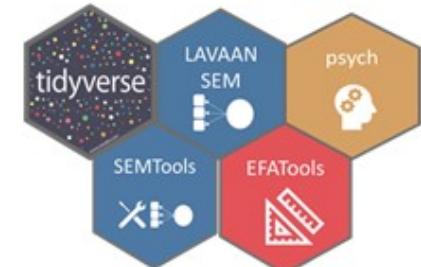


Structural Equation Modeling (SEM) using R

Intro to R

23 August 2021



Overview

- R objects
- R packages
- Reading data into R
- Basic data wrangling with tidyverse
 - `select()`
 - `filter()`
 - `mutate()`
 - `rename()`
 - `arrange()`
 - `group_by()` and `summarize()`
 - `%>%` pipe operator

It's normal to struggle but it gets better and exciting!

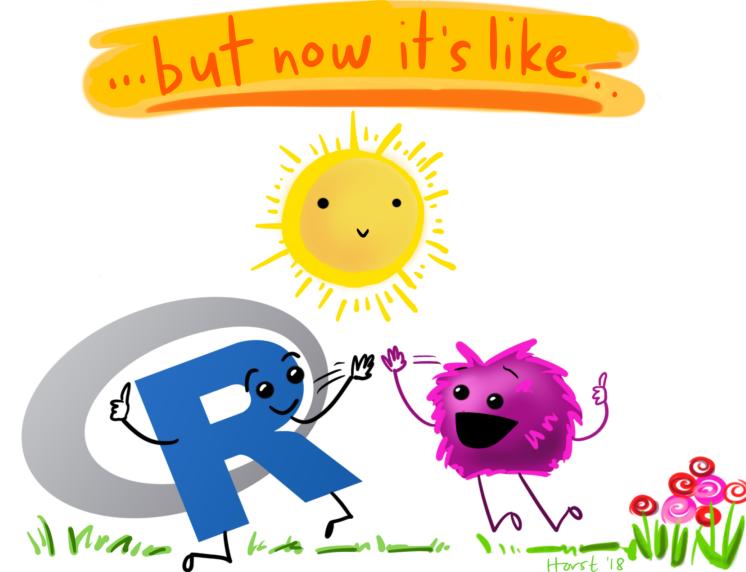


Illustration adapted from Allison Horst

R Objects

- You can consider R objects as "*saving information*"
- e.g., text, number, matrix, vector, dataframe.
- In other words everything in R is an object.



R Objects

- Objects are assigned a value using `<-` consider the piece of code.

```
a1 <- 10  
print(a1)
```

► Run

```
a2 <- 20  
a2
```

► Run

```
a3 <- c(10, 20, 30)  
a3
```

► Run

```
a1 * a2
```

► Run

```
st_name <- "christopher"  
st_age <- 23  
st_sex <- "male"
```

```
student <- c(st_name, st_age, st_sex)  
student
```

► Run

R Objects

- Object names can be anything here!
- I personally use lower-case style.
- Check-out the recommended good practices in R (e.g., naming objects, writing codes) by the tidyverse style guide

R packages

- Collection of functions that load into your working environment.
- It contain code that other R users have prepared for the community.
- Installing packages

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

- Loading packages

```
library(tidyverse)
```



Importing data

- SPSS, Stata, SAS files: `haven` package
- Excel files: `readxl` package
- CSV files: `readr` package

Reading data into R

SPSS, Stata & SAS using `haven` package

```
library(haven)
```

```
# SPSS  
read_sav("path/data.sav")
```

```
# Stata  
read_dta("path/data.dta")
```

```
# SAS  
read_sas("path/data.sas7bdat")
```



Reading data into R

Excel files using `readxl` package

```
library(readxl)
read_excel("path/dataset.xls")
```

```
# A tibble: 150 x 5
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
    <dbl>      <dbl>       <dbl>       <dbl>   <chr>
1       5.1        3.5        1.4        0.2  setosa
2       4.9        3.0        1.4        0.2  setosa
3       4.7        3.2        1.3        0.2  setosa
4       4.6        3.1        1.5        0.2  setosa
5       5.0        3.6        1.4        0.2  setosa
6       5.4        3.9        1.7        0.4  setosa
7       4.6        3.4        1.4        0.3  setosa
8       5.0        3.4        1.5        0.2  setosa
9       4.4        2.9        1.4        0.2  setosa
10      4.9       3.1        1.5        0.1  setosa
# ... with 140 more rows
```



Reading data into R

CSV files using `readr` package

```
install.packages("readr")  
library(readr)
```

```
# comma separated (CSV) files  
read_csv("path/data.csv")
```

```
# tab separated files  
read_tsv("path/data.tsv")
```

```
# general delimited files  
read_delim("path/data.delim")
```



Reading data into R

Tips on naming (file) names

- machine readable
 - avoid spaces, punctuation, accented, characters, case sensitivity
- human readable
 - easy to search for files later
 - easy narrow files lists based on names
 - easy to extract info from file names
- J. Bryan "How to name files"

NO

myabstract.docx
Joe's Filenames Use Spaces and Punctuation.xlsx
figure 1.png
fig 2.png
JW7d^(2sl@deletethisandyourcareerisoverWx2*.txt

YES

2014-06-08_abstract-for-sla.docx
joes-filenames-are-getting-better.xlsx
fig01_scatterplot-talk-length-vs-interest.png
fig02_histogram-talk-attendance.png
1986-01-28_raw-data-from-challenger-o-rings.txt

Illustration adapted from [Jennifer Bryan](#)

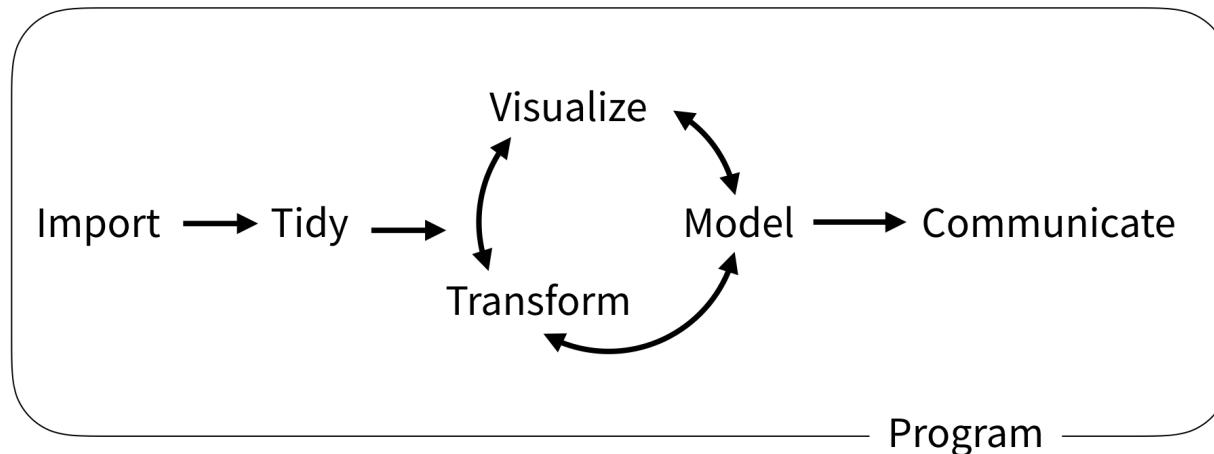


Tidyverse

What is a tidyverse?

A collection of R packages designed for data science.

All packages share an underlying philosophy, grammar, and data structure.



Tidyverse :: tidy data

“**TIDY DATA** is a standard way of mapping the meaning of a dataset to its structure.”

—HADLEY WICKHAM

In tidy data:

- each variable forms a column
- each observation forms a row
- each cell is a single measurement

each column a variable

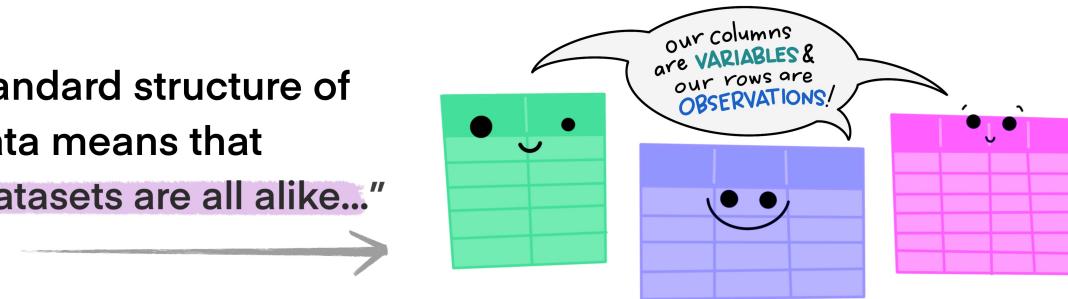
each row an observation

id	name	color
1	floof	gray
2	max	black
3	cat	orange
4	donut	gray
5	merlin	black
6	panda	calico

Wickham, H. (2014). Tidy Data. Journal of Statistical Software 59 (10). DOI: 10.18637/jss.v059.i10

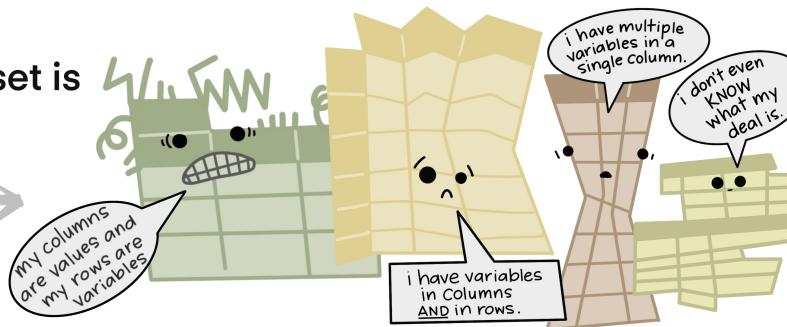
Tidyverse :: tidy data

The standard structure of
tidy data means that
“tidy datasets are all alike...”



“...but every messy dataset is
messy in its own way.”

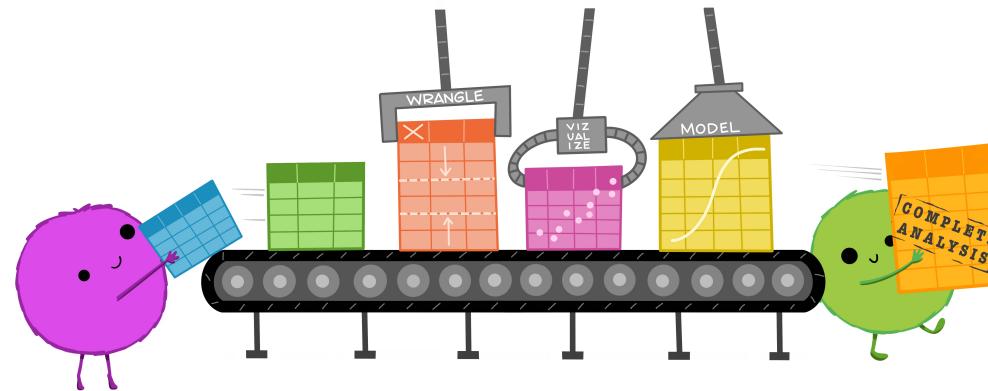
—HADLEY WICKHAM



Artist: Allison Horst

Tidyverse :: tidy data

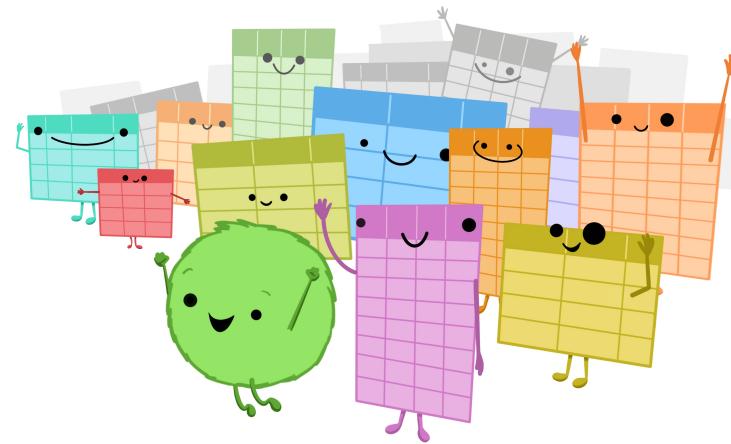
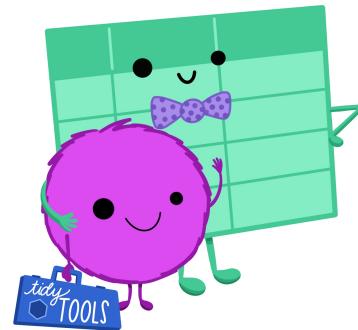
Tidy data makes it easier for reproducibility and reuse



Artist: Allison Horst

Tidyverse :: tidy data

Yehey! Tidy Data for the win!



Artist: Allison Horst

Data wrangling using `dplyr`

`dplyr` : go wrangling

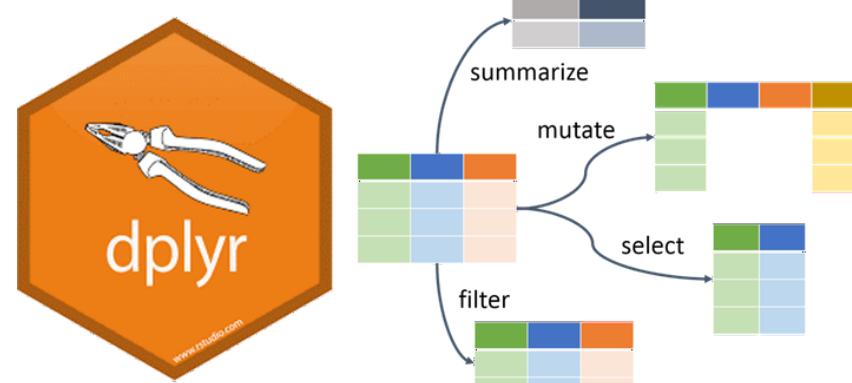


Artist: Allison Horst

dplyr

Overview

- `select()` picks variables based on their names
- `mutate()` adds new variables
- `filter()` picks cases based on their values
- `summarise()` reduces multiple values down to a single summary
- `arrange()` change the ordering of the rows



see [dplyr cheatsheets](#)

select()

```
data
```

```
# A tibble: 1,704 x 6
  country continent year lifeExp      pop
  <fct>    <fct>   <int>   <dbl>     <int>
1 Afghanistan Asia     1952     28.8  8425333
2 Afghanistan Asia     1957     30.3  9240934
3 Afghanistan Asia     1962     32.0  10267083
4 Afghanistan Asia     1967     34.0  11537966
5 Afghanistan Asia     1972     36.1  13079460
6 Afghanistan Asia     1977     38.4  14880372
7 Afghanistan Asia     1982     39.9  12881816
8 Afghanistan Asia     1987     40.8  13867957
9 Afghanistan Asia     1992     41.7  16317921
10 Afghanistan Asia    1997     41.8  22227415
# ... with 1,694 more rows
```

```
select(data, continent, country, pop)
```

```
# A tibble: 1,704 x 3
  continent country      pop
  <fct>    <fct>     <int>
1 Asia      Afghanistan 8425333
2 Asia      Afghanistan 9240934
3 Asia      Afghanistan 10267083
4 Asia      Afghanistan 11537966
5 Asia      Afghanistan 13079460
6 Asia      Afghanistan 14880372
7 Asia      Afghanistan 12881816
8 Asia      Afghanistan 13867957
9 Asia      Afghanistan 16317921
10 Asia     Afghanistan 22227415
# ... with 1,694 more rows
```

select()

We can also **remove** variables with a **-** (minus)

```
data
```

```
# A tibble: 1,704 x 6
  country continent year lifeExp      pop
  <fct>    <fct>   <int>   <dbl>     <int>
1 Afghanistan Asia     1952     28.8  8425333
2 Afghanistan Asia     1957     30.3  9240934
3 Afghanistan Asia     1962     32.0  10267083
4 Afghanistan Asia     1967     34.0  11537966
5 Afghanistan Asia     1972     36.1  13079460
6 Afghanistan Asia     1977     38.4  14880372
7 Afghanistan Asia     1982     39.9  12881816
8 Afghanistan Asia     1987     40.8  13867957
9 Afghanistan Asia     1992     41.7  16317921
10 Afghanistan Asia    1997     41.8  22227415
# ... with 1,694 more rows
```

```
select(data, -year, -pop)
```

```
# A tibble: 1,704 x 4
  country continent lifeExp gdpPercap
  <fct>    <fct>     <dbl>     <dbl>
1 Afghanistan Asia      28.8     779.
2 Afghanistan Asia      30.3     821.
3 Afghanistan Asia      32.0     853.
4 Afghanistan Asia      34.0     836.
5 Afghanistan Asia      36.1     740.
6 Afghanistan Asia      38.4     786.
7 Afghanistan Asia      39.9     978.
8 Afghanistan Asia      40.8     852.
9 Afghanistan Asia      41.7     649.
10 Afghanistan Asia     41.8     635.
# ... with 1,694 more rows
```

select()

Selection helpers

These *selection helpers* match variables according to a given pattern.

- `starts_with()` starts with a prefix
- `ends_with()` ends with a suffix
- `contains()` contains a literal string
- `matches()` matches regular expression

filter()

```
data
```

```
# A tibble: 1,704 x 6
  country continent year lifeExp      pop
  <fct>    <fct>   <int>   <dbl>     <int>
1 Afghanistan Asia     1952     28.8  8425333
2 Afghanistan Asia     1957     30.3  9240934
3 Afghanistan Asia     1962     32.0  10267083
4 Afghanistan Asia     1967     34.0  11537966
5 Afghanistan Asia     1972     36.1  13079460
6 Afghanistan Asia     1977     38.4  14880372
7 Afghanistan Asia     1982     39.9  12881816
8 Afghanistan Asia     1987     40.8  13867957
9 Afghanistan Asia     1992     41.7  16317921
10 Afghanistan Asia    1997     41.8  22227415
# ... with 1,694 more rows
```

```
filter(data, country == "Philippines")
```

```
# A tibble: 12 x 6
  country continent year lifeExp      pop
  <fct>    <fct>   <int>   <dbl>     <int>
1 Philippines Asia     1952     47.8  22438691
2 Philippines Asia     1957     51.3  26072194
3 Philippines Asia     1962     54.8  30325264
4 Philippines Asia     1967     56.4  35356600
5 Philippines Asia     1972     58.1  40850141
6 Philippines Asia     1977     60.1  46850962
7 Philippines Asia     1982     62.1  53456774
8 Philippines Asia     1987     64.2  60017788
9 Philippines Asia     1992     66.5  67185766
10 Philippines Asia    1997     68.6  75012988
11 Philippines Asia    2002     70.3  82995088
12 Philippines Asia    2007     71.7  91077287
```

mutate()

The `mutate` function will take a statement similar to this:

- `variable_name = do_some_calculation`
- `variable_name` will be attached at the end of the dataset.

mutate()

Let's calculate the gdp

```
data
```

```
# A tibble: 1,704 x 6
  country continent year lifeExp      pop
  <fct>    <fct>   <int>   <dbl>     <int>
1 Afghanistan Asia     1952    28.8  8425333
2 Afghanistan Asia     1957    30.3  9240934
3 Afghanistan Asia     1962    32.0  10267083
4 Afghanistan Asia     1967    34.0  11537966
5 Afghanistan Asia     1972    36.1  13079460
6 Afghanistan Asia     1977    38.4  14880372
7 Afghanistan Asia     1982    39.9  12881816
8 Afghanistan Asia     1987    40.8  13867957
9 Afghanistan Asia     1992    41.7  16317921
10 Afghanistan Asia    1997    41.8  22227415
# ... with 1,694 more rows
```

```
mutate(data, GDP = gdpPerCap * pop)
```

```
# A tibble: 1,704 x 7
  country continent year lifeExp      pop GDP
  <fct>    <fct>   <int>   <dbl>     <int> <dbl>
1 Afghanistan Asia     1952    28.8  8425333  2355.6
2 Afghanistan Asia     1957    30.3  9240934  2772.3
3 Afghanistan Asia     1962    32.0  10267083  3220.4
4 Afghanistan Asia     1967    34.0  11537966  3712.4
5 Afghanistan Asia     1972    36.1  13079460  4245.6
6 Afghanistan Asia     1977    38.4  14880372  4815.5
7 Afghanistan Asia     1982    39.9  12881816  5425.5
8 Afghanistan Asia     1987    40.8  13867957  6070.3
9 Afghanistan Asia     1992    41.7  16317921  6753.0
10 Afghanistan Asia    1997    41.8  22227415  8471.5
# ... with 1,694 more rows
```

rename()

Changes the variable name while keeping all else intact.

- `new_variable_name = old_variable_name`

```
data
```

```
# A tibble: 1,704 x 6
  country continent year lifeExp      pop ...
  <fct>    <fct>   <int>  <dbl>     <int> ...
 1 Afghanistan Asia     1952    28.8  8425333
 2 Afghanistan Asia     1957    30.3  9240934
 3 Afghanistan Asia     1962    32.0  10267083
 4 Afghanistan Asia     1967    34.0  11537966
 5 Afghanistan Asia     1972    36.1  13079460
 6 Afghanistan Asia     1977    38.4  14880372
 7 Afghanistan Asia     1982    39.9  12881816
 8 Afghanistan Asia     1987    40.8  13867957
 9 Afghanistan Asia     1992    41.7  16317921
10 Afghanistan Asia     1997    41.8  22227415
# ... with 1,694 more rows
```

```
rename(data, population = pop)
```

```
# A tibble: 1,704 x 6
  country continent year lifeExp population ...
  <fct>    <fct>   <int>  <dbl>     <int> ...
 1 Afghanistan Asia     1952    28.8  8425333
 2 Afghanistan Asia     1957    30.3  9240934
 3 Afghanistan Asia     1962    32.0  10267083
 4 Afghanistan Asia     1967    34.0  11537966
 5 Afghanistan Asia     1972    36.1  13079460
 6 Afghanistan Asia     1977    38.4  14880372
 7 Afghanistan Asia     1982    39.9  12881816
 8 Afghanistan Asia     1987    40.8  13867957
 9 Afghanistan Asia     1992    41.7  16317921
10 Afghanistan Asia     1997    41.8  22227415
# ... with 1,694 more rows
```

arrange()

You can order data by variable to show the highest or lowest values first.

consider lifeExp default is lowest first

```
data
```

```
# A tibble: 1,704 x 6
  country continent year lifeExp      pop
  <fct>    <fct>   <int>  <dbl>     <int>
1 Afghanistan Asia     1952    28.8  8425333
2 Afghanistan Asia     1957    30.3  9240934
3 Afghanistan Asia     1962    32.0  10267083
4 Afghanistan Asia     1967    34.0  11537966
5 Afghanistan Asia     1972    36.1  13079460
6 Afghanistan Asia     1977    38.4  14880372
7 Afghanistan Asia     1982    39.9  12881816
8 Afghanistan Asia     1987    40.8  13867957
9 Afghanistan Asia     1992    41.7  16317921
10 Afghanistan Asia    1997    41.8  22227415
# ... with 1,694 more rows
```

desc() sort lifeExp from highest to lowest

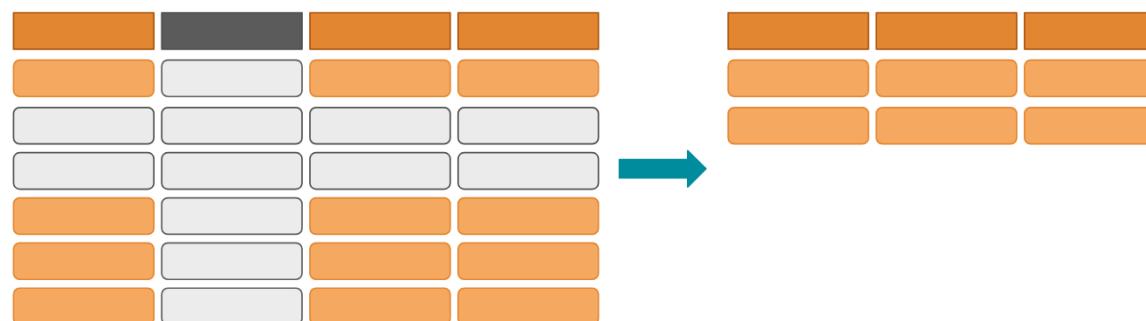
```
arrange(data, desc(lifeExp))
```

```
# A tibble: 1,704 x 6
  country continent year lifeExp      pop
  <fct>    <fct>   <int>  <dbl>     <int>
1 Japan        Asia    2007    82.6  12740000
2 Hong Kong, China Asia    2007    82.2  6980000
3 Japan        Asia    2002    82     12700000
4 Iceland       Europe  2007    81.8   3000000
5 Switzerland   Europe  2007    81.7   7500000
6 Hong Kong, China Asia    2002    81.5   6700000
7 Australia     Oceania 2007    81.2  20400000
8 Spain         Europe  2007    80.9  40400000
9 Sweden        Europe  2007    80.9   9000000
10 Israel        Asia    2007    80.7   6400000
# ... with 1,694 more rows
```

group_by and summarise()

- Use when you want to aggregate your data (by groups).
- Sometimes we want to calculate group statistics.

Customize with **group_by()** and **summarize()**



group_by and summarise()

Suppose we want to know the average population by continent.

```
data
```

```
# A tibble: 1,704 x 6
  country     continent   year lifeExp
  <fct>       <fct>     <int>   <dbl>
1 Afghanistan Asia      1952    28.8
2 Afghanistan Asia      1957    30.3
3 Afghanistan Asia      1962    32.0
4 Afghanistan Asia      1967    34.0
5 Afghanistan Asia      1972    36.1
6 Afghanistan Asia      1977    38.4
7 Afghanistan Asia      1982    39.9
8 Afghanistan Asia      1987    40.8
9 Afghanistan Asia      1992    41.7
10 Afghanistan Asia     1997    41.8
# ... with 1,694 more rows
```

```
grouped_by_continent <- group_by(data, continent)
summarise(grouped_by_continent, avg_pop = mean(pop))
```

```
# A tibble: 5 x 2
  continent   avg_pop
  <fct>        <dbl>
1 Africa      9916003.
2 Americas    24504795.
3 Asia        77038722.
4 Europe      17169765.
5 Oceania     8874672.
```

group_by and summarise()

Suppose we want to know the average population by continent.

```
data
```

```
# A tibble: 1,704 x 6
  country   continent   year lifeExp
  <fct>     <fct>     <int>   <dbl>
1 Afghanistan Asia      1952    28.8
2 Afghanistan Asia      1957    30.3
3 Afghanistan Asia      1962    32.0
4 Afghanistan Asia      1967    34.0
5 Afghanistan Asia      1972    36.1
6 Afghanistan Asia      1977    38.4
7 Afghanistan Asia      1982    39.9
8 Afghanistan Asia      1987    40.8
9 Afghanistan Asia      1992    41.7
10 Afghanistan Asia     1997    41.8
# ... with 1,694 more rows
```

```
grouped_by_continent <- group_by(data, continent)
summarised_data <- summarise(grouped_by_continent, avg_pop =
arrange(summarised_data, desc(avg_pop))
```

```
# A tibble: 5 x 2
  continent   avg_pop
  <fct>       <dbl>
1 Asia        77038722.
2 Americas    24504795.
3 Europe      17169765.
4 Africa      9916003.
5 Oceania     8874672.
```

Too many codes!

It's hard to follow!

It's hard to keep track of the codes!



`%>%` pipe operator



The %>% operator

The `%>%` helps you write code in a way that is easier to read and understand.

Calculating population by continent **without %>%**

```
grouped_by_continent <- group_by(data, continent  
summarised_data <- summarise(grouped_by_continen  
arrange(summarised_data, desc(avg_pop))
```

```
# A tibble: 5 x 2  
continent avg_pop  
<fct>     <dbl>  
1 Asia     77038722.  
2 Americas 24504795.  
3 Europe   17169765.  
4 Africa   9916003.  
5 Oceania  8874672.
```

Calculating population by continent **with %>%**

```
data %>%  
  group_by(continent) %>%  
  summarise(avg_pop = mean(pop)) %>%  
  arrange(desc(avg_pop))
```

```
# A tibble: 5 x 2  
continent avg_pop  
<fct>     <dbl>  
1 Asia     77038722.  
2 Americas 24504795.  
3 Europe   17169765.  
4 Africa   9916003.  
5 Oceania  8874672.
```

The %>% operator

Suppose we want to know the average life expectancy of Asian countries per year.

Calculating population by continent **without %>%**

```
filtered_by_asia <- filter(data, continent == "A"
grouped_by_country_year <- group_by(filtered_by_
summarise(grouped_by_country_year, avg_lifeExp =
```

Calculating population by continent **with %>%**

```
data %>%
  filter(continent == "Asia") %>%
  group_by(country, year) %>%
  summarise(avg_lifeExp = mean(lifeExp))
```

```
# A tibble: 396 x 3
# Groups:   country [33]
  country     year avg_lifeExp
  <fct>     <int>     <dbl>
1 Afghanistan 1952     28.8
2 Afghanistan 1957     30.3
3 Afghanistan 1962     32.0
4 Afghanistan 1967     34.0
5 Afghanistan 1972     36.1
6 Afghanistan 1977     38.4
7 Afghanistan 1982     39.9
8 Afghanistan 1987     40.8
```

```
# A tibble: 396 x 3
# Groups:   country [33]
  country     year avg_lifeExp
  <fct>     <int>     <dbl>
1 Afghanistan 1952     28.8
2 Afghanistan 1957     30.3
3 Afghanistan 1962     32.0
4 Afghanistan 1967     34.0
5 Afghanistan 1972     36.1
6 Afghanistan 1977     38.4
7 Afghanistan 1982     39.9
```

The %>% operator

Calculating population by continent **without %>%**

```
filtered_by_asia <- filter(data, continent == "A"
grouped_by_country <- group_by(filtered_by_asia,
summarised_by_country <- summarise(grouped_by_co
arrange(summarised_by_country, desc(avg_lifeExp)
```

```
# A tibble: 33 x 2
  country      avg_lifeExp
  <fct>          <dbl>
1 Japan            74.8
2 Israel           73.6
3 Hong Kong, China 73.5
4 Singapore        71.2
5 Taiwan            70.3
6 Kuwait             68.9
7 Sri Lanka         66.5
8 Lebanon            65.9
9 Bahrain            65.6
10 Korea, Rep.       65.0
```

Calculating population by continent **with %>%**

```
data %>%
  filter(continent == "Asia") %>%
  group_by(country) %>%
  summarise(avg_lifeExp = mean(lifeExp)) %>%
  arrange(desc(avg_lifeExp))
```

```
# A tibble: 33 x 2
  country      avg_lifeExp
  <fct>          <dbl>
1 Japan            74.8
2 Israel           73.6
3 Hong Kong, China 73.5
4 Singapore        71.2
5 Taiwan            70.3
6 Kuwait             68.9
7 Sri Lanka         66.5
8 Lebanon            65.9
9 Bahrain            65.6
```

Let's practice!

Thank you!

Some slide content were heavily adapted from Fabio Votta

Slides created via the R packages:



xaringan by Yihui



xaringanthemer and xaringanExtra
by Garrick