example ctd

```
earnings.panel <- earnings.panel %>%
  gather(key="year", value="wage",y1999:y2000)
earnings.panel
```

```
## # A tibble: 14 x 3
##    person  year   wage
##    <chr>   <chr> <dbl>
##  1 Elsa    y1999    10
##  2 Mickey  y1999    20
##  3 Ariel   y1999    17
##  4 Gaston  y1999    19
##  5 Jasmine y1999    32
##  6 Peter   y1999    22
##  7 Alice   y1999    11
##  8 Elsa    y2000    15
```

Spread

Spread tackles the other major problem - that often times (particularly in longitudinal data) many variables are condensed into just a "key" (or indicator) column and a value column.

```
wages2
```

```
##      person indicator      values
## 1      Elsa      wage          NA
## 2    Mickey      wage  174.932480
## 3     Ariel      wage  102.668810
## 4    Gaston      wage    1.690623
## 5   Jasmine      wage    2.166231
## 6     Peter      wage 1192.371925
## 7     Alice      wage   83.363705
## 8      Elsa      wage          NA
## 9    Mickey      wage  174.932480
```

Spread ctd

```
wages2 %>% spread("indicator", "values")
```

```
##       person        wage schooling exper
## 1       Elsa          NA        14     8
## 2     Mickey  174.932480        12     5
## 3      Ariel  102.668810        11     7
## 4     Gaston    1.690623        11     8
## 5    Jasmine    2.166231        14    10
## 6      Peter 1192.371925        12     8
## 7      Alice   83.363705        11     6
## 8       Elsa          NA        14     8
## 9     Mickey  174.932480        12     5
## 10     Ariel  102.668810        11     7
## 11    Gaston    1.690623        11     8
## 12   Jasmine    2.166231        14    10
```