# Tidy Data

## Stats 102A

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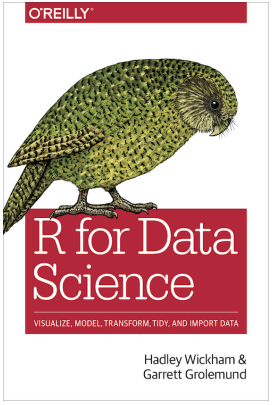
Week 3 Friday

UCLA

Section 1

# The tidyverse

# Resource: R For Data Science




Portions of this lecture are derived from the book. The book is Free to read: https://r4ds.had.co.nz/

# The tidyverse

"The tidyverse is an opinionated collection of R packages designed for data science. All packages share an underlying design philosophy, grammar, and data structures."

Core Packages that get loaded with `library(tidyverse)`:

- `ggplot2` (graphics)
- `tibble` (data frames with some tweaks)
- `tidyr` (making data tidy)
- `dplyr` (data manipulation)
- `readr` (importing data)
- `purrr` (functional programming)
- `stringr` (regular expressions)
- `forcats` (factors and categorical data)

Section 2

# Tibbles

# The tibble

The tidyverse works with the "tibble" instead of the traditional `data.frame`. Tibbles are data frames, but they tweak some older behaviors to make life a little easier. R is an old language, and some things that were useful 10 or 20 years ago now get in your way. It's difficult to change base R without breaking existing code, so most innovation occurs in packages. The tibble package provides opinionated data frames that make working in the tidyverse a little easier.

# Tibbles vs Data.Frames: Printing

Tibbles have a refined print method that shows only the first 10 rows, and all the columns that fit on screen. This makes it much easier to work with large data. In addition to its name, each column reports its type, a nice feature borrowed from str():

```
rand_vals <- runif(1e3)
x <- tibble(
  a = lubridate::now() + rand_vals * 86400,
  b = lubridate::today() + rand_vals * 30,
  c = 1:1e3,
  d = rand_vals,
  e = sample(letters, 1e3, replace = TRUE)
)
```

# Tibbles vs Data.Frames: Printing

```
print(x)
```

```
## # A tibble: 1,000 x 5
##    a                   b              c     d e
##    <dttm>              <date>     <int> <dbl> <chr>
##  1 2021-01-23 05:12:55 2021-02-03     1 0.411 x
##  2 2021-01-23 00:57:19 2021-01-28     2 0.233 x
##  3 2021-01-22 23:33:50 2021-01-27     3 0.175 j
##  4 2021-01-23 04:33:50 2021-02-02     4 0.383 t
##  5 2021-01-23 12:00:32 2021-02-11     5 0.694 j
##  6 2021-01-23 08:31:52 2021-02-07     6 0.549 r
##  7 2021-01-23 08:21:20 2021-02-07     7 0.541 t
##  8 2021-01-23 00:51:15 2021-01-28     8 0.229 a
##  9 2021-01-23 07:26:59 2021-02-06     9 0.504 k
## 10 2021-01-23 08:45:48 2021-02-07    10 0.558 r
## # ... with 990 more rows
```

# Tibbles vs Data Frames: Subsetting

Using single square brackets [] on a tibble will *always* return a tibble (unless you explicity use the drop argument).

```
tb <- tibble(x = 1:3, y = 3:1)
tb[, 1] # subset to the first column. Remains a tibble.
```

```
## # A tibble: 3 x 1
##       x
##   <int>
## 1     1
## 2     2
## 3     3
```

```
tb[, 1, drop = TRUE] # with drop = TRUE, it will simplify after subsetting.
```

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

# Tibbles vs Data Frames: Subsetting

In contrast, with a data frame, an operation like `df[ , 1]` will simplify and return a vector.

```
df <- data.frame(x = 1:3, y = 3:1)
df[, 1]
```

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

To extract the column as a vector from a tibble, you can use double square brackets `[[]]` or the dollar sign `$` as you do with data frames.

```
tb[[1]]
```

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

```
tb$x
```

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

# Tibble creation

Creating a tibble is easy. You can create a tibble the same way you do a data frame, specifying the name of a column and the values that go in the column.

```
tib <- tibble(
  a = sample(5),
  b = letters[sample(5)],
  c = rnorm(5)
)
```

You can also take an existing data frame and feed it into a tibble.

```
mtcars_tib <- tibble(mtcars)
```

# Tibble creation

Tibbles can also be created row-wise so that a person reading your code can easily see the values contained in the tibble without needing to print the tibble. This is achieved with the function `tribble`

```
tib_r <- tribble(
  ~colA, ~colB,
  "a",   1,
  "b",   2,
  "c",   3
)
print(tib_r)
```

```
## # A tibble: 3 x 2
##   colA   colB
##   <chr> <dbl>
## 1 a         1
## 2 b         2
## 3 c         3
```

Section 3

# Pivoting Data

# Tidy Data

**The Philosophy of the Tidyverse**

There are three rules which make a data set tidy:

- Every column is variable.
- Every row is an observation.
- Every cell is a single value.

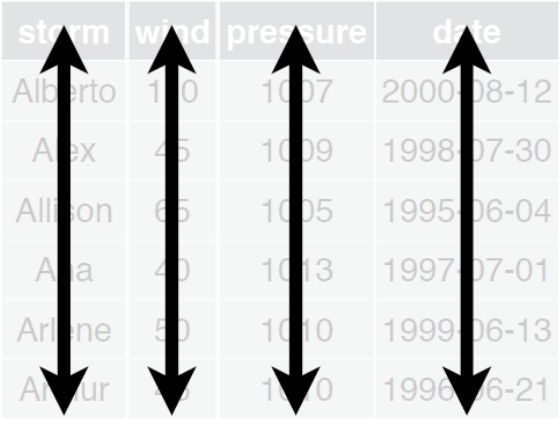
# Tidy Data

storms

| storm | wind | pressure | date |
|---|---|---|---|
| Alberto | 110 | 1007 | 2000-08-12 |
| Alex | 45 | 1009 | 1998-07-30 |
| Allison | 65 | 1005 | 1995-06-04 |
| Ana | 40 | 1013 | 1997-07-01 |
| Arlene | 50 | 1010 | 1999-06-13 |
| Arthur | 45 | 1010 | 1996-06-21 |

# Tidy Data

storms



| storm | wind | pressure | date |
|---|---|---|---|
| Alberto | 110 | 1007 | 2000-08-12 |
| Alex | 45 | 1009 | 1998-07-30 |
| Allison | 65 | 1005 | 1995-06-04 |
| Ana | 40 | 1013 | 1997-07-01 |
| Arlene | 50 | 1010 | 1999-06-13 |
| Arthur | 45 | 1010 | 1996-06-21 |

- Storm name
- Wind Speed (mph)
- Air Pressure
- Date

We have one column for each variable

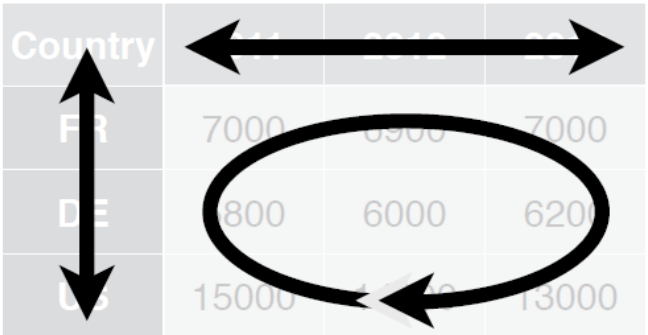
# Not Tidy Data

cases

| Country | 2011 | 2012 | 2013 |
|---|---|---|---|
| FR | 7000 | 6900 | 7000 |
| DE | 5800 | 6000 | 6200 |
| US | 15000 | 14000 | 13000 |

# Not Tidy Data

cases




- Country
- Year
- Count

One variable forms column headings, and the values are spread out across columns.

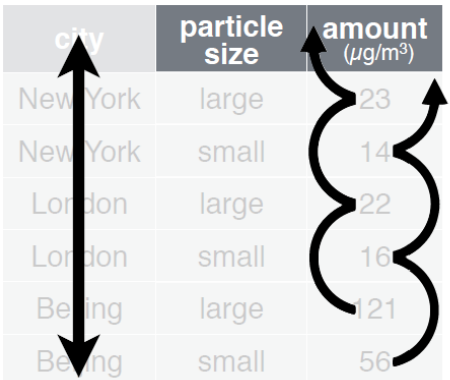
# Not Tidy Data

pollution

| city | particle size | amount ($\mu g/m^3$) |
|---|---|---|
| New York | large | 23 |
| New York | small | 14 |
| London | large | 22 |
| London | small | 16 |
| Beijing | large | 121 |
| Beijing | small | 56 |

# Not Tidy Data

pollution



| city | particle size | amount ($\mu g/m^3$) |
|---|---|---|
| New York | large | 23 |
| New York | small | 14 |
| London | large | 22 |
| London | small | 16 |
| Beijing | large | 121 |
| Beijing | small | 56 |

- City
- Amount of large particles
- Amount of small particles

The values of two different variables are stored in one column.

# Reading in the data

```
storms <- read_csv("https://raw.githubusercontent.com/rstudio/EDAWR/master/data-raw/storms.csv")
```

```
##
## -- Column specification --------------------------------------------------------
## cols(
##   storm = col_character(),
##   wind = col_double(),
##   pressure = col_double(),
##   date = col_date(format = "")
## )
```

```
cases <- read_csv("https://raw.githubusercontent.com/rstudio/EDAWR/master/data-raw/cases.csv")
```

```
##
## -- Column specification --------------------------------------------------------
## cols(
##   country = col_character(),
##   `2011` = col_double(),
##   `2012` = col_double(),
##   `2013` = col_double()
## )
```

```
pollution <- read_csv("https://raw.githubusercontent.com/rstudio/EDAWR/master/data-raw/pollution.csv")
```

```
##
## -- Column specification --------------------------------------------------------
## cols(
##   city = col_character(),
##   size = col_character(),
##   amount = col_double()
```

# Vectorized operations work for tidy data

```
storms$ratio <- storms$pressure / storms$wind
# 1007 / 110 = 9.15, 1009 / 45 = 22.4, etc.
storms
```

```
## # A tibble: 6 x 5
##   storm    wind pressure date       ratio
##   <chr>   <dbl>    <dbl> <date>     <dbl>
## 1 Alberto   110     1007 2000-08-03  9.15
## 2 Alex       45     1009 1998-07-27 22.4
## 3 Allison    65     1005 1995-06-03 15.5
## 4 Ana        40     1013 1997-06-30 25.3
## 5 Arlene     50     1010 1999-06-11 20.2
## 6 Arthur     45     1010 1996-06-17 22.4
```

# The Cases table

```
cases
```

```
## # A tibble: 3 x 4
##   country `2011` `2012` `2013`
##   <chr>    <dbl>  <dbl>  <dbl>
## 1 FR        7000   6900   7000
## 2 DE        5800   6000   6200
## 3 US       15000  14000  13000
```

# Getting things tidy

The variables are: country, year, count

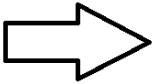
If we want to make this tidy, what will be the dimensions of the resulting data?

cases

| Country | 2011 | 2012 | 2013 |
|---|---|---|---|
| FR | 7000 | 6900 | 7000 |
| DE | 5800 | 6000 | 6200 |
| US | 15000 | 14000 | 13000 |

# Result: a 9 x 3 tibble

| Country | 2011 | 2012 | 2013 |
|---|---|---|---|
| FR | 7000 | 6900 | 7000 |
| DE | 5800 | 6000 | 6200 |
| US | 15000 | 14000 | 13000 |



| Country | Year | n |
|---|---|---|
| FR | 2011 | 7000 |
| DE | 2011 | 5800 |
| US | 2011 | 15000 |
| FR | 2012 | 6900 |
| DE | 2012 | 6000 |
| US | 2012 | 14000 |
| FR | 2013 | 7000 |
| DE | 2013 | 6200 |
| US | 2013 | 13000 |

# pivot_longer()

To achieve the desired result, we use the function `pivot_longer()` because we want the resulting data set to be longer than the original data. (older versions called this `gather()`)

```
pivot_longer(cases,
             cols = "2011":"2013",
             names_to = "year",
             values_to = "cases")
```

```
## # A tibble: 9 x 3
##   country year  cases
##   <chr>   <chr> <dbl>
## 1 FR      2011   7000
## 2 FR      2012   6900
## 3 FR      2013   7000
## 4 DE      2011   5800
## 5 DE      2012   6000
## 6 DE      2013   6200
## 7 US      2011  15000
## 8 US      2012  14000
## 9 US      2013  13000
```

# The pivot_longer() function

```
pivot_longer(data = cases,
             cols = "2011":"2013",
             names_to = "year",
             values_to = "cases")
```

The pivot_longer() function takes in a few arguments:

- data is the name of the data.frame or tibble that we will pivot
- cols are the names of the columns that will be pivoted. In this case, we want the columns named "2011" through "2013". With tidyr, you can specify a range of column names with the : operator. Otherwise, you can provide a vector of column names
- names_to is a character string with what you want to call the resulting column of names. The former column names will be put into this column.
- values_to is a character string with what you want to call the resulting column of values. The former cell values will be put into this column.

# The names are arbitrary

```
pivot_longer(cases,
             cols = "2011":"2013",
             names_to = "when it happened",
             values_to = "how many")
```

```
## # A tibble: 9 x 3
##   country `when it happened` `how many`
##   <chr>   <chr>                   <dbl>
## 1 FR      2011                     7000
## 2 FR      2012                     6900
## 3 FR      2013                     7000
## 4 DE      2011                     5800
## 5 DE      2012                     6000
## 6 DE      2013                     6200
## 7 US      2011                    15000
## 8 US      2012                    14000
## 9 US      2013                    13000
```

# What happens if?

```
## # A tibble: 3 x 4
##   country `2011` `2012` `2013`
##   <chr>    <dbl>  <dbl>  <dbl>
## 1 FR        7000   6900   7000
## 2 DE        5800   6000   6200
## 3 US       15000  14000  13000
```

What happens if the columns I pivot are only "2012" and "2013"?

```
pivot_longer(cases,
             cols = "2012":"2013",
             names_to = "year",
             values_to = "cases")
```

# Answer

What happens if the columns I pivot are only “2012” and “2013”?

The columns that are not pivoted are duplicated for the new rows created.

```
pivot_longer(cases,
             cols = "2012":"2013",
             names_to = "year",
             values_to = "cases")
```

```
## # A tibble: 6 x 4
##   country `2011` year  cases
##   <chr>    <dbl> <chr> <dbl>
## 1 FR        7000 2012   6900
## 2 FR        7000 2013   7000
## 3 DE        5800 2012   6000
## 4 DE        5800 2013   6200
## 5 US       15000 2012  14000
## 6 US       15000 2013  13000
```

# What happens if?

```
## # A tibble: 3 x 4
##   country `2011` `2012` `2013`
##   <chr>    <dbl>  <dbl>  <dbl>
## 1 FR        7000   6900   7000
## 2 DE        5800   6000   6200
## 3 US       15000  14000  13000
```

What happens if I include "country" in the columns I pivot?

```
pivot_longer(cases,
             cols = "country":"2013",
             names_to = "name",
             values_to = "value")
```

# Answer

What happens if I include “country” in the columns I pivot?

```
pivot_longer(cases,
             cols = "country":"2013",
             names_to = "name",
             values_to = "value")
```

```
## Error: Can't combine `country` <character> and `2011` <double>.
```

# Answer

What happens if I include "country" in the columns I pivot? (I've converted everything to character.)

```
cases2 <- data.frame(lapply(cases[,1:4], as.character))
names(cases2) <- c("country", "2011", "2012", "2013")
pivot_longer(cases2,
             cols = "country":"2013",
             names_to = "name",
             values_to = "value")
```

```
## # A tibble: 12 x 2
##    name    value
##    <chr>   <chr>
##  1 country FR
##  2 2011    7000
##  3 2012    6900
##  4 2013    7000
##  5 country DE
##  6 2011    5800
##  7 2012    6000
##  8 2013    6200
##  9 country US
## 10 2011    15000
## 11 2012    14000
## 12 2013    13000
```

# The pollution table

```
pollution
```

```
## # A tibble: 6 x 3
##   city     size  amount
##   <chr>    <chr>  <dbl>
## 1 New York large     23
## 2 New York small     14
## 3 London   large     22
## 4 London   small     16
## 5 Beijing  large    121
## 6 Beijing  small     56
```

# Getting things tidy

The variables are: city, large particle amount, small particle amount

If we want to make this tidy, what will be the dimensions of the resulting data?

pollution

| city | particle size | amount ($\mu g/m^3$) |
|---|---|---|
| New York | large | 23 |
| New York | small | 14 |
| London | large | 22 |
| London | small | 16 |
| Beijing | large | 121 |
| Beijing | small | 56 |

# Result: a 3 x 3 tibble

| city | size | amount |
|---|---|---|
| New York | large | 23 |
| New York | small | 14 |
| London | large | 22 |
| London | small | 16 |
| Beijing | large | 121 |
| Beijing | small | 56 |

| city | large | small |
|---|---|---|
| New York | 23 | 14 |
| London | 22 | 16 |
| Beijing | 121 | 56 |

# pivot_wider()

To achieve the desired result, we use the function `pivot_wider()` because we want the resulting dataset to be wider than the original data. (older versions called this `spread()`)

```
pivot_wider(pollution,
            names_from = "size",
            values_from = "amount")
```

```
## # A tibble: 3 x 3
##   city     large small
##   <chr>    <dbl> <dbl>
## 1 New York    23    14
## 2 London      22    16
## 3 Beijing    121    56
```

# pivot_wider()

```
pivot_wider(pollution,
            names_from = "size",
            values_from = "amount")
```

The `pivot_wider()` function takes in a few arguments:

- `data` is the name of the data.frame or tibble that we will pivot
- `names_from` is the name of the column that has the names that will become column headers
- `values_from` is the name of the column that has the values

# pivot_wider() is sensitive to spelling differences

What will happen?

```
pollution2 <- pollution
pollution2[1,1] <- "NYC"
pollution2
```

```
## # A tibble: 6 x 3
##   city     size  amount
##   <chr>    <chr>  <dbl>
## 1 NYC      large     23
## 2 New York small     14
## 3 London   large     22
## 4 London   small     16
## 5 Beijing  large    121
## 6 Beijing  small     56
```

```
pivot_wider(pollution2,
            names_from = "size",
            values_from = "amount")
```

# Result

```
pivot_wider(pollution2,
            names_from = "size",
            values_from = "amount")
```

```
## # A tibble: 4 x 3
##   city     large small
##   <chr>    <dbl> <dbl>
## 1 NYC         23    NA
## 2 New York    NA    14
## 3 London      22    16
## 4 Beijing    121    56
```

# Result

Sometimes you truly do have a scenario where you want to pivot wider and some entries do not exist. If you don't want NAs to show, you can specify a fill value.

```
pivot_wider(pollution2,
            names_from = "size",
            values_from = "amount",
            values_fill = 0)
```

```
## # A tibble: 4 x 3
##   city     large small
##   <chr>    <dbl> <dbl>
## 1 NYC         23     0
## 2 New York     0    14
## 3 London      22    16
## 4 Beijing    121    56
```

# Another example

What will happen?

```
pollution2 <- pollution
pollution2[1,2] <- "LARGE"
pollution2
```

```
## # A tibble: 6 x 3
##   city     size  amount
##   <chr>    <chr>  <dbl>
## 1 New York LARGE     23
## 2 New York small     14
## 3 London   large     22
## 4 London   small     16
## 5 Beijing  large    121
## 6 Beijing  small     56
```

```
pivot_wider(pollution2,
            names_from = "size",
            values_from = "amount")
```

# Result

```
pivot_wider(pollution2,
            names_from = "size",
            values_from = "amount")
```

```
## # A tibble: 3 x 4
##   city     LARGE small large
##   <chr>    <dbl> <dbl> <dbl>
## 1 New York    23    14    NA
## 2 London      NA    16    22
## 3 Beijing     NA    56   121
```

# pivot_longer() and pivot_wider() are inverse operations

```
pollution
```

```
## # A tibble: 6 x 3
##   city     size  amount
##   <chr>    <chr>  <dbl>
## 1 New York large     23
## 2 New York small     14
## 3 London   large     22
## 4 London   small     16
## 5 Beijing  large    121
## 6 Beijing  small     56
```

```
w <- pivot_wider(pollution, names_from = "size", values_from = "amount")
w
```

```
## # A tibble: 3 x 3
##   city     large small
##   <chr>    <dbl> <dbl>
## 1 New York    23    14
## 2 London      22    16
## 3 Beijing    121    56
```

# pivot_longer() and pivot_wider() are inverse operations

```
w
```

```
## # A tibble: 3 x 3
##   city     large small
##   <chr>    <dbl> <dbl>
## 1 New York    23    14
## 2 London      22    16
## 3 Beijing    121    56
```

```
pivot_longer(w, cols = "large":"small", names_to = "size", values_to = "amount")
```

```
## # A tibble: 6 x 3
##   city     size  amount
##   <chr>    <chr>  <dbl>
## 1 New York large     23
## 2 New York small     14
## 3 London   large     22
## 4 London   small     16
## 5 Beijing  large    121
## 6 Beijing  small     56
```

# pivot_longer() and pivot_wider() are inverse operations

```
cases
```

```
## # A tibble: 3 x 4
##   country `2011` `2012` `2013`
##   <chr>     <dbl>  <dbl>  <dbl>
## 1 FR         7000   6900   7000
## 2 DE         5800   6000   6200
## 3 US        15000  14000  13000
```

```
l <- pivot_longer(cases, cols = "2011":"2013", names_to = "year", values_to = "count")
l
```

```
## # A tibble: 9 x 3
##   country year  count
##   <chr>   <chr> <dbl>
## 1 FR      2011   7000
## 2 FR      2012   6900
## 3 FR      2013   7000
## 4 DE      2011   5800
## 5 DE      2012   6000
## 6 DE      2013   6200
## 7 US      2011  15000
## 8 US      2012  14000
## 9 US      2013  13000
```

# pivot_longer() and pivot_wider() are inverse operations

```
l
```

```
## # A tibble: 9 x 3
##   country year  count
##   <chr>   <chr> <dbl>
## 1 FR      2011   7000
## 2 FR      2012   6900
## 3 FR      2013   7000
## 4 DE      2011   5800
## 5 DE      2012   6000
## 6 DE      2013   6200
## 7 US      2011  15000
## 8 US      2012  14000
## 9 US      2013  13000
```

```
pivot_wider(l, names_from = "year", values_from = "count")
```

```
## # A tibble: 3 x 4
##   country `2011` `2012` `2013`
##   <chr>    <dbl>  <dbl>  <dbl>
## 1 FR        7000   6900   7000
## 2 DE        5800   6000   6200
## 3 US       15000  14000  13000
```

# More tidyr

Today's lecture is a summary of pivoting - https://tidyr.tidyverse.org/articles/pivot.html

Other important operations include "rectangling" - https://tidyr.tidyverse.org/articles/rectangle.html