Introduction to R

Ariel M. Aloe[1]

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[1]The majority of these materials had been developed by “Brandon LeBeau” for his “PSQF:6250 Computer Packages for Statistical Analysis” class. All errors are my own.

Outline

Section 1

Basic R

Background

- In an attempt to get you "doing things" in R quickly, I've omitted a lot of discussion surrounding internal R workings.
- R is an object oriented language, this is much different than many other software languages.
- Within the R environment:
  - Everything that exist is an object
  - Everything that happens is a functional call
  - Possible to interface with other software
- But lets start simple

R works as a calculator

R can be used as a calculator to do any type of addition, subtraction, multiplication, or division (among other things).

```
1 + 2 - 3
```

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

```
5 * 7
```

```
## [1] 35
```

```
2/1
```

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

```
sqrt(4)
```

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

Objects

Being an object oriented system, values can directly saved within an object to be used later. As an example:

```r
x <- 1 + 3
x
```

```
## [1] 4
```

This can then be used later in other calculations:

```r
x * 3
```

```
## [1] 12
```

This simplistic example is a bit too simple to show all the benefits of this approach, but will become more apparent when we start reading in data and doing more complicated data munging type tasks.

Naming conventions

- This is a topic in which you will not get a single answer, but rather a different answer for everyone you ask.
- I prefer something called **snake_case** using underscores to separate words in an object.
- Others use **titleCase** as a way to distinguish words others yet use **period.to.separate** words in object names.
- The most important thing is to be consistent. Pick a convention that works for you and stick with it through out. Avoiding this **Mixed.TypeOf_conventions** at all costs.

R is case sensitive

This can cause problems and make debugging a bit more difficult. Be careful with typos and with case. Here is an example:

```r
case_sensitive <- 10
case_sensitive
```

```
## [1] 10
```

```r
#  Case_sensitive will produce an error
```

Functions

- A function consists of at least two parts, the *function name* and the *arguments* as follows:
  - `function_name(arg1 = num, arg2 = num)`.
- The arguments are always inside of parentheses, take on some value, and are always named. To call a function, use the `function_name` followed by parentheses with the arguments inside the parentheses.
- For example, using the `rnorm` function to generate values from a random normal distribution:

```
set.seed(1)
rnorm(n = 10, mean = 0, sd = 1)
```

```
##  [1] -0.6264538  0.1836433 -0.8356286  1.5952808  0.3295
##  [7]  0.4874291  0.7383247  0.5757814 -0.3053884
```

The bad pratice

Notice I called the arguments by name directly, this is good practice, however, this code will generate the same values (the values are the same because I'm using `set.seed` here):

```r
set.seed(1)
rnorm(10, 0, 1)
```

```
##  [1] -0.6264538  0.1836433 -0.8356286  1.5952808  0.3295
##  [7]  0.4874291  0.7383247  0.5757814 -0.3053884
```

The ugly practice

The key when arguments are not called via their names is the order of the arguments. Look at `?rnorm` to see that the first three arguments are indeed `n`, `mean`, and `sd`. When you name arguments, they can be specified in any order (generally bad practice).

```
set.seed(1)
rnorm(sd = 1, n = 10, mean = 0)
```

```
##  [1] -0.6264538  0.1836433 -0.8356286  1.5952808  0.3295
##  [7]  0.4874291  0.7383247  0.5757814 -0.3053884
```

If needed

You can save this result to an object to be used later.

```
set.seed(1)
norm_values <- rnorm(n = 10, mean = 0, sd = 1)
```

Notice the result is no longer printed to the screen, but rather is saved to the object `norm_values`. To see the result, you could just type `norm_values` in the console.

Errors

Errors are going to happen. If you encounter an error I recommend doing the following few things first:

1. Use `?function_name` to explore the details of the function. The examples at the bottom of every R help page can be especially helpful.
2. If this does not help, copy and paste the error and search on the internet. Chances are someone else has had this error and has asked how to fix it. This is how I fix most errors I am unable to figure out with the R help.
3. If these two steps still do not help, you can post your error in places such as `https://stackoverflow.com` you will need to include the following things:
    - The error message directly given from R
    - A reproducible example of the code. The reproducible example is one in which helpers can run the code directly with no modifications.

Graphics

Background

- We are going to start by exploring graphics with R using the `midwest` data.
- To access this data, run the following commands:

```r
install.packages("tidyverse")
```

```r
library(tidyverse)
```

midwest data I

- Let's explore these data closer, just type the name of he data set in the console.

```
midwest
```

- This will bring up the first 10 rows of the data (hiding the additional 8,592) rows.
- A first common step to explore our research question (e.g., How does population density influence the percentage of the population with at least a college degree?) is to plot the data.
- To do this we are going to use the R package, `ggplot2`, which was installed when running the `install.packages` command above.
- You can explore the `midwest` data by calling up the help file as well with `?midwest`.

midwest data II

```
## # A tibble: 437 × 28
##      PID    county state  area poptotal popdensity popwhite popblack
##    <int>     <chr> <chr> <dbl>    <int>      <dbl>    <int>    <int>
## 1    561     ADAMS    IL 0.052    66090  1270.9615    63917     1702
## 2    562 ALEXANDER    IL 0.014    10626   759.0000     7054     3496
## 3    563      BOND    IL 0.022    14991   681.4091    14477      429
## 4    564     BOONE    IL 0.017    30806  1812.1176    29344      127
## 5    565     BROWN    IL 0.018     5836   324.2222     5264      547
## 6    566    BUREAU    IL 0.050    35688   713.7600    35157       50
## 7    567   CALHOUN    IL 0.017     5322   313.0588     5298        1
## 8    568   CARROLL    IL 0.027    16805   622.4074    16519      111
## 9    569      CASS    IL 0.024    13437   559.8750    13384       16
## 10   570 CHAMPAIGN    IL 0.058   173025  2983.1897   146506    16559
## # ... with 427 more rows, and 20 more variables: popamerindian <int>,
## #   popasian <int>, popother <int>, percwhite <dbl>, percblack <dbl>,
## #   percamerindan <dbl>, percasian <dbl>, percother <dbl>,
## #   popadults <int>, perchsd <dbl>, percollege <dbl>, percprof <dbl>,
## #   poppovertyknown <int>, percpovertyknown <dbl>, percbelowpoverty <dbl>,
## #   percchildbelowpovert <dbl>, percadultpoverty <dbl>,
## #   percelderlypoverty <dbl>, inmetro <int>, category <chr>
```

midwest data III

Another useful functions to explore your data are:

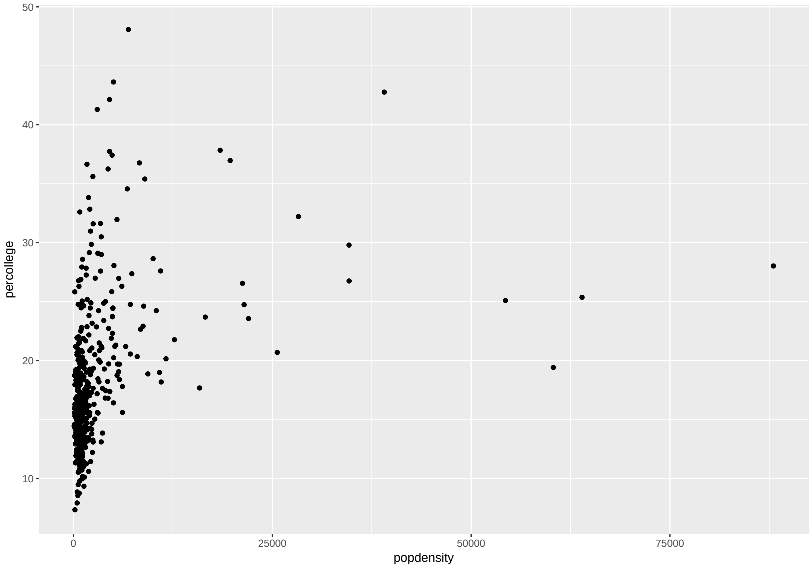
- `str(midwest)`, and
- `View(midwest)`

Create a ggplot I

- To plot these two variables from the `midwest` data, we will use the function `ggplot` and `geom_point` to add a layer of points.
- We will treat `popdensity` as the x variable and `percollege` as the y variable.

```r
ggplot(data = midwest) +
  geom_point(mapping = aes(x = popdensity,
                           y = percollege))
```

Create a ggplot II



Try the following

1. Plotting `popdensity` by `state`.
2. Plotting `county` by `state`. Does this plot work?
3. Just using the `ggplot(data = midwest)` from above. What do you get? Does this make sense?

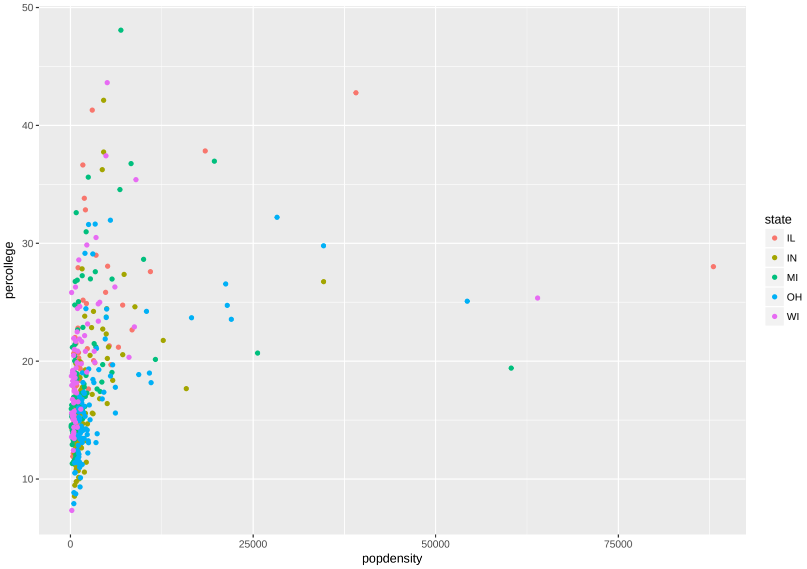
Note: You should be able to modify the structure of the code above to do this.

Add Aesthetics I

- Aesthetics are a way to explore more complex interactions within the data.
- Particularly, from the above example, lets add in the state variable to the plot via an aesthetic.

```
ggplot(data = midwest) +
  geom_point(mapping = aes(x = popdensity,
                           y = percollege,
                           color = state))
```

Add Aesthetics II



As you can see, we simply colored the points by the state they belong in. Does there appear to be a trend?

Examples

1. Using the same aesthetic structure as above, instead of using colors, make the shape of the points different for each state.
2. Instead of color, use `alpha` instead. What does this do to the plot?

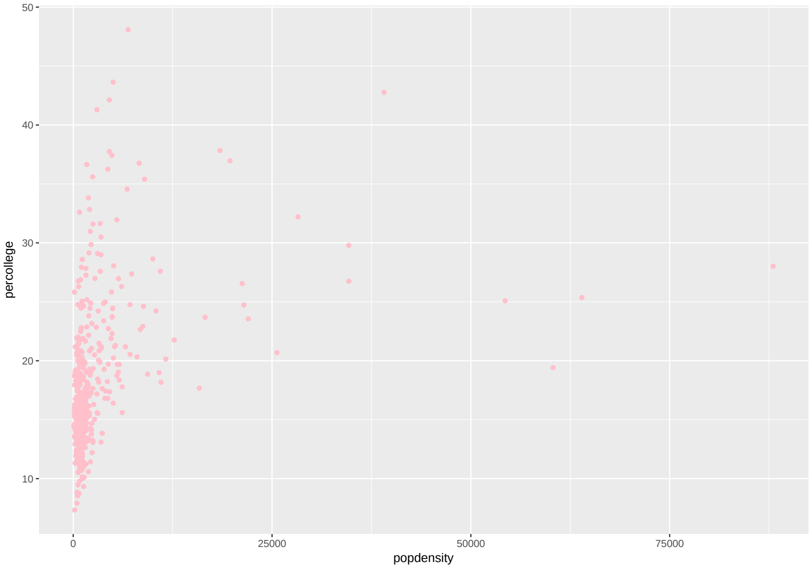
Global Aesthetics I

- Above, we specified a variable to an aesthetic, which is a common use of aesthetics.
- However, the aesthetics can also be assigned globally.
- Here are two examples using the first scatterplot created.

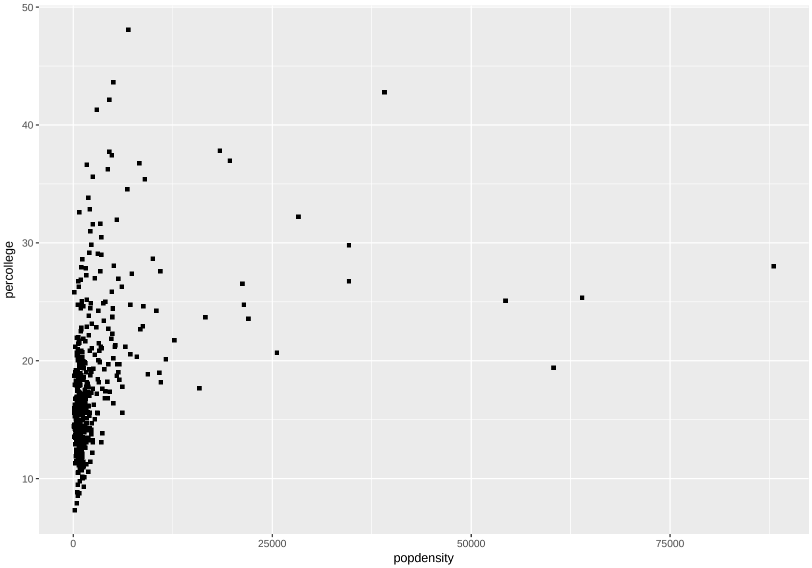
```r
ggplot(data = midwest) +
  geom_point(mapping = aes(x = popdensity,
                           y = percollege),
             color = 'pink')
```

```r
ggplot(data = midwest) +
  geom_point(mapping = aes(x = popdensity,
                           y = percollege),
             shape = 15)
```

Global Aesthetics II - color = ‘pink’



Global Aesthetics III - shape = 15



Global Aesthetics IV

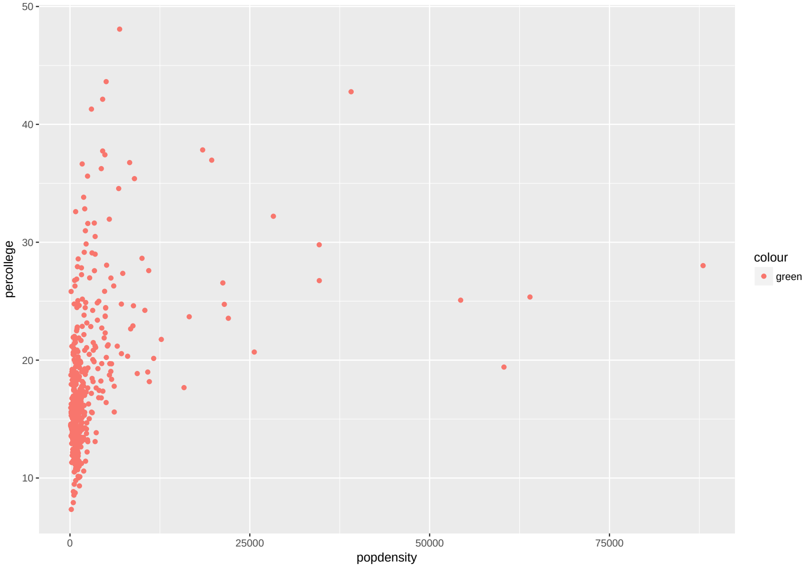
- These two plots changed the aesthetics for all of the points.
- Notice, the suttle difference between the code for these plots and that for the plot above.
- The placement of the aesthetic is crucial, if it is within the parentheses for `aes()` then it should be assigned a variable.
- If it is outside, as in the last two examples, it will define the aesthetic for all the data.

Examples

1. Try the following command: `colors()`. This will print a vector of all the color names within R, try a few to find your favorites.
2. What happens if you use the following code:

```r
ggplot(data = midwest) +
  geom_point(mapping = aes(x = popdensity,
                           y = percollege,
                           color = 'green'))
```

Examples cont. 2



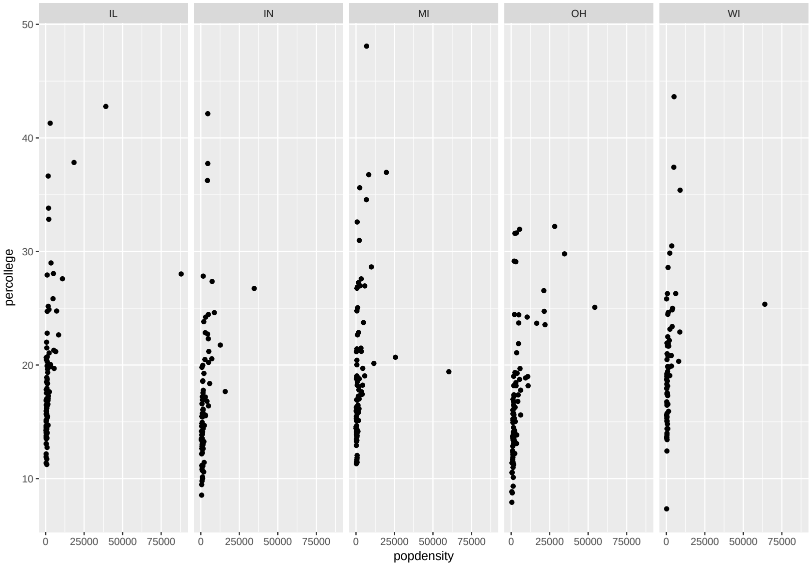
What is the problem?

Facets I

- Instead of defining an aesthetic to change the color or shape of points by a third variable, we can also plot each groups data in a single plot and combine them.
- The process is easy with `ggplot2` by using facets.

```
ggplot(data = midwest) +
  geom_point(mapping = aes(x = popdensity,
                           y = percollege)) +
  facet_grid(. ~ state)
```

Facets II

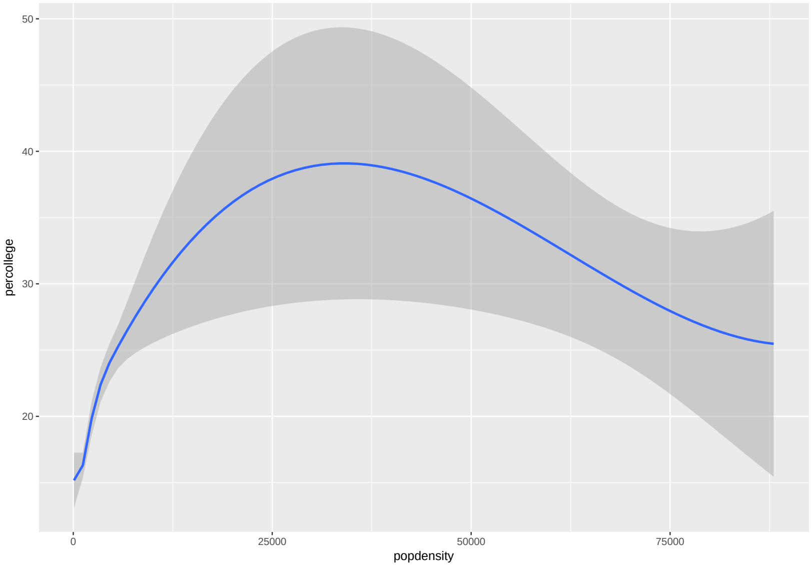

IL
IN
MI
OH
WI
percollege
popdensity
10
20
30
40
50
0
25000
50000
75000

Geoms I

- ggplot2 uses a grammar of graphics which makes it easy to switch different plot types (called geoms) once you are comfortable with the basic syntax.
- For example, how does the following plot differ from the scatterplot first generated above? What is similar?

```r
ggplot(data = midwest) +
  geom_smooth(mapping = aes(x = popdensity,
                            y = percollege))
```

Geoms II



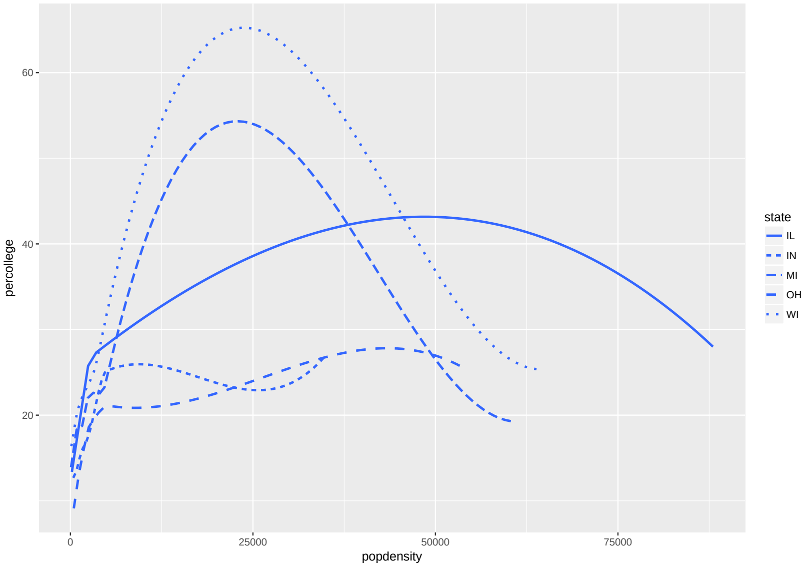
Geoms IV

We can also do this plot by states

```
ggplot(data = midwest) +
  geom_smooth(mapping = aes(x = popdensity,
                            y = percollege,
                            linetype = state),
              se = FALSE)
```

Note, I also removed the standard error shading from the plot as well.

Geoms IV



What about the code above gave me the different lines for each state?

Examples

1. It is possible to combine geoms, which we will do next, but try it first. Try to recreate this plot.

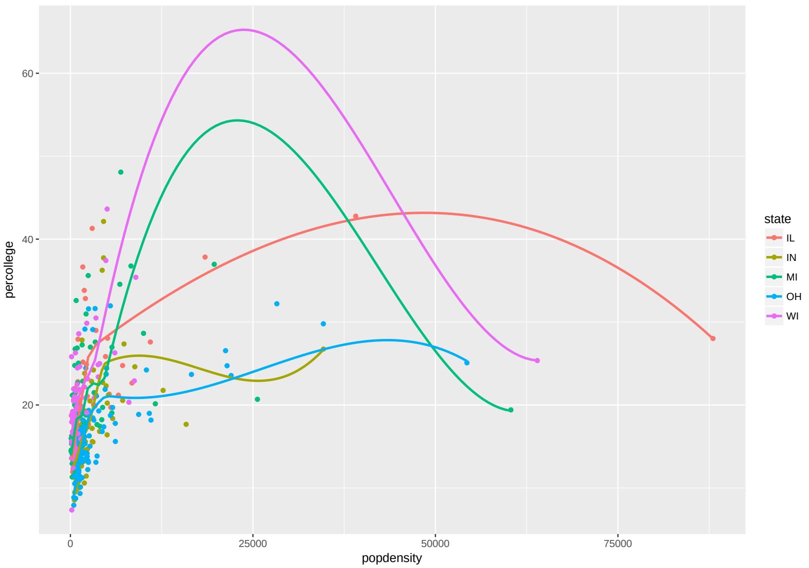
```r
ggplot(data = midwest) +
  geom_point(aes(x = popdensity,
                 y = percollege,
                 color = state)) +
  geom_smooth(mapping = aes(x = popdensity,
                            y = percollege,
                            color = state),
              se = FALSE)
```

Combining multiple geoms I

- Combining more than one geom into a single plot is relatively straightforward, but a few considerations are important.
- Essentially to do the task, we just simply need to combine the two geoms we have used:

```
ggplot(data = midwest) +
  geom_point(aes(x = popdensity,
                 y = percollege,
                 color = state)) +
  geom_smooth(mapping = aes(x = popdensity,
                            y = percollege,
                            color = state),
              se = FALSE)
```

Combining multiple geoms II



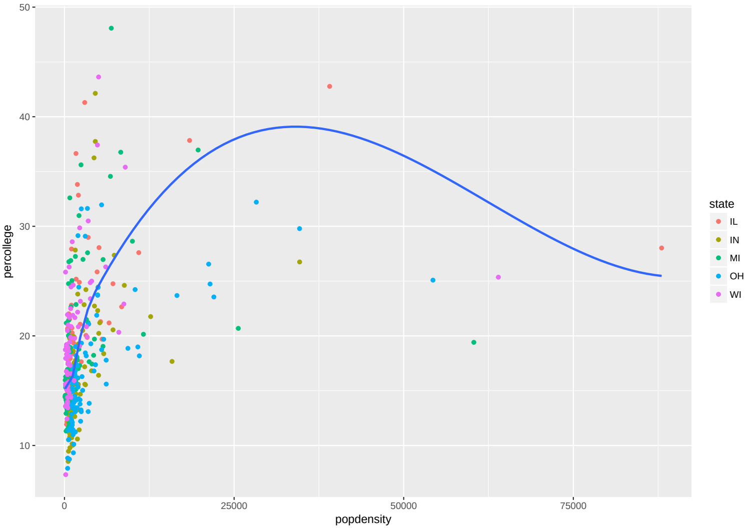
Combining multiple geoms III

- A couple points about combining geoms, first, the order matters.
- In the above example, we called `geom_point` first, then `geom_smooth`.
- When plotting these data, the points will then be plotted first followed by the lines.
- Try flipping the order of the two geoms to see how the plot differs.
- We can also simplify this code to not duplicate typing:

```r
ggplot(data = midwest, mapping = aes(x = popdensity,
                                     y = percollege,
                                     color = state)) +
  geom_point() +
  geom_smooth(se = FALSE)
```

Examples

1. Can you recreate the following figure?



Other geom examples

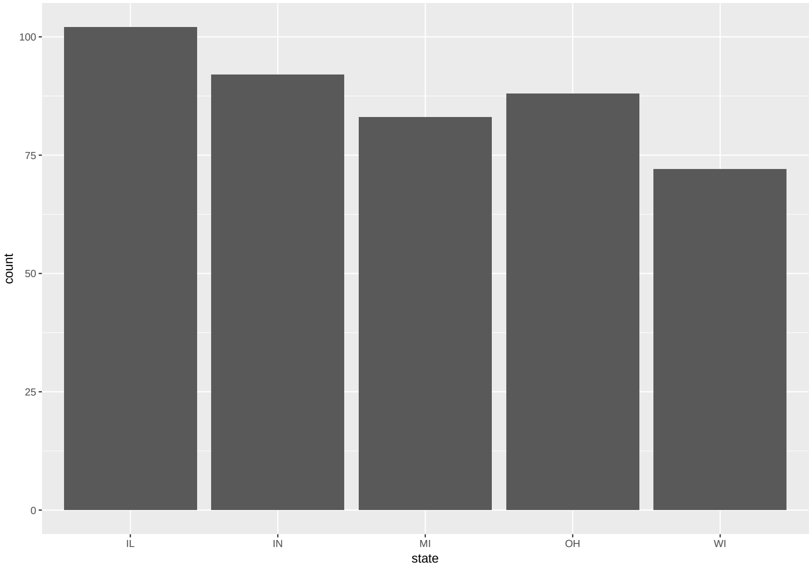
- There are many other geoms available to use.
- To see them all, visit `http://docs.ggplot2.org/current/index.html` which gives examples of all the possibilities.
- This is a handy resource that I keep going back to.

Geoms for single variables I

The introduction to plotting has been with two variables, but lets take a step back and focus on one variable with a bar chart.

```r
ggplot(data = midwest, mapping = aes(x = state)) +
  geom_bar()
```

Geoms for single variables II

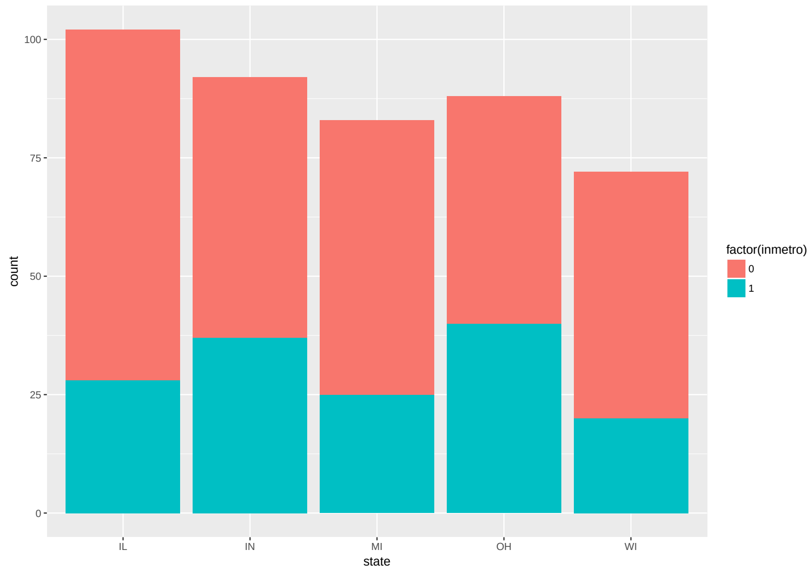


Geoms for single variables III

You can also easily add aesthetics this base plot as shown before.

```
ggplot(data = midwest, mapping = aes(x = state)) +
  geom_bar(aes(fill = factor(inmetro)))
```

Geoms for single variables IV



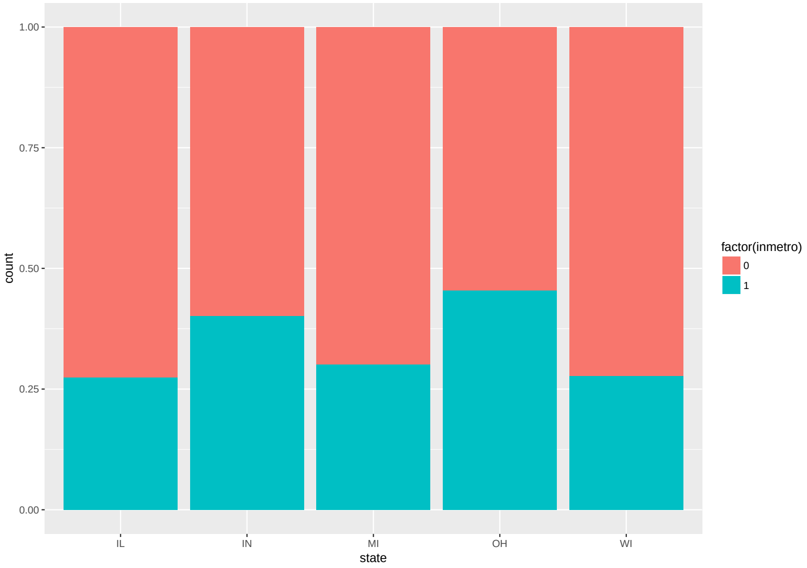
Geoms for single variables V

A few additions can help interpretation of this plot:

```r
ggplot(data = midwest, mapping = aes(x = state)) +
geom_bar(aes(fill = factor(inmetro)),
         position = 'fill')
```

Geoms for single variables VI

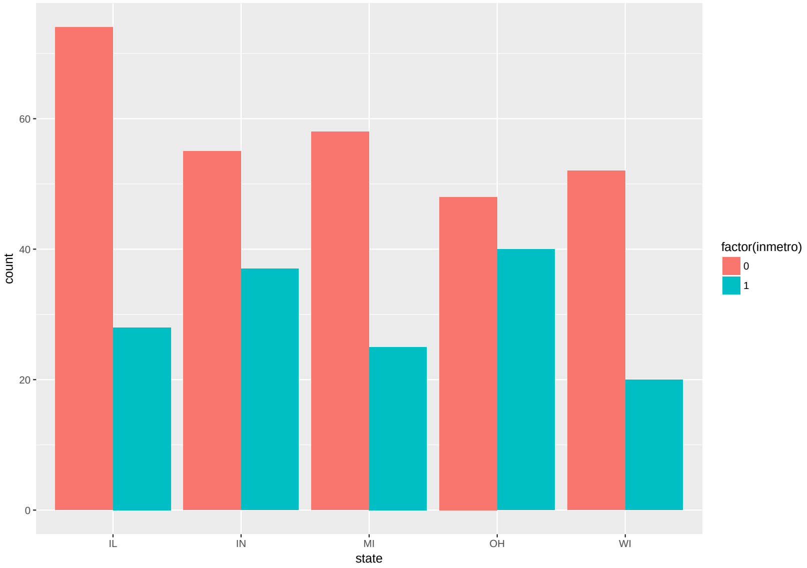
A few additions can help interpretation of this plot:



Geoms for single variables VII

```r
ggplot(data = midwest, mapping = aes(x = state)) +
  geom_bar(aes(fill = factor(inmetro)),
           position = 'dodge')
```

Geoms for single variables VIII



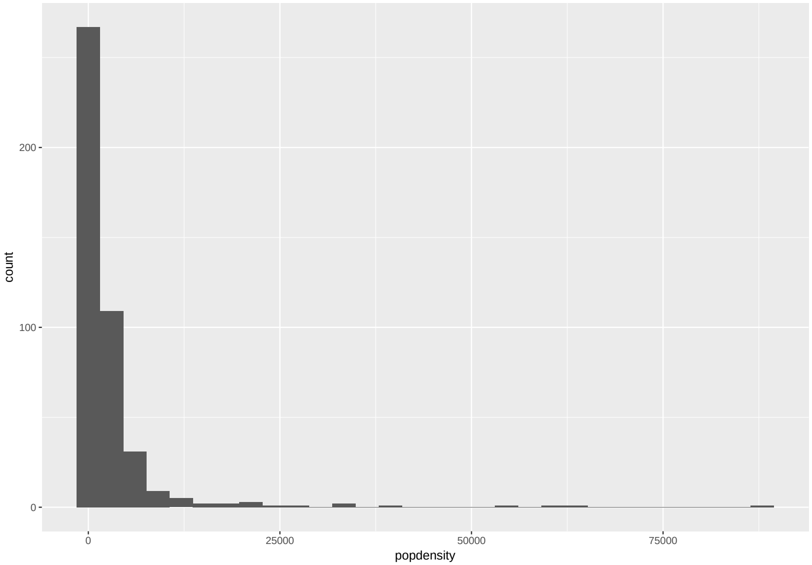
Geoms for single variables IX

It is also possible to do a histogram of a quantitative variable:

```r
ggplot(data = midwest, mapping = aes(x = popdensity)) +
  geom_histogram()
```

Geoms for single variables X

```
## `stat_bin()` using `bins = 30`. Pick better value with `
```

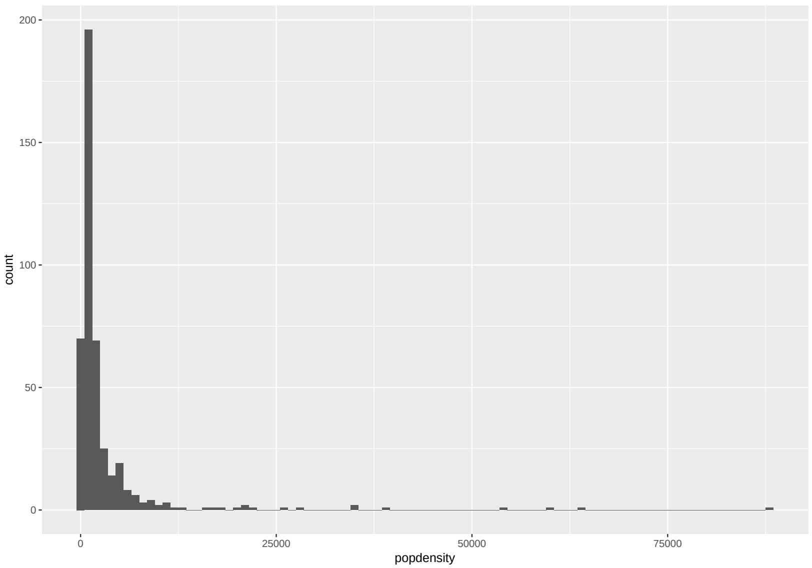


Geoms for single variables XI

You can adjust the binwidth directly:

```r
ggplot(data = midwest, mapping = aes(x = popdensity)) +
  geom_histogram(binwidth = 1000)
```

Geoms for single variables XII

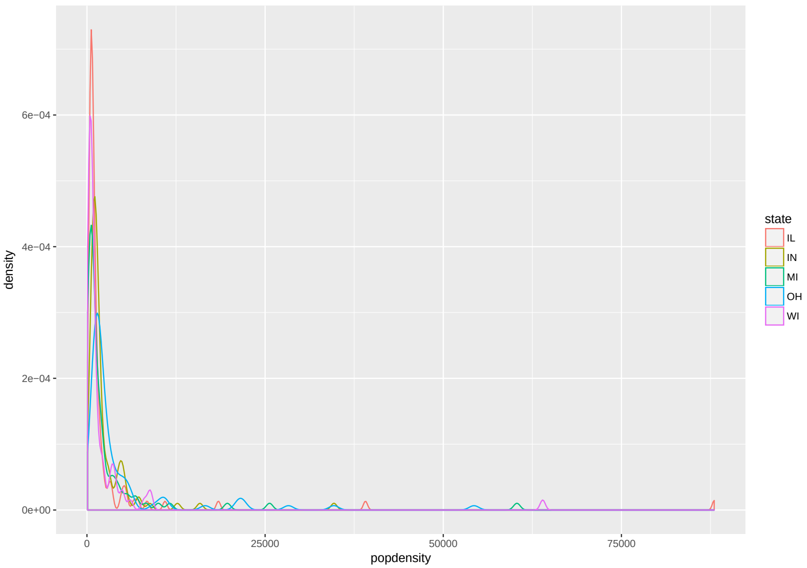


Examples

- With more than two groups, histograms are difficult to interpret due to overlap.
- Instead, use the `geom_density` to create a density plot for `popdensity` for each state.
- The final plot should look similar to this:

```r
ggplot(data = midwest, mapping = aes(x = popdensity)) +
  geom_density(aes(color = state))
```

Examples cont.

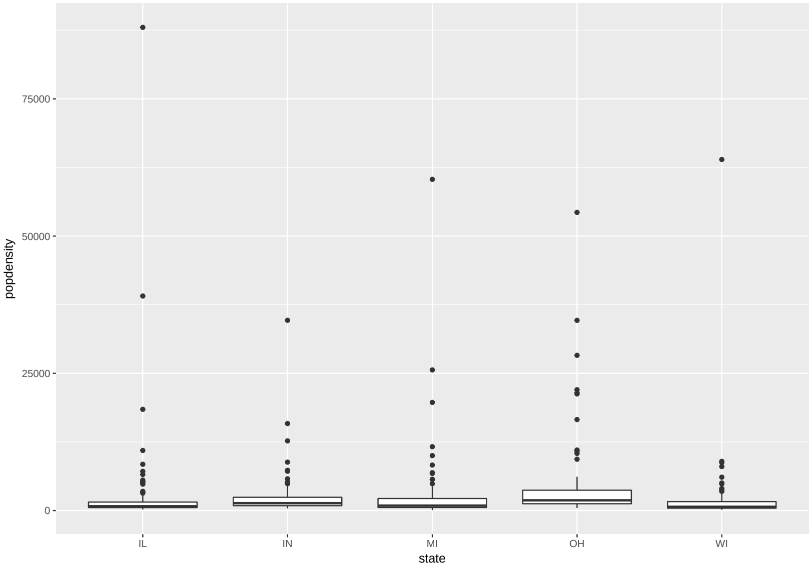


Examples cont.

- Using `geom_boxplot`, create boxplots with `popdensity` as the y variable and `state` as the x variable.
- Bonus: facet this plot by the variable `inmetro`.

```
ggplot(midwest, aes(x = state,
                    y = popdensity)) +
  geom_boxplot()
```

Examples cont.



Plot Customization

There are many many ways to adjust the look of the plot, I will discuss a few that are common.

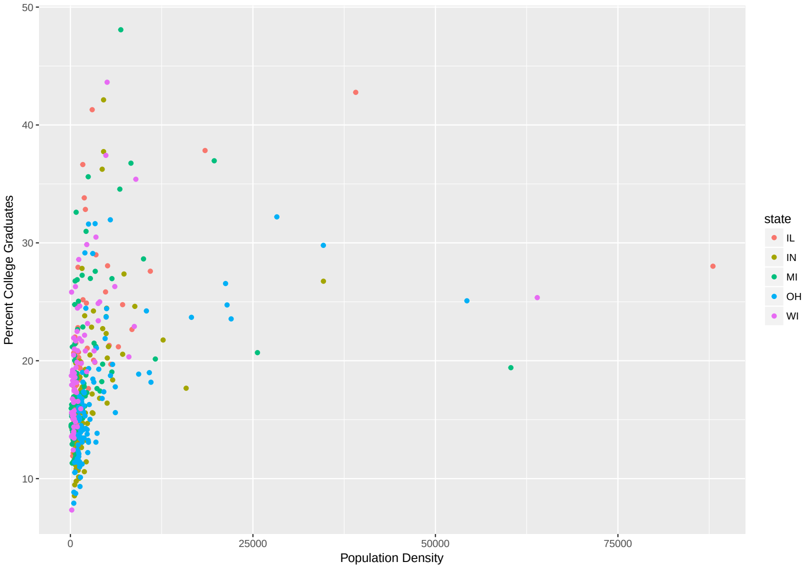
Change axes

Axes are something that are commonly altered, particularly to give them a good name and also to alter the values shown on the axes. These are generally done with `scale_x_*` and `scale_y_*` where `*` is a filler based on the type of variable on the axes.

- For example:

```r
ggplot(data = midwest, mapping = aes(x = popdensity,
                                     y = percollege,
                                     color = state)) +
  geom_point() +
  scale_x_continuous("Population Density") +
  scale_y_continuous("Percent College Graduates")
```

Change axes cont.



Chage legend tittle

To change the legend title, the `scale_color_discrete` command can be used to adjust the color aesthetic and the variable is discrete.

```
ggplot(data = midwest, mapping = aes(x = popdensity,
                                     y = percollege,
                                     color = state)) +
  geom_point() +
  scale_x_continuous("Population Density") +
  scale_y_continuous("Percent College Graduates") +
  scale_color_discrete("State")
```

Chage breaks

- We can also alter the breaks showing on the x-axis.

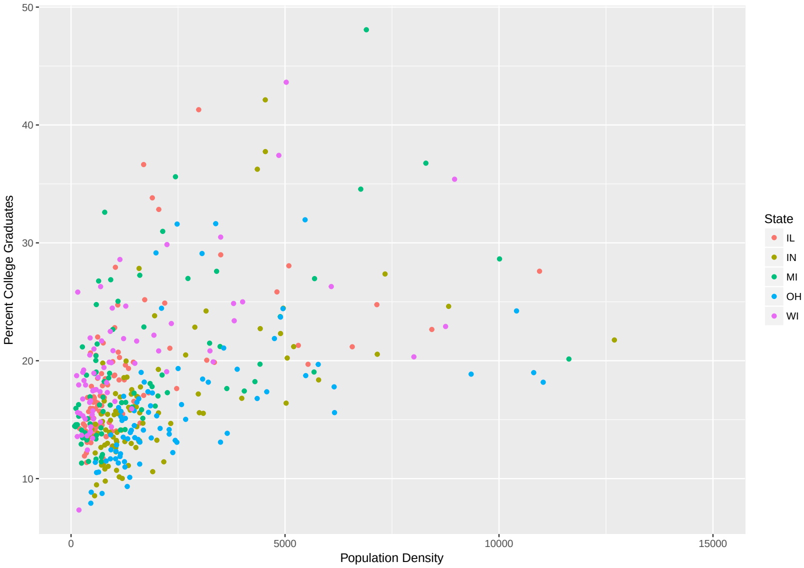
```r
ggplot(data = midwest, mapping = aes(x = popdensity,
                                     y = percollege,
                                     color = state)) +
  geom_point() +
  scale_x_continuous("Population Density",
                     breaks = seq(0, 80000, 20000)) +
  scale_y_continuous("Percent College Graduates") +
  scale_color_discrete("State")
```

Zoom in on plot I

- You'll notice that there are outliers in this scatterplot due to larger population density values for some counties.
- It may be of interest to zoom in on the plot.
- The plot can be zoomed in by using the `coord_cartesian` command as follows.
- This can also be achieved using the `xlim` argument to `scale_x_continuous` above, however this will cause some points to not be plotted.

```r
ggplot(data = midwest, mapping = aes(x = popdensity,
                                     y = percollege,
                                     color = state)) +
  geom_point() +
  scale_x_continuous("Population Density") +
  scale_y_continuous("Percent College Graduates") +
  scale_color_discrete("State") +
  coord_cartesian(xlim = c(0, 15000))
```

Zoom in on plot II



R Script

R scripts I

- I want to talk very briefly about R scripts.
- You may have been using these already within your workflow for this course, but these are best practice instead of simply running code in the console.
- Creating `R` scripts are a crucial step to ensure the data analyses are reproducible, the script will act as a log of all the things that are done to the data to go from data import to any outputs (model results, tables, figures, etc.).

R scripts II

- To create an R script with RStudio, the short cut is CTRL/CMD + SHIFT + N.
- You can also create a new script by going to File > New File > R Script.
- Both of these commands will open up a blank script window.
- In this script window, I would recommend loading any R packages first at the top of the file.
- Then proceed with the analysis.
- Commands can be sent to the console using CRTL/CMD + ENTER.
- By default RStudio will run any commands that span more than one line with a single CRTL/CMD + ENTER call.

R scripts III

- For more details about R Scripts, the R for Data Science text has detail with screenshots in Chapter 6.
- I recommend trying to create a simple script and sending these commands from the script to the console to be run with R.

R scripts IV

- If you are a `Linux` user you can type and save your R Script using, for example `gedit`
- Then in your terminal, you will:
  - set your working directory, `setwd()`
  - and read the R script, `source()`

Data Import

Background

- So far we have solely used data that is already found within R by way of packages.
- Obviously, we will want to use our own data and this involves importing data directly into R.
- We are going to focus on two types of data structures to read in, text files and excel files.

The following two packages will be used in this section:

```r
library(tidyverse)
# install.packages("readxl")
library(readxl)
```

Text Files I

- Through the use of the `readr` package, we are going to read in flat text files.
- In many cases, these text files are saved as csv files.
- The csv stands for comma separated values files meaning that columns in the data are separated by columns.
- As a side note, this is the most common way that I save data and read in data.
- The nice aspect of csv files is that if needed, they can be opened in programs like Excel for viewing, but are still just text files which are simple and lightweight.

Text Files II

- To read in a csv file, we are going to use the `read_csv` function from the `readr` package. We are going to read in some UFO data (the data can be found on ICON).
- A special note here, first, I am going to assume throughout that you are using RStudio projects and that the data file is in a folder called "Data".
- If this is not the case, the path for the files listed below will not work.
- You could use `read.csv(file.choose())` to open a file browser.
- Or using the `getwd` function can help debug issues. See the lectures on R projects or `http://r4ds.had.co.nz/workflow-projects.html` for additional information.

```r
ufo <- read_csv("Data/ufo.csv")
```

Text Files III

```
## Parsed with column specification:
## cols(
##   `Date / Time` = col_character(),
##   City = col_character(),
##   State = col_character(),
##   Shape = col_character(),
##   Duration = col_character(),
##   Summary = col_character(),
##   Posted = col_character()
## )
```

Text Files IV

- Note again, similar to `dplyr`, when saving the data to an object, it will not be printed.
- We can now view the first 10 rows by typing the object name.

```
ufo
```

Text Files V

```
## # A tibble: 8,031 × 7
##     `Date / Time`                         City State    Shape    Duration
##             <chr>                        <chr> <chr>    <chr>       <chr>
## 1  12/12/14 17:30                  North Wales    PA Triangle   5 minutes
## 2  12/12/14 12:40                 Cartersville    GA  Unknown 3.6 minutes
## 3  12/12/14 06:30 Isle of Man (UK/England)  <NA>    Light   2 seconds
## 4  12/12/14 01:00                   Miamisburg    OH Changing        <NA>
## 5  12/12/14 00:00                 Spotsylvania    VA  Unknown    1 minute
## 6  12/11/14 23:25                       Kenner    LA  Chevron   ~1 minute
## 7  12/11/14 23:15                       Eugene    OR     Disk   2 minutes
## 8  12/11/14 20:04                      Phoenix    AZ  Chevron   3 minutes
## 9  12/11/14 20:00                     Franklin    NC     Disk   5 minutes
## 10 12/11/14 18:30                     Longview    WA Cylinder  10 seconds
## # ... with 8,021 more rows, and 2 more variables: Summary <chr>,
## #   Posted <chr>
```

Text Files VI

- By default, the `read_csv` function uses the first row of the data file as the names of the variables.
- To override this behavior, set `col_names = FALSE` or better yet, specify the names with the `col_names` argument.
- In addition, if the file has header metadata, rows of the data can be skipped with the `skip` argument.
- For example, reading in the same data as above, but skipping the first row and specifying the names manually would look as follows:

```r
read_csv("Data/ufo.csv", skip = 1,
         col_names = c('Date/Time',
                       'City', 'State',
                       'Shape', 'Duration', 'Summary',
                       'Posted'))
```

Text Files VII

```
## Parsed with column specification:
## cols(
##   `Date/Time` = col_character(),
##   City = col_character(),
##   State = col_character(),
##   Shape = col_character(),
##   Duration = col_character(),
##   Summary = col_character(),
##   Posted = col_character()
## )

## # A tibble: 8,031 × 7
##       `Date/Time`                      City State    Shape    Duration
##             <chr>                     <chr> <chr>    <chr>       <chr>
## 1  12/12/14 17:30               North Wales    PA Triangle   5 minutes
## 2  12/12/14 12:40              Cartersville    GA  Unknown 3.6 minutes
## 3  12/12/14 06:30 Isle of Man (UK/England)  <NA>    Light   2 seconds
## 4  12/12/14 01:00                Miamisburg    OH Changing        <NA>
## 5  12/12/14 00:00              Spotsylvania    VA  Unknown    1 minute
## 6  12/11/14 23:25                    Kenner    LA  Chevron   ~1 minute
## 7  12/11/14 23:15                    Eugene    OR     Disk   2 minutes
## 8  12/11/14 20:04                   Phoenix    AZ  Chevron   3 minutes
## 9  12/11/14 20:00                  Franklin    NC     Disk   5 minutes
## 10 12/11/14 18:30                  Longview    WA Cylinder  10 seconds
## # ... with 8,021 more rows, and 2 more variables: Summary <chr>,
```

Manually Specifying Column Types I

- You may have noticed above that we just needed to give the `read_csv` function the path to the data file, we did not need to tell the function the types of columns.
- Instead, the function guessed the type from the first 1000 rows.
- This can be useful for interactive work, but for truly reproducible code, it is best to specify these manually.
- There are two ways to specify the column types, one is verbose and the other is simpler, but both use the argument `col_types`.

Manually Specifying Column Types II

First the verbose solution:

```
read_csv("Data/ufo.csv",
         col_types = c(
           'Date/Time' = col_character(),
           City = col_character(),
           State = col_character(),
           Shape = col_character(),
           Duration = col_character(),
           Summary = col_character(),
           Posted = col_character()
         ))
```

Manually Specifying Column Types III

```
## # A tibble: 8,031 × 7
##     `Date / Time`                             City State    Shape    Duration
##             <chr>                            <chr> <chr>    <chr>       <chr>
## 1  12/12/14 17:30                      North Wales    PA Triangle   5 minutes
## 2  12/12/14 12:40                     Cartersville    GA  Unknown 3.6 minutes
## 3  12/12/14 06:30 Isle of Man (UK/England)  <NA>    Light   2 seconds
## 4  12/12/14 01:00                       Miamisburg    OH Changing        <NA>
## 5  12/12/14 00:00                     Spotsylvania    VA  Unknown    1 minute
## 6  12/11/14 23:25                           Kenner    LA  Chevron   ~1 minute
## 7  12/11/14 23:15                           Eugene    OR     Disk   2 minutes
## 8  12/11/14 20:04                          Phoenix    AZ  Chevron   3 minutes
## 9  12/11/14 20:00                         Franklin    NC     Disk   5 minutes
## 10 12/11/14 18:30                         Longview    WA Cylinder  10 seconds
## # ... with 8,021 more rows, and 2 more variables: Summary <chr>,
## #   Posted <chr>
```

Manually Specifying Column Types IV

As all variables are being read in as characters, there is a simple shortcut to use.

```
read_csv("Data/ufo.csv",
         col_types = c('ccccccc'))
```

Manually Specifying Column Types V

- To show the reason the more verbose is useful, suppose we wished to convert the 'Data/Time' variable to the correct type, a date time variable.

```r
read_csv("Data/ufo.csv",
         col_types = c(
           'Date / Time' = col_datetime(),
           City = col_character(),
           State = col_character(),
           Shape = col_character(),
           Duration = col_character(),
           Summary = col_character(),
           Posted = col_character()
         ))
```

```
## Error: Unknown shortcut:
```

Manually Specifying Column Types VI

- Here we get an error, which is caused by the fact that the date time variable specification needs a format statement, we can directly specify this.

```
ufo_date <- read_csv("Data/ufo.csv",
         col_types = list(
'Date / Time' = col_datetime(format = "%m/%d/%y %H:%M"),
           City = col_character(),
           State = col_character(),
           Shape = col_character(),
           Duration = col_character(),
           Summary = col_character(),
           Posted = col_character()
         ))
```

Manually Specifying Column Types VII

```
## # A tibble: 8,031 × 7
##          `Date / Time`                         City State    Shape    Duration
##                 <dttm>                        <chr> <chr>    <chr>       <chr>
## 1  2014-12-12 17:30:00                  North Wales    PA Triangle   5 minutes
## 2  2014-12-12 12:40:00                Cartersville    GA  Unknown 3.6 minutes
## 3  2014-12-12 06:30:00 Isle of Man (UK/England)  <NA>    Light   2 seconds
## 4  2014-12-12 01:00:00                  Miamisburg    OH Changing        <NA>
## 5  2014-12-12 00:00:00                Spotsylvania    VA  Unknown    1 minute
## 6  2014-12-11 23:25:00                      Kenner    LA  Chevron   ~1 minute
## 7  2014-12-11 23:15:00                      Eugene    OR     Disk   2 minutes
## 8  2014-12-11 20:04:00                     Phoenix    AZ  Chevron   3 minutes
## 9  2014-12-11 20:00:00                    Franklin    NC     Disk   5 minutes
## 10 2014-12-11 18:30:00                    Longview    WA Cylinder  10 seconds
## # ... with 8,021 more rows, and 2 more variables: Summary <chr>,
## #   Posted <chr>
```

Manually Specifying Column Types VIII

- Notice even though I was careful in the column specification, there was still issues when parsing this column as a date/time column. The data is still returned, but there are issues.
- These issues can be viewed using the `problems` function such as `problems(ufo_date)`.

```
## # A tibble: 56 × 5
##      row         col                 expected   actual            file
##    <int>       <chr>                    <chr>    <chr>           <chr>
## 1    119 Date / Time date like %m/%d/%y %H:%M  12/1/14 'Data/ufo.csv'
## 2    194 Date / Time date like %m/%d/%y %H:%M 11/27/14 'Data/ufo.csv'
## 3    236 Date / Time date like %m/%d/%y %H:%M 11/24/14 'Data/ufo.csv'
## 4    407 Date / Time date like %m/%d/%y %H:%M 11/15/14 'Data/ufo.csv'
## 5    665 Date / Time date like %m/%d/%y %H:%M 10/31/14 'Data/ufo.csv'
## 6    797 Date / Time date like %m/%d/%y %H:%M 10/25/14 'Data/ufo.csv'
## 7    946 Date / Time date like %m/%d/%y %H:%M 10/19/14 'Data/ufo.csv'
## 8   1081 Date / Time date like %m/%d/%y %H:%M 10/14/14 'Data/ufo.csv'
## 9   1122 Date / Time date like %m/%d/%y %H:%M 10/12/14 'Data/ufo.csv'
## 10  1123 Date / Time date like %m/%d/%y %H:%M 10/12/14 'Data/ufo.csv'
## # ... with 46 more rows
```

Other Text Formats

- There are other text formats used to read in data.
- They are listed below with the function used to read in that type.
- Note, that the function calls are identical to those specified above.
  - tsv - tab separated files - `read_tsv`
  - fixed width files - `read_fwf`
  - white space generally - `read_table`
  - delimiter generally - `read_delim`

Exercises

1. Instead of specifying the path, use the function `file.choose()`. For example, `read_tsv(file.choose())`. What does this function use? Would you recommend this to be used in a reproducible document?
2. Run the `getwd()` function from the R console. What does this function return?

Excel Files I

- Although I commonly use text files (e.g. csv) files, reality is that many people still use Excel for storing of data files.
- There are good and bad aspects of this, but reading in Excel files may be needed.
- The `readxl` package is useful for this task.
- Suppose we wished to read in the Excel file found on the US Census Bureau website related to Education: `https://www.census.gov/support/USACdataDownloads.html`
- To do this, we can do this directly with the `read_excel` function with the data already downloaded and posted on ICON.

```
read_excel('Data/EDU01.xls')
```

Excel Files II

```
## # A tibble: 3,198 × 42
##        Area_name STCOU EDU010187F EDU010187D EDU010187N1 EDU010187N2
##            <chr> <chr>      <dbl>      <dbl>       <chr>       <chr>
## 1  UNITED STATES 00000          0   40024299        0000        0000
## 2        ALABAMA 01000          0     733735        0000        0000
## 3    Autauga, AL 01001          0       6829        0000        0000
## 4    Baldwin, AL 01003          0      16417        0000        0000
## 5    Barbour, AL 01005          0       5071        0000        0000
## 6       Bibb, AL 01007          0       3557        0000        0000
## 7     Blount, AL 01009          0       7319        0000        0000
## 8    Bullock, AL 01011          0       2014        0000        0000
## 9     Butler, AL 01013          0       4640        0000        0000
## 10   Calhoun, AL 01015          0      20939        0000        0000
## # ... with 3,188 more rows, and 36 more variables: EDU010188F <dbl>,
## #   EDU010188D <dbl>, EDU010188N1 <chr>, EDU010188N2 <chr>,
## #   EDU010189F <dbl>, EDU010189D <dbl>, EDU010189N1 <chr>,
## #   EDU010189N2 <chr>, EDU010190F <dbl>, EDU010190D <dbl>,
## #   EDU010190N1 <chr>, EDU010190N2 <chr>, EDU010191F <dbl>,
## #   EDU010191D <dbl>, EDU010191N1 <chr>, EDU010191N2 <chr>,
## #   EDU010192F <dbl>, EDU010192D <dbl>, EDU010192N1 <chr>,
## #   EDU010192N2 <chr>, EDU010193F <dbl>, EDU010193D <dbl>,
## #   EDU010193N1 <chr>, EDU010193N2 <chr>, EDU010194F <dbl>,
## #   EDU010194D <dbl>, EDU010194N1 <chr>, EDU010194N2 <chr>,
## #   EDU010195F <dbl>, EDU010195D <dbl>, EDU010195N1 <chr>,
## #   EDU010195N2 <chr>, EDU010196F <dbl>, EDU010196D <dbl>,
## #   EDU010196N1 <chr>, EDU010196N2 <chr>,
```

Excel Files III

- By default, the function will read in the first sheet and will treat the first row as the column names.
- If you wish to read in another sheet, you can use the `sheet` argument.
- For example:

```r
read_excel('Data/EDU01.xls', sheet = 2)
read_excel('Data/EDU01.xls', sheet = 'EDU01B')
```

- If there is metadata or no column names, these can be added in the same fashion as discussed above with the `read_csv` function.

Writing Files I

- Most of the `read_*` functions also come with functions that allow you to write out files as well.
- I'm only going to cover the `write_csv` function, however, there are others that may be of use.
- Similarly to reading in files, the functionality is the same across the `write_*` functions.

Writing Files II

- Suppose we created a new column with the `ufo` data and wished to save this data to a csv file, this can be accomplished with the following series of commands:

```
ufo_count <- ufo %>%
  group_by(State) %>%
  mutate(num_state = n())
write_csv(ufo_count, path = 'path/to/save/file.csv')
```

- Notice there are two arguments to the `write_csv` function, the first argument is the object you wish to save.
- The second is the path to the location to save the object.
- You must specify `path =` otherwise the `write_csv` function will look for that object in the R session.

Other Data Formats

- There are still other data formats, particularly from proprietary statistical software such as Stata, SAS, or SPSS.
- To read these files in the `haven` function would be useful.
- I leave this as an exercise for you if you have these types of files to read into R.

Data Munging with R

Data Munging

- Data munging (i.e. data transformations, variable creation, filtering) is a common task that is often overlooked in traditional statistics textbooks and courses.
- Data from the `fivethirtyeight` package is used in this section to show the use of the `dplyr` verbs for data munging.
- This package can be installed with the following command:

```
congress_age <- read_csv("Data/congress_age.csv")
```

Loading packages and exploring data

- To get started with this set of notes, you will need the following packages loaded:

```
library(readr)
library(tidyverse)
congress_age <- read_csv("Data/congress_age.csv")
```

- We are going to explore the `congress_age` data set in more detail.
- Take a couple minutes to familiarize yourself with the data.

```
View(congress_age)
?congress_age
```

congress_age

```
## # A tibble: 18,635 × 13
##    congress chamber bioguide firstname middlename  lastname suffix
##       <int>   <chr>    <chr>     <chr>      <chr>     <chr>  <chr>
## 1        80   house  M000112    Joseph  Jefferson Mansfield   <NA>
## 2        80   house  D000448    Robert        Lee  Doughton   <NA>
## 3        80   house  S000001    Adolph    Joachim    Sabath   <NA>
## 4        80   house  E000023   Charles     Aubrey     Eaton   <NA>
## 5        80   house  L000296   William       <NA>     Lewis   <NA>
## 6        80   house  G000017     James         A. Gallagher   <NA>
## 7        80   house  W000265   Richard     Joseph     Welch   <NA>
## 8        80   house  B000565       Sol       <NA>     Bloom   <NA>
## 9        80   house  H000943    Merlin       <NA>      Hull   <NA>
## 10       80   house  G000169   Charles   Laceille   Gifford   <NA>
## # ... with 18,625 more rows, and 6 more variables: birthday <date>,
## #   state <chr>, party <chr>, incumbent <lgl>, termstart <date>, age <dbl>
```

Using `dplyr` for data munging

- The `dplyr` package uses verbs for common data manipulation tasks. These include:
  - `filter()`
  - `arrange()`
  - `select()`
  - `mutate()`
  - `summarise()`
- The great aspect of these verbs are that they all take a similar data structure, the first argument is always the data, the other arguments are unquoted column names.
- These functions also always return a data frame in which the rows are observations and the columns are variables.

Examples with `filter()` I

- The `filter` function selects rows that match a specified condition(s).
- For example, suppose we wanted to select only the rows in the data that are a part of the 80th congress.
- The following code will do this action:

```
filter(congress_age, congress == 80)
```

Examples with `filter()` II

- The `filter` function selects rows that match a specified condition(s).
- For example, suppose we wanted to select only the rows in the data that are a part of the 80th congress.
- The following code will do this action:

```
## # A tibble: 555 × 13
##    congress chamber bioguide firstname middlename  lastname suffix
##       <int>   <chr>    <chr>     <chr>      <chr>     <chr>  <chr>
## 1        80   house  M000112    Joseph  Jefferson Mansfield   <NA>
## 2        80   house  D000448    Robert        Lee  Doughton   <NA>
## 3        80   house  S000001    Adolph    Joachim    Sabath   <NA>
## 4        80   house  E000023   Charles     Aubrey     Eaton   <NA>
## 5        80   house  L000296   William       <NA>     Lewis   <NA>
## 6        80   house  G000017     James         A. Gallagher   <NA>
## 7        80   house  W000265   Richard     Joseph     Welch   <NA>
## 8        80   house  B000565       Sol       <NA>     Bloom   <NA>
## 9        80   house  H000943    Merlin       <NA>      Hull   <NA>
## 10       80   house  G000169   Charles   Laceille   Gifford   <NA>
## # ... with 545 more rows, and 6 more variables: birthday <date>,
## #   state <chr>, party <chr>, incumbent <lgl>, termstart <date>, age <dbl>
```

Examples with `filter()` III

- Notice from the previous slide two things, first, the function returned a new data frame.
- Therefore, if this subsetted data is to be saved, we need to save it to an object, for example, as follows:

```r
congress_80 <- filter(congress_age, congress == 80)
```

Examples with `filter()` IV

```
## # A tibble: 555 × 13
##    congress chamber bioguide firstname middlename  lastname suffix
##       <int>   <chr>    <chr>     <chr>      <chr>     <chr>  <chr>
## 1        80   house  M000112    Joseph  Jefferson Mansfield   <NA>
## 2        80   house  D000448    Robert        Lee  Doughton   <NA>
## 3        80   house  S000001    Adolph    Joachim    Sabath   <NA>
## 4        80   house  E000023   Charles     Aubrey     Eaton   <NA>
## 5        80   house  L000296   William       <NA>     Lewis   <NA>
## 6        80   house  G000017     James         A. Gallagher   <NA>
## 7        80   house  W000265   Richard     Joseph     Welch   <NA>
## 8        80   house  B000565       Sol       <NA>     Bloom   <NA>
## 9        80   house  H000943    Merlin       <NA>      Hull   <NA>
## 10       80   house  G000169   Charles   Laceille   Gifford   <NA>
## # ... with 545 more rows, and 6 more variables: birthday <date>,
## #   state <chr>, party <chr>, incumbent <lgl>, termstart <date>, age <dbl>
```

Example cont.

- Notice from the previous slide that equality in `R` is done with == not just a single =.
- The single = is used for named arguments, therefore when testing for equality you need to be sure to use ==, this is a common frustration and source of bugs when getting started with `R`.
- Selecting values based on a character vector are similar to numeric values.
- For example, suppose we wanted to select only those rows pertaining to those from the senate.
- The following code will do that:

```r
senate <- filter(congress_age, chamber == 'senate')
```

Example cont.

```
## # A tibble: 3,552 × 13
##    congress chamber bioguide firstname middlename lastname suffix
##       <int>   <chr>    <chr>     <chr>      <chr>    <chr>  <chr>
## 1        80  senate  C000133    Arthur       <NA>   Capper   <NA>
## 2        80  senate  G000418  Theodore    Francis    Green   <NA>
## 3        80  senate  M000499   Kenneth    Douglas McKellar   <NA>
## 4        80  senate  R000112     Clyde     Martin     Reed   <NA>
## 5        80  senate  M000895    Edward       Hall    Moore   <NA>
## 6        80  senate  O000146      John     Holmes  Overton   <NA>
## 7        80  senate  M001108     James     Edward   Murray   <NA>
## 8        80  senate  M000308   Patrick    Anthony McCarran   <NA>
## 9        80  senate  T000165     Elmer       <NA>   Thomas   <NA>
## 10       80  senate  W000021    Robert  Ferdinand   Wagner   <NA>
## # ... with 3,542 more rows, and 6 more variables: birthday <date>,
## #   state <chr>, party <chr>, incumbent <lgl>, termstart <date>, age <dbl>
```

Combining Logical Operations I

- The `filter` function becomes much more useful with more complex operations.
- For example, suppose we were interested in selecting the rows that belong to the 80th senate.

```r
filter(congress_age, congress == 80, chamber == 'senate')
```

Combining Logical Operations II

```
## # A tibble: 102 × 13
##    congress chamber bioguide firstname middlename lastname suffix
##       <int>   <chr>    <chr>     <chr>      <chr>    <chr>  <chr>
## 1        80  senate  C000133    Arthur       <NA>   Capper   <NA>
## 2        80  senate  G000418  Theodore    Francis    Green   <NA>
## 3        80  senate  M000499   Kenneth    Douglas McKellar   <NA>
## 4        80  senate  R000112     Clyde     Martin     Reed   <NA>
## 5        80  senate  M000895    Edward       Hall    Moore   <NA>
## 6        80  senate  O000146      John     Holmes  Overton   <NA>
## 7        80  senate  M001108     James     Edward   Murray   <NA>
## 8        80  senate  M000308   Patrick    Anthony McCarran   <NA>
## 9        80  senate  T000165     Elmer       <NA>   Thomas   <NA>
## 10       80  senate  W000021    Robert  Ferdinand   Wagner   <NA>
## # ... with 92 more rows, and 6 more variables: birthday <date>,
## #   state <chr>, party <chr>, incumbent <lgl>, termstart <date>, age <dbl>
```

Logical arguments I

- By default, the `filter` function uses AND when combining multiple arguments.
- Therefore, the above command returned only the 102 rows belonging to senators from the 80th congress.
- The following figure gives a list of all other possible boolean operations.

Logical arguments II

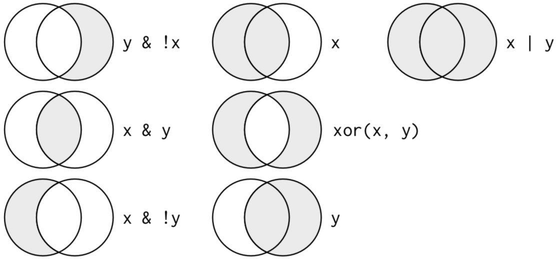


Figure 5.1: Complete set of boolean operations. `x` is the left-hand circle, `y` is the right-hand circle, and the shaded region show which parts each operator selects.

- Note: This graphic is from the “R for Data Science” book

Logical arguments III

- Using an example of the OR operator using | to select the 80th and 81st congress:

```
filter(congress_age, congress == 80 | congress == 81)
```

Logical arguments IV

- Using an example of the OR operator using | to select the 80th and 81st congress:

```
## # A tibble: 1,112 × 13
##    congress chamber bioguide firstname middlename  lastname suffix
##       <int>   <chr>    <chr>     <chr>      <chr>     <chr>  <chr>
## 1        80   house  M000112    Joseph  Jefferson Mansfield   <NA>
## 2        80   house  D000448    Robert        Lee  Doughton   <NA>
## 3        80   house  S000001    Adolph    Joachim    Sabath   <NA>
## 4        80   house  E000023   Charles     Aubrey     Eaton   <NA>
## 5        80   house  L000296   William       <NA>     Lewis   <NA>
## 6        80   house  G000017     James         A. Gallagher   <NA>
## 7        80   house  W000265   Richard     Joseph     Welch   <NA>
## 8        80   house  B000565       Sol       <NA>     Bloom   <NA>
## 9        80   house  H000943    Merlin       <NA>      Hull   <NA>
## 10       80   house  G000169   Charles   Laceille   Gifford   <NA>
## # ... with 1,102 more rows, and 6 more variables: birthday <date>,
## #   state <chr>, party <chr>, incumbent <lgl>, termstart <date>, age <dbl>
```

Logical arguments V

- Note that to do the OR operator, you need to name the variable twice.
- When selecting multiple values in the same variable, a handy shortcut is `%in%`.
- The same command can be run with the following shorthand: handy shortcut is `%in%`.
- The same command can be run with the following shorthand

```r
filter(congress_age, congress %in% c(80, 81))
```

Not Operator I

- Another useful operator that deserves a bit more discussion is the not operator, `!`.
- For example, suppose we wanted to omit the 80th congress:

```
filter(congress_age, congress != 80)
```

Not Operator II

```
## # A tibble: 18,080 × 13
##    congress chamber bioguide firstname middlename lastname suffix
##       <int>   <chr>    <chr>     <chr>      <chr>    <chr>  <chr>
## 1        81   house  D000448    Robert        Lee Doughton   <NA>
## 2        81   house  S000001    Adolph    Joachim   Sabath   <NA>
## 3        81   house  E000023   Charles     Aubrey    Eaton   <NA>
## 4        81   house  W000265   Richard     Joseph    Welch   <NA>
## 5        81   house  B000565       Sol       <NA>    Bloom   <NA>
## 6        81   house  H000943    Merlin       <NA>     Hull   <NA>
## 7        81   house  B000545  Schuyler       Otis    Bland   <NA>
## 8        81   house  K000138      John      Hosea     Kerr   <NA>
## 9        81   house  C000932    Robert       <NA>  Crosser   <NA>
## 10       81   house  K000039      John       <NA>      Kee   <NA>
## # ... with 18,070 more rows, and 6 more variables: birthday <date>,
## #   state <chr>, party <chr>, incumbent <lgl>, termstart <date>, age <dbl>
```

Not Operator III

It is also possible to do not with an AND operator as follows:

```
filter(congress_age, congress == 80 & !chamber == 'senate'
```

Exercises

1. Using the congress data, select the rows belonging to the democrats (party = D) from the senate of the 100th congress.
2. Select all congress members who are older than 80 years old.

Note on Missing Data

- Missing data within R are represented with `NA` which stands for not available.
- There are no missing data in the congress data, however, by default the `filter` function will not return any missing values.
- In order to select missing data, you need to use the `is.na` function.

Exercise

1. Given the following simple vector, run one filter that selects all values greater than 100. Write a second filter command that selects all the rows greater than 100 and also the NA value.

```r
df <- tibble(x = c(200, 30, NA, 45, 212))
```

Examples with `arrange()` I

- The `arrange` function is used for ordering rows in the data.
- For example, suppose we wanted to order the rows in the congress data by the state the members of congress lived in.
- This can be done using the `arrange` function as follows:

```
arrange(congress_age, state)
```

Examples with arrange() II

```
## # A tibble: 18,635 × 13
##    congress chamber bioguide firstname middlename lastname suffix
##       <int>   <chr>    <chr>     <chr>      <chr>    <chr>  <chr>
## 1        80   house  B000201    Edward      Lewis Bartlett   <NA>
## 2        81   house  B000201    Edward      Lewis Bartlett   <NA>
## 3        82   house  B000201    Edward      Lewis Bartlett   <NA>
## 4        83   house  B000201    Edward      Lewis Bartlett   <NA>
## 5        84   house  B000201    Edward      Lewis Bartlett   <NA>
## 6        85   house  B000201    Edward      Lewis Bartlett   <NA>
## 7        86   house  R000282     Ralph     Julian   Rivers   <NA>
## 8        86  senate  G000508    Ernest       <NA> Gruening   <NA>
## 9        86  senate  B000201    Edward      Lewis Bartlett   <NA>
## 10       87   house  R000282     Ralph     Julian   Rivers   <NA>
## # ... with 18,625 more rows, and 6 more variables: birthday <date>,
## #   state <chr>, party <chr>, incumbent <lgl>, termstart <date>, age <dbl>
```

Example with `arrange()` III

- Similar to the filter function, additional arguments can be added to add more layers to the ordering.
- For example, if we were interested in ordering the rows by state and then by party affiliation.

```
arrange(congress_age, state, party)
```

Example with `arrange()` IV

```
## # A tibble: 18,635 × 13
##    congress chamber bioguide firstname middlename lastname suffix
##       <int> <chr>   <chr>    <chr>     <chr>      <chr>    <chr>
## 1        80  house   B000201    Edward      Lewis Bartlett   <NA>
## 2        81  house   B000201    Edward      Lewis Bartlett   <NA>
## 3        82  house   B000201    Edward      Lewis Bartlett   <NA>
## 4        83  house   B000201    Edward      Lewis Bartlett   <NA>
## 5        84  house   B000201    Edward      Lewis Bartlett   <NA>
## 6        85  house   B000201    Edward      Lewis Bartlett   <NA>
## 7        86  house   R000282     Ralph     Julian   Rivers   <NA>
## 8        86 senate   G000508    Ernest       <NA> Gruening   <NA>
## 9        86 senate   B000201    Edward      Lewis Bartlett   <NA>
## 10       87  house   R000282     Ralph     Julian   Rivers   <NA>
## # ... with 18,625 more rows, and 6 more variables: birthday <date>,
## #   state <chr>, party <chr>, incumbent <lgl>, termstart <date>, age <dbl>
```

Example with `arrange()` V

- More variables can easily be added to the `arrange` function.
- Notice from the above two commands that the ordering of the rows is in ascending order, if descending order is desired, the `desc` function.
- For example, to order the data starting with the latest congress first:

```r
arrange(congress_age, desc(congress))
```

Example with `arrange()` VI

```
## # A tibble: 18,635 × 13
##    congress chamber bioguide firstname middlename  lastname suffix
##       <int>   <chr>    <chr>     <chr>      <chr>     <chr>  <chr>
## 1       113   house  H000067     Ralph         M.      Hall   <NA>
## 2       113   house  D000355      John         D.   Dingell   <NA>
## 3       113   house  C000714      John       <NA>   Conyers    Jr.
## 4       113   house  S000480    Louise   McIntosh Slaughter   <NA>
## 5       113   house  R000053   Charles         B.    Rangel   <NA>
## 6       113   house  J000174       Sam     Robert   Johnson   <NA>
## 7       113   house  Y000031        C.    W. Bill     Young   <NA>
## 8       113   house  C000556    Howard       <NA>     Coble   <NA>
## 9       113   house  L000263    Sander         M.     Levin   <NA>
## 10      113   house  Y000033       Don         E.     Young   <NA>
## # ... with 18,625 more rows, and 6 more variables: birthday <date>,
## #   state <chr>, party <chr>, incumbent <lgl>, termstart <date>, age <dbl>
```

Examples with `select()` I

- The `select` function is used to select columns (i.e. variables) from the data but keep all the rows.
- For example, maybe we only needed the congress number, the chamber, the party affiliation, and the age of the members of congress.
- We can reduce the data to just these variables using `select`.

```r
select(congress_age, congress, chamber, party, age)
```

Examples with `select()` II

```
## # A tibble: 18,635 × 4
##    congress chamber party   age
##       <int>   <chr> <chr> <dbl>
## 1        80   house     D  85.9
## 2        80   house     D  83.2
## 3        80   house     D  80.7
## 4        80   house     R  78.8
## 5        80   house     R  78.3
## 6        80   house     R  78.0
## 7        80   house     R  77.9
## 8        80   house     D  76.8
## 9        80   house     R  76.0
## 10       80   house     R  75.8
## # ... with 18,625 more rows
```

Examples with select() III

- Similar to the arrange functions, the variables that you wish to keep are separated by commas and come after the data argument.
- For more complex selection, the dplyr package has additional functions that are helpful for variable selection. These include:
  - starts_with()
  - ends_with()
  - contains()
  - matches()
  - num_range()
- These helper functions can be useful for selecting many variables that match a specific pattern.
- For example, suppose we were interested in selecting all the name variables, this can be accomplished using the contains function as follows:

```r
select(congress_age, contains('name'))
```

Examples with `select()` IV

```
## # A tibble: 18,635 × 3
##    firstname middlename  lastname
##        <chr>      <chr>     <chr>
## 1     Joseph  Jefferson Mansfield
## 2     Robert        Lee  Doughton
## 3     Adolph    Joachim    Sabath
## 4    Charles     Aubrey     Eaton
## 5    William       <NA>     Lewis
## 6      James         A. Gallagher
## 7    Richard     Joseph     Welch
## 8        Sol       <NA>     Bloom
## 9     Merlin       <NA>      Hull
## 10   Charles   Laceille   Gifford
## # ... with 18,625 more rows
```

Examples with `select()` V

- Another useful shorthand to select multiple columns in succession is the `:` operator.
- For example, suppose we wanted to select all the variables between congress and birthday.

```r
select(congress_age, congress:birthday)
```

Rename variables

- The select function does allow you to rename variables, however, using the select function to rename variables is not usually advised as you may end up missing a variable that you wish to keep during the renaming operation.
- Instead, using the `rename` function is better practice.

```
rename(congress_age, first_name = firstname,
       last_name = lastname)
```

- By default, the rename function will not save changes to the object, if you wish to save the name differences (very likely), be sure to save this new step to an object.

Exercises

1. Using the `dplyr` helper functions, select all the variables that start with the letter '`c`'.
2. Rename the first three variables in the congress data to '`x1`', '`x2`', '`x3`'.
3. After renaming the first three variables, use this new data (ensure you saved the previous step to an object) to select these three variables with the `num_range` function.

Examples with `mutate()` I

- `mutate` is a useful verb that allows you to add new columns to the existing data set.
- Actions done with `mutate` include adding a column of means, counts, or other transformations of existing variables.
- Suppose for example, we wished to convert the party affiliation of the members of congress into a dummy (indicator) variable.
- This may be useful to more easily compute a proportion or count for instance.

Examples with `mutate()` II

- This can be done with the `mutate` function.
- Below, I'm first going to use `select` to reduce the number of columns to make it easier to see the operation.

```r
congress_red <- select(congress_age, congress,
                       chamber, state, party)

mutate(congress_red,
       democrat = ifelse(party == 'D', 1, 0),
       num_democrat = sum(democrat)
       )
```

Examples with `mutate()` III

```
## # A tibble: 18,635 × 6
##    congress chamber state party democrat num_democrat
##       <int> <chr>   <chr> <chr>    <dbl>        <dbl>
## 1        80 house   TX    D            1        10290
## 2        80 house   NC    D            1        10290
## 3        80 house   IL    D            1        10290
## 4        80 house   NJ    R            0        10290
## 5        80 house   KY    R            0        10290
## 6        80 house   PA    R            0        10290
## 7        80 house   CA    R            0        10290
## 8        80 house   NY    D            1        10290
## 9        80 house   WI    R            0        10290
## 10       80 house   MA    R            0        10290
## # ... with 18,625 more rows
```

Examples with `mutate()` IV

- You'll notice that the number of rows in the data are the same (18635) as it was previously, but now the two new columns have been added to the data.
- One converted the party affiliation to a series of 0/1 values and the other variable counted up the number of democrats elected since the 80th congress.
- Notice how this last variable is simply repeated for all values in the data.
- The operation done here is not too exciting, however, we will learn another utility later that allows us to group the data to calculate different values for each group.

Examples with `mutate()` V

- Lastly, from the output above, notice that I was able to reference a variable that I created previously in the mutate command.
- This is unique to the `dplyr` package and allows you to create a single `mutate` command to add many variables, even those that depend on prior calculations.
- Obviously, if you need to reference a calculation in another calculation, they need to be done in the proper order

Creation Functions

- There are many useful operators to use when creating additional variables.
- The R for Data Science text has many examples shown in section 5.5.1.
- In general useful operators include addition, subtraction, multiplication, division, descriptive statistics (we will talk more about these in week 4), ranks, logical comparisons, and many more.
- The exercises will have you explore some of these operations in more detail.

Exercises

1. Using the `diamonds` data, use `?diamonds` for more information on the data, use the `mutate` function to calculate the price per carat. Hint, this operation would involve standardizing the price variable so that all are comparable at 1 carat.
2. Calculate the rank of the original price variable and the new price variable calculated above using the `min_rank` function. Are there differences in the ranking of the prices? Hint, it may be useful to test if the two ranks are equal to explore this.

Useful summary functions I

- There are many useful summary functions.
- Suppose for instance we were interested in the knowing the youngest and oldest member of congress for each congress.
- There are actually two ways of doing this, one is using the `min` and `max` functions on the grouped data.

```
summarise(congress_grp,
          youngest = min(age),
          oldest = max(age)
)
```

Useful summary functions II

```
## # A tibble: 34 × 3
##    congress youngest oldest
##       <int>    <dbl>  <dbl>
## 1        80     25.9   85.9
## 2        81     27.2   85.2
## 3        82     27.9   87.2
## 4        83     26.7   85.3
## 5        84     28.5   87.3
## 6        85     30.5   89.3
## 7        86     31.0   91.3
## 8        87     28.9   86.0
## 9        88     29.0   85.3
## 10       89     25.0   87.3
## # ... with 24 more rows
```

Exercises

1. For each congress, calculate a summary using the following command: `n_distinct(state)`. What does this value return?
2. What happens when you use a logical expression within a `sum` function call? For example, what do you get in a summarise when you do: `sum(age > 75)`?
3. What happens when you try to use `sum` or `mean` on the variable incumbent?

Chaining together multiple operations I

- Now that you have seen all of the basic `dplyr` data manipulation verbs, it is useful to chain these together to create more complex operations.
- In many instances, intermediate steps are not useful to us.
- In these cases you can chain operations together.
- Suppose we are interested in calculating the proportion of democrats for each chamber of congress, but only since the 100th congress?

Chaining together multiple operations II

- There are two ways to do this, the difficult to read and the easier to read.
- I first shown the difficult to read.

```r
summarise(
  group_by(
    mutate(
      filter(
        congress_age, congress >= 100
      ),
      democrat = ifelse(party == 'D', 1, 0)
    ),
    congress, chamber
  ),
  num_democrat = sum(democrat),
  total = n(),
  prop_democrat = num_democrat / total
)
```

Chaining together multiple operations III

```
## Source: local data frame [28 x 5]
## Groups: congress [?]
##
##    congress chamber num_democrat total prop_democrat
##       <int>   <chr>        <dbl> <int>         <dbl>
## 1       100   house          263   443     0.5936795
## 2       100  senate           55   101     0.5445545
## 3       101   house          266   445     0.5977528
## 4       101  senate           56   101     0.5544554
## 5       102   house          272   443     0.6139955
## 6       102  senate           59   104     0.5673077
## 7       103   house          261   443     0.5891648
## 8       103  senate           58   105     0.5523810
## 9       104   house          206   441     0.4671202
## 10      104  senate           47   103     0.4563107
## # ... with 18 more rows
```

Chaining together multiple operations IV

- How difficult do you find the code above to read? This is valid R code, but the first operation done is nested in the middle (it is the `filter` function that is run first).
- This makes for difficult code to debug and write in my opinion.
- In my opinion, the better way to write code is through the pipe operator, %>%.
- The same code above can be achieved with the following much easier to read code:

Chaining together multiple operations V

```r
congress_age %>%
  filter(congress >= 100) %>%
  mutate(democrat = ifelse(party == 'D', 1, 0)) %>%
  group_by(congress, chamber) %>%
  summarise(
    num_democrat = sum(democrat),
    total = n(),
    prop_democrat = num_democrat / total
  )
```

Chaining together multiple operations VI

- The pipe allows for more readable code by humans and progresses from top to bottom, left to right.
- The best word to substitute when translating the %>% code above is 'then'.
- So the code above says, using the `congress_age` data, then `filter`, then `mutate`, then `group_by`, then `summarise`.
- This is much easier to read and follow the chain of commands.
- I highly recommend using the pipe in your code. For more details on what is actually happening, the R for Data Science book has a good explanation in Section 5.6.1.

Exercises

1. Look at the following nested code and determine what is being done. Then translate this code to use the pipe operator.

Exercises cont.

```
summarise(
  group_by(
    mutate(
      filter(
        diamonds,
  color %in% c('D', 'E', 'F') & cut %in% c('Fair',
                                             'Good',
                                             'Very Good')),
      f_color = ifelse(color == 'F', 1, 0),
      vg_cut = ifelse(cut == 'Very Good', 1, 0)),
    clarity ),
  avg = mean(carat),
  sd = sd(carat),
  avg_p = mean(price),
  num = n(),
  summary_f_color = mean(f_color),
  summary_vg_cut = mean(vg_cut) )
```

Section 6

Joining Data

Background I

- Another common data manipulation task is to join multiple data sources into a single data file for an analysis.
- This task is most easily accomplished using a set of `join` functions found in the `dplyr` package.
- In this set of notes we are going to focus on mutating joins and filtering joins.
- There is another class of joins called set operations.
- I use these much less frequently, but for those interested, see the text in the R for Data Science book `http://r4ds.had.co.nz/relational-data.html`.

Packages

For this section, we are going to make use of two packages:

```r
library(tidyverse)
# install.packages('Lahman')
library(Lahman)
```

Lahman Package

- The `Lahman` package contains data from the Major League Baseball (MLB), a professional baseball association in the United States.
- For this section, we are going to focus on the following three data tables, `Teams`, `Salaries`, and `Managers`.
- You can print the first ten rows of the data for each table below.

```
Teams
Salaries
Managers
```

Inner Join I

- The most basic join is the inner join.
- This join takes two tables and returns values if key variables match in both tables.
- If rows do not match on the key variables, these observations are removed.
- Suppose for example, we wanted to select the rows that matched between the `Teams` and `Salaries` data.
- This would be useful for example if we wished to calculate the average salary of the players for each team for every year.

Inner Join II

This join could be done with the `inner_join` function.

```r
team_salary <- inner_join(Teams, Salaries)
# team_salary
```

Inner Join III

- You'll notice that there is only data from 1985 onward, the data in the Teams data from before 1985 have automatically been removed due to no matching data in the Salaries data.
- You may have also noticed, that I did not specify the variables to join by above, for interactive work this can be okay, but to be more reproducible, specifying the variables to join on would be better.
- The function call above can be modified to include this information.

```r
team_salary <- inner_join(Teams,
                          Salaries, by = c('yearID',
                                           'teamID',
                                           'lgID'))
# team_salary
```

dplyr verbs and then plot I

We could then use other dplyr verbs to calculate the average salary for every team by year and plot these.

```r
team_salary %>%
  group_by(yearID, teamID) %>%
  summarise(avg_salary = mean(salary, na.rm = TRUE)) %>%
  ggplot(aes(x = yearID, y = avg_salary)) +
  geom_line(size = 1) +
  facet_wrap(~teamID)
```

dplyr verbs and then plot II

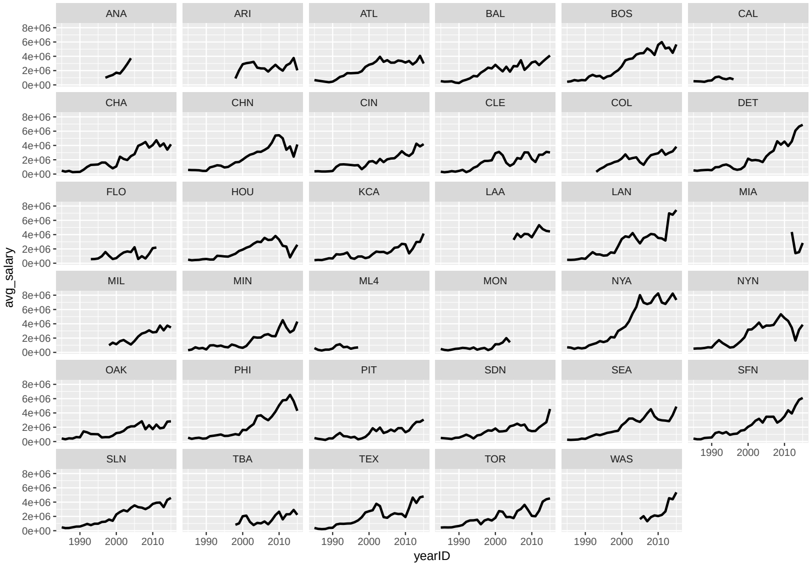
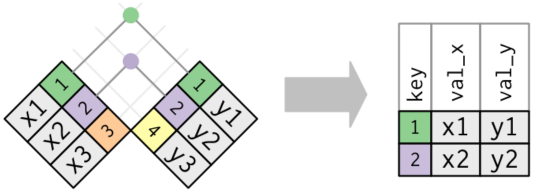


Diagram I

Below is a diagram of the inner join found in the R for Data Science text:



key	val1_x	val1_y
1	x1	y1
2	x2	y2

Left Join I

- This is by far the most common join I perform.
- Left join is more formally part of a group of operations called outer joins.
- Outer joins are useful when you want to use one data table as a base data set in which variables will be added to this data if the keys match. It is likely best shown with an example.
- Suppose we wish to add the salary information to the `Teams` data.
- However, instead of using a `inner_join`, let's use `left_join` to see the difference.

```r
left_join(Teams, Salaries)
```

Left Join II

- The first thing to notice is that now there are years in the yearID variable from before 1985, this was not the case in the above data joined using `inner_join`.
- If you scroll over to explore variables to the right, there are missing values for the salary variable.
- What `left_join` does when it doesn't find a match in the table is to produce NA values, so all records within the joined data will be NA before 1985.
- This is the major difference between outer joins and inner joins.
- Outer joins will preserve data in the keyed data that do not match and NA values are returned for non-matching values.
- For inner joins, any keys that do not match are removed.

Right Join

- A right join is similar to a left join, except the keyed table is the second one specified (the rightmost data).
- For example, if we wished for the salary information to be the keyed table, we could do that same specification as above, but use `right_join` instead of `left_join`.

```
right_join(Teams, Salaries)
```

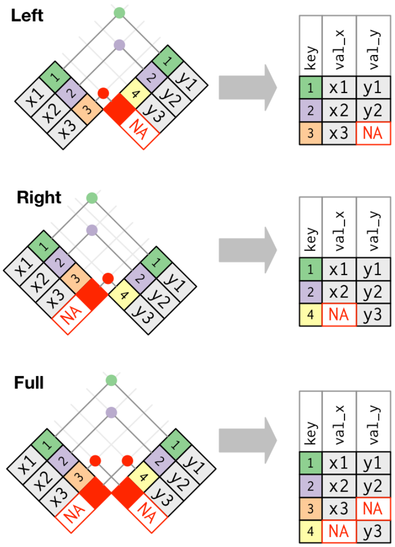
Full Join

- Full join is the last type of outer join and this will return all values from both tables and NAs will be given for those keys that do not match.
- For example,

```
full_join(Teams, Salaries)
```

Diagram II

Below is a diagram of the inner join found in the R for Data Science text:



key	val_x	val_y
1	x1	y1
2	x2	y2
3	x3	NA

key	val_x	val_y
1	x1	y1
2	x2	y2
4	NA	y3

key	val_x	val_y
1	x1	y1
2	x2	y2
3	x3	NA
4	NA	y3

Filtering Joins I

- We can also use filtering joins, however, these are useful to connect summary data back to the original rows in the data.
- For example, using the `team_salary` data created above, let's select only the top 10 teams in terms of average salary from the year 2015.

```r
top_salary_15 <- team_salary %>%
  group_by(yearID, teamID) %>%
  summarise(avg_salary = mean(salary, na.rm = TRUE)) %>%
  filter(yearID == 2015) %>%
  arrange(desc(avg_salary)) %>%
  head(10)
top_salary_15
```

Filtering Joins II

```
## Source: local data frame [10 x 3]
## Groups: yearID [1]
##
##    yearID teamID avg_salary
##     <int>  <chr>      <dbl>
## 1    2015    LAN    7441103
## 2    2015    NYA    7336274
## 3    2015    DET    6891390
## 4    2015    SFN    6100056
## 5    2015    BOS    5659481
## 6    2015    WAS    5365085
## 7    2015    SEA    4888348
## 8    2015    TEX    4791426
## 9    2015    SLN    4586212
## 10   2015    SDN    4555435
```

Exercises

1. Using the `Teams` and `Managers` data, join the two tables and only keep the matching observations in both tables. Note, you may need to specify the column names directly you wish to join by. What happens to the columns that have the same names but are not keys?
2. Using the same data tables from #1, add all the `Managers` variables to the `Teams` data while retaining all the rows for the `Teams` data.

Section 7

Data Restructuring

Background I

- Data restructuring is often a useful tool to have.
- By data restructuring, I mean transforming data from long to wide format or vice versa.
- For the most part, long format is much easier to use when plotting and computing summary statistics. A related topic, called tidy data, can be read about in more detail here: `http://www.jstatsoft.org/v59/i10/paper`.
- The data we are going to use for this section of notes is called "LongitudinalEx.csv" and can be found on ICON.
- The packages needed for this section and loading the data file, assuming it is found in the "Data" folder and the working directory is set to the root of the project, are as follows:

```r
library(tidyverse)
long_data <- read_csv("Data/LongitudinalEx.csv")
```

Long/Stacked Data I

- The data read in above is in a format that is commonly referred to as long or stacked data.
- These data do not have one individual per row, instead each row is a individual by wave combination and are stacked for each individual (notice the three rows for id $= 4$).
- The variables in this case each have there own column in the data and all of them are time varying (change for each wave of data within an individual).
- This is also an example of “tidy data” from the paper linked to above, where each row is a unique observation (id, wave pair), variables are in the columns, and each cell of the data is a value.

Long/Stacked Data II

```
## Parsed with column specification:
## cols(
##   id = col_integer(),
##   wave = col_integer(),
##   agegrp = col_double(),
##   age = col_double(),
##   piat = col_integer(),
##   agegrp.c = col_integer(),
##   age.c = col_double()
## )

## # A tibble: 27 × 7
##       id  wave agegrp       age  piat agegrp.c      age.c
##    <int> <int>  <dbl>     <dbl> <int>    <int>      <dbl>
## 1      4     1    6.5  6.000000    18        0 -0.5000000
## 2      4     2    8.5  8.500000    31        2  2.0000000
## 3      4     3   10.5 10.666667    50        4  4.1666667
## 4     27     1    6.5  6.250000    19        0 -0.2500000
## 5     27     2    8.5  9.166667    36        2  2.6666667
## 6     27     3   10.5 10.916667    57        4  4.4166667
## 7     31     1    6.5  6.333333    18        0 -0.1666667
## 8     31     2    8.5  8.833333    31        2  2.3333333
## 9     31     3   10.5 10.916667    51        4  4.4166667
## 10    33     1    6.5  6.333333    18        0 -0.1666667
## # ... with 17 more rows
```

Extra Long Data I

- To progress through data restructuring, we first need to transform this data is extra long format.
- This format is not entirely useful by itself, however it will help use show the use of a few functions from the `tidyr` package. - To go to extra long data, we will make use of the `gather` and `unite` functions.

```
extra_long <- long_data %>%
  gather(variable, value, agegrp:age.c) %>%
  unite(var_wave, variable, wave)
extra_long
```

Extra Long Data II

```
## # A tibble: 135 × 3
##       id var_wave value
## *  <int>    <chr> <dbl>
## 1      4 agegrp_1   6.5
## 2      4 agegrp_2   8.5
## 3      4 agegrp_3  10.5
## 4     27 agegrp_1   6.5
## 5     27 agegrp_2   8.5
## 6     27 agegrp_3  10.5
## 7     31 agegrp_1   6.5
## 8     31 agegrp_2   8.5
## 9     31 agegrp_3  10.5
## 10    33 agegrp_1   6.5
## # ... with 125 more rows
```

Extra Long Data III

- Now there are only three columns in the data and that there are now 135 rows in data.
- This extra long data format gathered all of the variables into two columns, one that identify the variable and wave and the other that simply lists the value.

Wide Data I

- We can now take the extra long data and turn this into wide data.
- Wide data is characterized by one row per individual with columns representing the variable and wave combinations.

```
wide <- extra_long %>%
  spread(var_wave, value)
wide
```

Wide Data II

```
## # A tibble: 9 × 16
##      id   age.c_1  age.c_2  age.c_3    age_1    age_2    age_3 agegrp.c_1
## * <int>     <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>      <dbl>
## 1     4 -0.5000000 2.000000 4.166667 6.000000 8.500000 10.66667          0
## 2    27 -0.2500000 2.666667 4.416667 6.250000 9.166667 10.91667          0
## 3    31 -0.1666667 2.333333 4.416667 6.333333 8.833333 10.91667          0
## 4    33 -0.1666667 2.416667 4.250000 6.333333 8.916667 10.75000          0
## 5    41 -0.1666667 2.250000 4.333333 6.333333 8.750000 10.83333          0
## 6    49  0.0000000 2.250000 4.166667 6.500000 8.750000 10.66667          0
## 7    69  0.1666667 2.666667 4.833333 6.666667 9.166667 11.33333          0
## 8    77  0.3333333 1.583333 3.500000 6.833333 8.083333 10.00000          0
## 9    87  0.4166667 2.916667 5.000000 6.916667 9.416667 11.50000          0
## # ... with 8 more variables: agegrp.c_2 <dbl>, agegrp.c_3 <dbl>,
## #   agegrp_1 <dbl>, agegrp_2 <dbl>, agegrp_3 <dbl>, piat_1 <dbl>,
## #   piat_2 <dbl>, piat_3 <dbl>
```

Wide Data III

- You'll notice from the data above, there are now only 9 rows, but now 16 columns in the data.
- Each variable except for id now also has a number appended to it to represent the wave of the data.
- This data structure is common, particularly for users of SPSS or Excel for data entry or processing.
- Unfortunately, when working with data in R (and in general), data in wide format is often difficult to work with.
- Therefore it is common to need to restructure the data from wide to long format.

Back to Long Format I

- Fortunately, we can use the same functions as we used above, but now in inverse to get from wide to long format.

```r
wide %>%
  gather(variable, value, -id) %>%
  separate(variable, into = c('variable', 'wave'),
           sep = "_") %>%
  arrange(id, wave) %>%
  spread(variable, value)
```

Back to Long Format I

```
## # A tibble: 27 × 7
##        id  wave       age      age.c agegrp agegrp.c  piat
## *   <int> <chr>     <dbl>      <dbl>  <dbl>    <dbl> <dbl>
## 1       4     1  6.000000 -0.5000000    6.5        0    18
## 2       4     2  8.500000  2.0000000    8.5        2    31
## 3       4     3 10.666667  4.1666667   10.5        4    50
## 4      27     1  6.250000 -0.2500000    6.5        0    19
## 5      27     2  9.166667  2.6666667    8.5        2    36
## 6      27     3 10.916667  4.4166667   10.5        4    57
## 7      31     1  6.333333 -0.1666667    6.5        0    18
## 8      31     2  8.833333  2.3333333    8.5        2    31
## 9      31     3 10.916667  4.4166667   10.5        4    51
## 10     33     1  6.333333 -0.1666667    6.5        0    18
## # ... with 17 more rows
```

Back to Long Format I

- In addition, below is the code that would go directly from long to wide.

```
long_data %>%
  gather(variable, value, agegrp:age.c) %>%
  unite(var_wave, variable, wave) %>%
  spread(var_wave, value)
```

Exercises

1. Using the following data generation code, convert these data to long format.

```r
set.seed(10)
messy <- data.frame(
  id = 1:4,
  trt = sample(rep(c('control', 'treatment'), each = 2)),
  work.T1 = runif(4),
  home.T1 = runif(4),
  work.T2 = runif(4),
  home.T2 = runif(4)
)
```

2. Once successfully converted to long format, convert back to wide format.

Factor Variables in R

Background I

- When using the `readr` or `readxl` packages to read in data, the variables are read in as character strings instead of factors.
- However, there are situations when factors are useful.
- This set of notes will make use of the following three packages:

```
library(tidyverse)
library(forcats)
```

Uses for Factors I

To see a few of the benefits of a factor, assume we have a variable that represents the levels of a survey question with five possible responses and we only saw three of those response categories.

```r
resp <- c('Disagree', 'Agree', 'Neutral')
```

Uses for Factors II

- This type of variable has a natural order, namely the disagree side of the scale (i.e. strongly disagree) to the agree side of the scale (i.e. strongly agree) with neutral belonging in the middle.
- However, if we sort this variable, this ordering will not be taken into account with a character string.

```r
sort(resp)
```

```
## [1] "Agree"    "Disagree" "Neutral"
```

Uses for Factors III

- Notice, these are actually in alphabetical order, likely not what we wanted.
- This can be fixed by defining this variable as a factor with levels of the variable specified.

```r
scale_levels <- c('Strongly Disagree', 'Disagree',
                  'Neutral', 'Agree', 'Strongly Agree')
resp_fact <- factor(resp, levels = scale_levels)
resp_fact
sort(resp_fact)
```

Uses for Factors III

```
## [1] Disagree Agree    Neutral
## Levels: Strongly Disagree Disagree Neutral Agree Strongly Agree
```

```
## [1] Disagree Neutral  Agree
## Levels: Strongly Disagree Disagree Neutral Agree Strongly Agree
```

Uses for Factors IV

- Another benefit, if values that are not found in the levels of the factor variable, these will be replaced with NAs.
- For example,

```
knitr::asis_output("\\scriptsize") # ignore this line
```

```
factor(c('disagree', 'Agree', 'Strongly Agree'),
       levels = scale_levels)
```

```
## [1] <NA>           Agree          Strongly Agree
## Levels: Strongly Disagree Disagree Neutral Agree Strongly Agree
```

Uses for Factors V

- We can also explore valid levels of a variables with the `levels` function.

```r
knitr::asis_output("\\scriptsize") # ignore this line
```

```r
levels(resp_fact)
```

```
## [1] "Strongly Disagree" "Disagree"          "Neutral"
## [4] "Agree"             "Strongly Agree"
```

Exercises

1. How are factors stored internally by R? To explore this, use the `str` function on a factor variable and see what it looks like?
2. To further this idea from #1, what happens when you do each of the following commands? Why is this happening?

```r
as.numeric(resp)
as.numeric(resp_fact)
```