Data import, tidy data, and relational data

Week 4

AEM 2850: R for Business Analytics

Cornell Dyson

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Acknowledgements: Grant McDermott, Jenny Bryan, Allison Horst

Announcements

Late assignments will get a ✔– going forward

- If something comes up, email me and Hui in advance

Reminders:

- Submit assignments via canvas
  - Lab 3 was due yesterday (Monday) at 11:59pm
  - Reflection - Week 4 is due Wednesday at 11:59pm
- Bring your laptop to class on Thursday

Questions before we get started?

Plan for today

Prologue

Data import

Tidy data

Relational data

Summary

Prologue

What are our concentrations?

Take a guess: what's the most common concentration among classmates?

```
## # A tibble: 39 × 1
##    value
##    <chr>
##  1 Business Analytics (AEM) Interactive Technologies (IS)
##  2 Finance
##  3 Business Analytics
##  4 Data Science and Finance
##  5 Sustainable Business and Economic Policy
##  6 Finance
##  7 Finance
##  8 Business Analytics and Strategy
##  9 Finance, Business Analytics
## 10 Finance
## # … with 29 more rows
```

What are our concentrations?

After some processing to get concentration counts, we get:

```
## # A tibble: 1 × 7
##   accounting    ba  entr enviro finance  food strategy
##        <int> <int> <int>  <int>   <int> <int>    <int>
## 1          2    21     2      3      19     2        4
```

What is the "level of observation" in this data frame? (i.e., what are the rows?)

Is the best way to organize concentration counts?

How would you use counts to compute shares in this data frame?

What are our "tidy" concentrations?

Let's `pivot_longer` and `arrange` to get the top 3:

```
## # A tibble: 3 × 2
##   concentration count
##   <chr>         <int>
## 1 ba               21
## 2 finance          19
## 3 strategy          4
```

How would you use counts to compute shares in this data frame?

```
tidy_concentrations %>% mutate(share = count / sum(count)) # easy!
```

```
## # A tibble: 3 × 3
##   concentration count  share
##   <chr>         <int>  <dbl>
## 1 ba               21 0.396
## 2 finance          19 0.358
## 3 strategy          4 0.0755
```

Data import

Data import

Plain-text rectangular files are a common way to store and share data:

- comma delimited files (`readr::read_csv`)
- tab delimited files (`readr::read_tsv`)
- fixed width files (`readr::read_fwf`)

We will just cover csv files since `readr` syntax is transferable

Super bowl ads: a csv example

Super bowl ads in csv format

Super bowl ads in csv format

Getting from a csv to a data frame

How are data frames and csv files similar?

- both are rectangular
- csv lines often correspond to rows
- csv commas delineate columns

How are they different?

- csv files do not store column types!

1) readr::read_csv

`read_csv` helps us get from point a to point b:

- you give it the path to your csv file
- it takes the first line of data as column names by default
- it guesses column types and builds up a data frame

Most csv files can be read using the defaults, so we will focus on that

If you run into special cases, consult `?read_csv`

An aside on paths

First we need to figure out what path to give `read_csv`

We have several options:

- absolute paths
  - `/Users/todd/aem2850/slides/data/superbowl.csv`
  - `C:\aem2850\slides\data\superbowl.csv`
- relative paths
  - `data/superbowl.csv`
- links
  - `https://raw.githubusercontent.com/superbowl-ads.csv`
- others
  - see `?read_csv`

An aside on paths

Relative paths are nice: work if you move R code to another directory or device

But what are they relative to?

The working directory

But where is the working directory?

R scripts (.R) in an R Project: default working directory is the project directory

R Markdown (.Rmd): default working directory is the location of the .Rmd file

In our RStudio Cloud projects, these will both be `/cloud/project`, which is the default directory for our projects and where we store our .Rmd templates

An aside on paths

More generally, can check your working directory using `getwd()`

For example, here's the working directory for the slides' .Rmd source code:

```
getwd()
```

```
## [1] "/Users/todd/Documents/GitHub/aem2850/content/slides"
```

`setwd()` will alter the working directory

An aside on paths

Just for context, here is a list of (some) directories below the working directory

```
## .
## ├── css
## ├── data
## ├── img
## └── libs
```

Now list (some of) the .csv files in the folder `data`:

```
## data
## └── superbowl.csv
```

`data/superbowl.csv` is the relative path from our working directory to our csv

1) readr::read_csv

So all we need to do is give that relative path to `read_csv`:

```
ads <- read_csv("data/superbowl.csv")
```

```
## Rows: 247 Columns: 25

## ── Column specification ────────────────────────────────────────────────────────
## Delimiter: ","
## chr  (10): brand, superbowl_ads_dot_com_url, youtube_url, id, kind, etag, ti...
## dbl   (7): year, view_count, like_count, dislike_count, favorite_count, comm...
## lgl   (7): funny, show_product_quickly, patriotic, celebrity, danger, animal...
## dttm  (1): published_at

##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

That was easy!

Now we're back to our old tricks

```
ads %>%
  group_by(funny) %>%
  count() %>%
  arrange(desc(n))
```

```
## # A tibble: 2 × 2
## # Groups:   funny [2]
##   funny     n
##   <lgl> <int>
## 1 TRUE    171
## 2 FALSE    76
```

```
ads %>%
  group_by(brand) %>%
  summarize(likes = sum(like_count, na.rm = T)) %>%
  arrange(desc(likes))
```

```
## # A tibble: 10 × 2
##    brand      likes
##    <chr>      <dbl>
##  1 Doritos   326151
##  2 NFL       224263
##  3 Coca-Cola 160231
##  4 Bud Light 104380
##  5 Budweiser  88765
##  6 Pepsi      14796
##  7 Toyota      5316
##  8 Hynudai     4204
##  9 E-Trade     2624
## 10 Kia         2127
```

2) readr::write_csv

Use `write_csv` to write data to a `.csv`:

```
write_csv(ads, "data/superbowl.csv") # overwrite the raw data (bad idea!)

ads %>%
  select(year, brand, youtube_url) %>%
  write_csv("superbowl-urls.csv") # write modified output to a new file
```

csv is not always the best storage medium

To preserve column specifications and save time when working in R, use `write_rds()` and `read_rds()` to save and open data frames in .RDS format

For multiple objects, `save()` and `load()` are handy functions from base R that work with the .RData format

Importing excel data

Wait, what about getting data from excel spreadsheets?

Use `readxl::read_excel()` for data that is stored in `.xls` or `.xlsx` format

`readxl` isn't loaded as part of the core tidyverse, so we need to load it first:

```
library(readxl)
excel_sheets("data/readxl/datasets.xlsx") # list the sheets in datasets.xlsx
```

```
## [1] "iris"     "mtcars"   "chickwts" "quakes"
```

Importing excel data

```
read_excel("data/readxl/datasets.xlsx", sheet = "mtcars")
```

```
## # A tibble: 32 × 11
##      mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gear  carb
##    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
##  1  21       6  160    110  3.9   2.62  16.5     0     1     4     4
##  2  21       6  160    110  3.9   2.88  17.0     0     1     4     4
##  3  22.8     4  108     93  3.85  2.32  18.6     1     1     4     1
##  4  21.4     6  258    110  3.08  3.22  19.4     1     0     3     1
##  5  18.7     8  360    175  3.15  3.44  17.0     0     0     3     2
##  6  18.1     6  225    105  2.76  3.46  20.2     1     0     3     1
##  7  14.3     8  360    245  3.21  3.57  15.8     0     0     3     4
##  8  24.4     4  147.    62  3.69  3.19  20       1     0     4     2
##  9  22.8     4  141.    95  3.92  3.15  22.9     1     0     4     2
## 10  19.2     6  168.   123  3.92  3.44  18.3     1     0     4     4
## # … with 22 more rows
```

Importing excel data

Can also use arguments like `range` to get data using excel lingo

```
read_excel("data/readxl/datasets.xlsx",
           range = "mtcars!A1:D6") # note the combination of sheet and cell range
```

```
## # A tibble: 5 × 4
##     mpg   cyl  disp    hp
##   <dbl> <dbl> <dbl> <dbl>
## 1  21       6   160   110
## 2  21       6   160   110
## 3  22.8     4   108    93
## 4  21.4     6   258   110
## 5  18.7     8   360   175
```

Tidy data

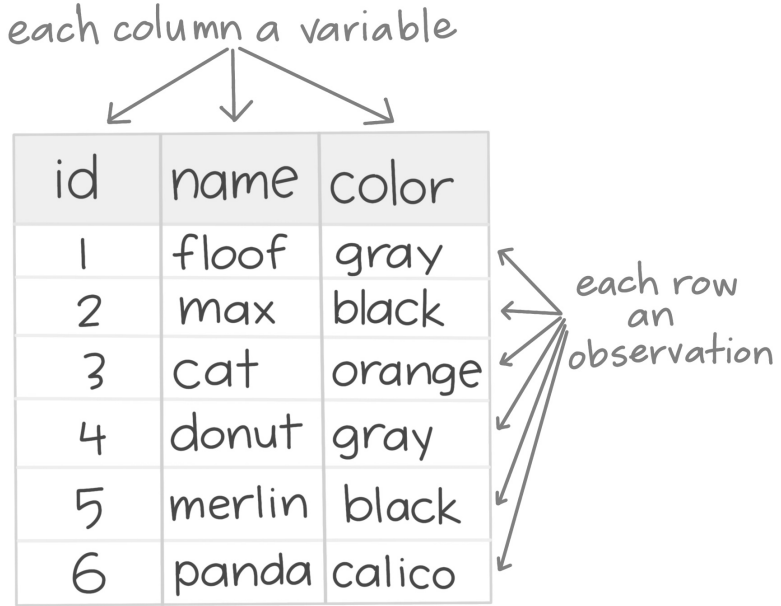
WHAT is "tidy" data?

"TIDY DATA is a standard way of mapping the meaning of a dataset to its structure."

–HADLEY WICKHAM

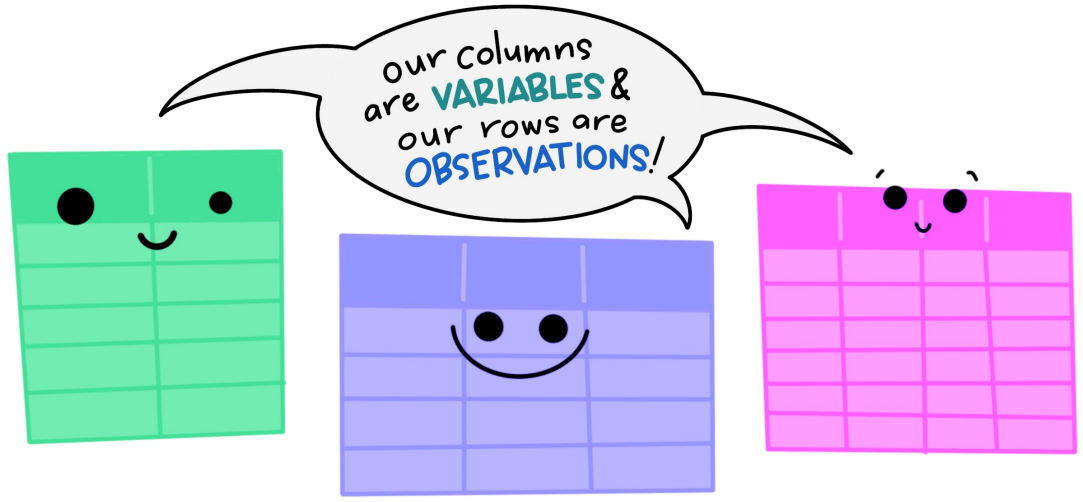
In tidy data:

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



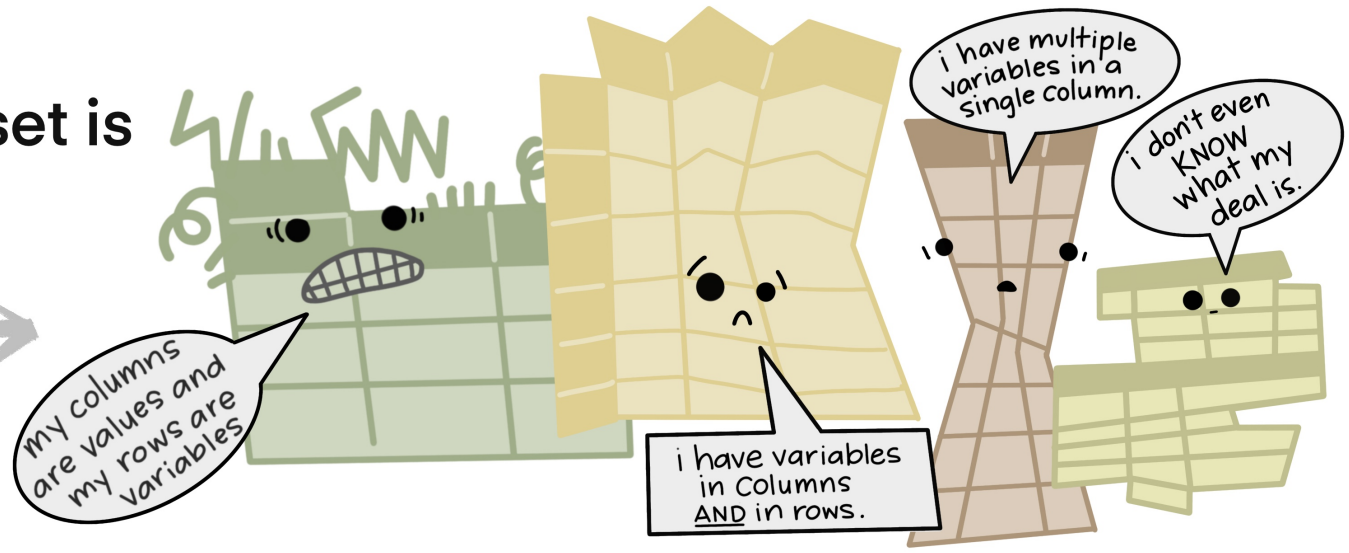
Wickham, H. (2014). Tidy Data. Journal of Statistical Software *59* (10). DOI: 10.18637/jss.v059.i10

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



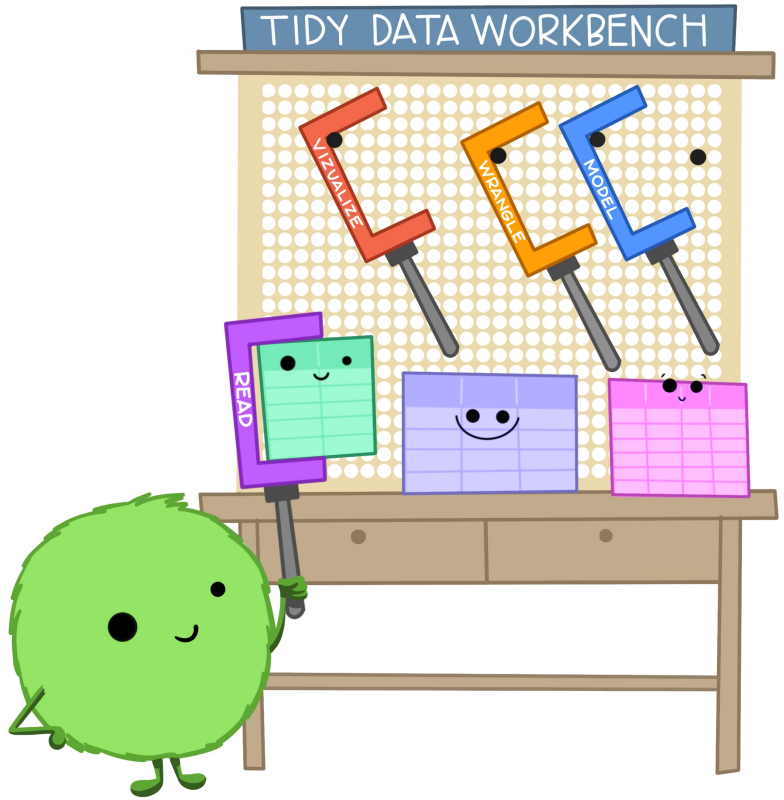
"...but every messy dataset is messy in its own way."

–HADLEY WICKHAM

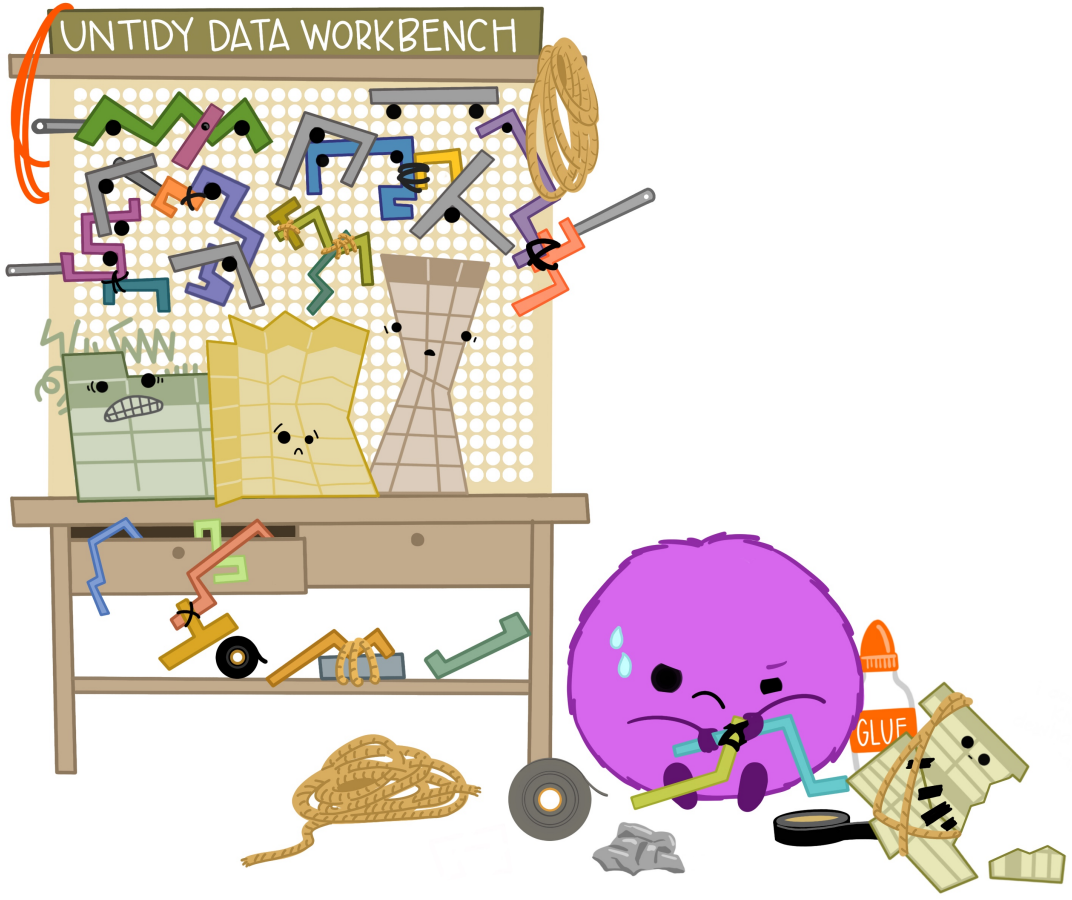


WHY "tidy" data?

When working with tidy data, we can use the same tools in similar ways for different datasets...



...but working with untidy data often means reinventing the wheel with one-time approaches that are hard to iterate or reuse.



HOW can we "tidy" data?

Key tidyr verbs

1. `pivot_longer`: Pivot wide data into long format (updated version of `gather`)
2. `pivot_wider`: Pivot long data into wide format (updated version of `spread`)
3. `separate`: Split one column into multiple columns
4. `unite`: Combine multiple columns into one

Let's start with an untidy dataset

```
stocks <- data.frame( # could use "tibble" instead of "data.frame" if you prefer
  time = as.Date('2009-01-01') + 0:1,
  X = rnorm(2, 0, 1),
  Y = rnorm(2, 0, 2),
  Z = rnorm(2, 0, 4)
  )
stocks
```

```
##         time          X           Y         Z
## 1 2009-01-01  1.614301 -0.01930472  1.061836
## 2 2009-01-02 -1.455784 -1.41667892 -2.207808
```

We have 4 columns, the date and the stocks

How do we get this in tidy form?

1) tidyr::pivot_longer

We need to pivot the stock name columns `X`, `Y`, `Z` longer

1. Choose columns using `X:Z` or `-time`
2. Decide what variable holds the names: `names_to = "stock"`
3. Decide what variable holds the values: `values_to = "price"`

1) tidyr::pivot_longer

```
stocks %>% pivot_longer(X:Z, names_to = "stock", values_to = "price")
```

```
## # A tibble: 6 × 3
##   time       stock   price
##   <date>     <chr>   <dbl>
## 1 2009-01-01 X      1.61
## 2 2009-01-01 Y     -0.0193
## 3 2009-01-01 Z      1.06
## 4 2009-01-02 X     -1.46
## 5 2009-01-02 Y     -1.42
## 6 2009-01-02 Z     -2.21
```

Let's save the "tidy" (i.e., long) stocks data frame for use on the next slide

```
tidy_stocks <- stocks %>%
  pivot_longer(-time, names_to = "stock", values_to = "price")
```

2) tidyr::pivot_wider

```
tidy_stocks %>% pivot_wider(names_from = stock, values_from = price)
```

```
## # A tibble: 2 × 4
##   time            X       Y     Z
##   <date>      <dbl>   <dbl> <dbl>
## 1 2009-01-01  1.61 -0.0193  1.06
## 2 2009-01-02 -1.46 -1.42   -2.21
```

```
tidy_stocks %>% pivot_wider(names_from = time, values_from = price)
```

```
## # A tibble: 3 × 3
##   stock `2009-01-01` `2009-01-02`
##   <chr>        <dbl>        <dbl>
## 1 X            1.61         -1.46
## 2 Y           -0.0193       -1.42
## 3 Z            1.06         -2.21
```

Note that the second example effectively transposed the original data

3) tidyr::separate

```
halftime_openers <- data.frame(name = c("Dr.Dre", "Snoop.Dogg"))
halftime_openers
```

```
##          name
## 1     Dr.Dre
## 2 Snoop.Dogg
```

```
halftime_openers %>% separate(name, c("first_name", "last_name"))
```

```
##   first_name last_name
## 1         Dr       Dre
## 2      Snoop      Dogg
```

This command is clever: it splits at non-alphanumeric values. To avoid ambiguity, you can specify the separation character with `separate(..., sep=".")`

3) tidyr::separate

```
halftime_performers <- data.frame(name = c("Dr..Dre", "Snoop.Dogg", "Eminem", "Mary.J.Blige",
                                           "Kendrick.Lamar", "50.Cent", "Anderson..Paak"))
```

```
halftime_performers %>% separate(name, c("first_name", "last_name"))
```

```
## Warning: Expected 2 pieces. Additional pieces discarded in 1 rows [4].

## Warning: Expected 2 pieces. Missing pieces filled with `NA` in 1 rows [3].

##   first_name last_name
## 1         Dr       Dre
## 2      Snoop      Dogg
## 3     Eminem      <NA>
## 4       Mary         J
## 5   Kendrick     Lamar
## 6         50      Cent
## 7   Anderson      Paak
```

What happened? Did we lose any information?

4) tidyr::unite

```
gdp <- data.frame(
  yr = rep(2016, times = 4),
  mnth = rep(1, times = 4),
  dy = 1:4,
  gdp = rnorm(4, mean = 100, sd = 2)
  )
gdp
```

```
##     yr mnth dy       gdp
## 1 2016    1  1  99.22901
## 2 2016    1  2 101.99159
## 3 2016    1  3 103.50551
## 4 2016    1  4  98.10842
```

4) tidyr::unite

```
# combine "yr", "mnth", and "dy" into one "date" column
gdp %>% unite(date, c("yr", "mnth", "dy"), sep = "-")
```

```
##       date       gdp
## 1 2016-1-1  99.22901
## 2 2016-1-2 101.99159
## 3 2016-1-3 103.50551
## 4 2016-1-4  98.10842
```

4) tidyr::unite

Note that `unite` will automatically create a character variable:

```
gdp_u <- gdp %>% unite(date, c("yr", "mnth", "dy"), sep = "-") %>% as_tibble()
gdp_u
```

```
## # A tibble: 4 × 2
##   date       gdp
##   <chr>    <dbl>
## 1 2016-1-1  99.2
## 2 2016-1-2 102.
## 3 2016-1-3 104.
## 4 2016-1-4  98.1
```

To convert it to something else (e.g., date or numeric), modify it using `mutate`

4) tidyr::unite

```
library(lubridate) # the lubridate package has helpful date conversion functions
gdp_u %>% mutate(date = ymd(date))
```

```
## # A tibble: 4 × 2
##   date         gdp
##   <date>     <dbl>
## 1 2016-01-01  99.2
## 2 2016-01-02 102.
## 3 2016-01-03 104.
## 4 2016-01-04  98.1
```

tidyr resources

Data tidying with tidyr : : CHEAT SHEET (link downloads a pdf)

Vignette (from the **tidyr** package)

```
vignette("tidy-data")
```

Original paper (Hadley Wickham, 2014 JSS)

Relational data

What are relational data?

Multiple tables of data with pairwise relations

Relations across >2 data tables are determined by the relations between each pair

Relational data verbs from dplyr

1. **Mutating joins**: add new variables
    - `left_join()`
    - `right_join()`
    - `inner_join()`
    - `full_join()`
2. **Filtering joins**: filter observations
    - `semi_join()`
    - `anti_join()`

Joins

Let's learn these join commands using two small data frames

```
superheroes
```

```
## # A tibble: 7 × 4
##   name      alignment gender publisher
##   <chr>     <chr>     <chr>  <chr>
## 1 Magneto   bad       male   Marvel
## 2 Storm     good      female Marvel
## 3 Mystique  bad       female Marvel
## 4 Batman    good      male   DC
## 5 Joker     bad       male   DC
## 6 Catwoman  bad       female DC
## 7 Hellboy   good      male   Dark Horse Comics
```

```
publishers
```

```
## # A tibble: 3 × 2
##   publisher yr_founded
##   <chr>           <int>
## 1 DC               1934
## 2 Marvel           1939
## 3 Image            1992
```

1) dplyr::left_join(x, y)

```
left_join(superheroes, publishers)
```

```
## Joining, by = "publisher"

## # A tibble: 7 × 5
##   name     alignment gender publisher         yr_founded
##   <chr>    <chr>     <chr>  <chr>                  <int>
## 1 Magneto  bad       male   Marvel                  1939
## 2 Storm    good      female Marvel                  1939
## 3 Mystique bad       female Marvel                  1939
## 4 Batman   good      male   DC                      1934
## 5 Joker    bad       male   DC                      1934
## 6 Catwoman bad       female DC                      1934
## 7 Hellboy  good      male   Dark Horse Comics         NA
```

`left_join` is a **mutating join**: it adds variables to `x`

`left_join` returns all rows from `x`

2) dplyr::right_join(x, y)

```
right_join(superheroes, publishers)
```

```
## Joining, by = "publisher"
```

```
## # A tibble: 7 × 5
##   name     alignment gender publisher yr_founded
##   <chr>    <chr>     <chr>  <chr>           <int>
## 1 Magneto  bad       male   Marvel           1939
## 2 Storm    good      female Marvel           1939
## 3 Mystique bad       female Marvel           1939
## 4 Batman   good      male   DC               1934
## 5 Joker    bad       male   DC               1934
## 6 Catwoman bad       female DC               1934
## 7 <NA>     <NA>      <NA>   Image            1992
```

`right_join` is a **mutating join**: it adds variables to `y`

`right_join` returns all rows from `y`

3) dplyr::inner_join(x, y)

```
inner_join(superheroes, publishers)
```

```
## Joining, by = "publisher"

## # A tibble: 6 × 5
##   name     alignment gender publisher yr_founded
##   <chr>    <chr>     <chr>  <chr>           <int>
## 1 Magneto  bad       male   Marvel           1939
## 2 Storm    good      female Marvel           1939
## 3 Mystique bad       female Marvel           1939
## 4 Batman   good      male   DC               1934
## 5 Joker    bad       male   DC               1934
## 6 Catwoman bad       female DC               1934
```

How is `inner_join` different from `left_join` and `right_join`?

`inner_join` returns all rows in `x` **AND** `y`

4) dplyr::full_join(x, y)

```
full_join(superheroes, publishers) # how many rows will this produce?
```

```
## Joining, by = "publisher"

## # A tibble: 8 × 5
##   name     alignment gender publisher         yr_founded
##   <chr>    <chr>     <chr>  <chr>                  <int>
## 1 Magneto  bad       male   Marvel                  1939
## 2 Storm    good      female Marvel                  1939
## 3 Mystique bad       female Marvel                  1939
## 4 Batman   good      male   DC                      1934
## 5 Joker    bad       male   DC                      1934
## 6 Catwoman bad       female DC                      1934
## 7 Hellboy  good      male   Dark Horse Comics         NA
## 8 <NA>     <NA>      <NA>   Image                   1992
```

`full_join` returns all rows in `x` **OR** `y`

5) dplyr::semi_join(x, y)

```
superheroes
```

```
## # A tibble: 7 × 4
##   name     alignment gender publisher
##   <chr>    <chr>     <chr>  <chr>
## 1 Magneto  bad       male   Marvel
## 2 Storm    good      female Marvel
## 3 Mystique bad       female Marvel
## 4 Batman   good      male   DC
## 5 Joker    bad       male   DC
## 6 Catwoman bad       female DC
## 7 Hellboy  good      male   Dark Horse Comics
```

```
semi_join(superheroes, publishers)
```

```
## Joining, by = "publisher"

## # A tibble: 6 × 4
##   name     alignment gender publisher
##   <chr>    <chr>     <chr>  <chr>
## 1 Magneto  bad       male   Marvel
## 2 Storm    good      female Marvel
## 3 Mystique bad       female Marvel
## 4 Batman   good      male   DC
## 5 Joker    bad       male   DC
## 6 Catwoman bad       female DC
```

`semi_join` is a **filtering join**: it keeps observations in `x` that have a match in `y`

Note that the variables do not change

6) dplyr::anti_join(x, y)

```
superheroes
```

```
## # A tibble: 7 × 4
##   name     alignment gender publisher
##   <chr>    <chr>     <chr>  <chr>
## 1 Magneto  bad       male   Marvel
## 2 Storm    good      female Marvel
## 3 Mystique bad       female Marvel
## 4 Batman   good      male   DC
## 5 Joker    bad       male   DC
## 6 Catwoman bad       female DC
## 7 Hellboy  good      male   Dark Horse Comics
```

```
anti_join(superheroes, publishers)
```

```
## Joining, by = "publisher"

## # A tibble: 1 × 4
##   name    alignment gender publisher
##   <chr>   <chr>     <chr>  <chr>
## 1 Hellboy good      male   Dark Horse Comics
```

`anti_join` is a **filtering join**: it keeps obs. in `x` that **DO NOT** have a match in `y`

Note that the variables do not change

Key variables

How do `dplyr` join commands know what variables to use as **keys**?

By default, `*_join()` uses all variables that are common across `x` and `y`

```
intersect(names(superheroes), names(publishers)) # variable used for matching before
```

```
## [1] "publisher"
```

Alternatively, we can specify what to join `by`: `*_join(..., by = "publisher")`

More on joins

Let's explore this using the **nycflights13** data

```
library(nycflights13)
flights
```

```
## # A tibble: 336,776 × 19
##     year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
##  1  2013     1     1      517            515         2      830            819
##  2  2013     1     1      533            529         4      850            830
##  3  2013     1     1      542            540         2      923            850
##  4  2013     1     1      544            545        -1     1004           1022
##  5  2013     1     1      554            600        -6      812            837
##  6  2013     1     1      554            558        -4      740            728
##  7  2013     1     1      555            600        -5      913            854
##  8  2013     1     1      557            600        -3      709            723
##  9  2013     1     1      557            600        -3      838            846
## 10  2013     1     1      558            600        -2      753            745
## # … with 336,766 more rows, and 11 more variables: arr_delay <dbl>,
## #   carrier <chr>, flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
```

More on joins

```
planes
```

```
## # A tibble: 3,322 × 9
##    tailnum  year type           manufacturer   model  engines seats speed engine
##    <chr>   <int> <chr>          <chr>          <chr>    <int> <int> <int> <chr>
##  1 N10156   2004 Fixed wing m… EMBRAER        EMB-1…       2    55    NA Turbo-…
##  2 N102UW   1998 Fixed wing m… AIRBUS INDUST… A320-…       2   182    NA Turbo-…
##  3 N103US   1999 Fixed wing m… AIRBUS INDUST… A320-…       2   182    NA Turbo-…
##  4 N104UW   1999 Fixed wing m… AIRBUS INDUST… A320-…       2   182    NA Turbo-…
##  5 N10575   2002 Fixed wing m… EMBRAER        EMB-1…       2    55    NA Turbo-…
##  6 N105UW   1999 Fixed wing m… AIRBUS INDUST… A320-…       2   182    NA Turbo-…
##  7 N107US   1999 Fixed wing m… AIRBUS INDUST… A320-…       2   182    NA Turbo-…
##  8 N108UW   1999 Fixed wing m… AIRBUS INDUST… A320-…       2   182    NA Turbo-…
##  9 N109UW   1999 Fixed wing m… AIRBUS INDUST… A320-…       2   182    NA Turbo-…
## 10 N110UW   1999 Fixed wing m… AIRBUS INDUST… A320-…       2   182    NA Turbo-…
## # … with 3,312 more rows
```

More on joins

Let's perform a left join on the flights and planes data frames

- I'm going subset columns after the join, just to keep text on the slide

```
left_join(flights, planes) %>%
  select(year, month, day, dep_time, arr_time, carrier, flight, tailnum, type, model)
```

```
## Joining, by = c("year", "tailnum")
```

```
## # A tibble: 336,776 × 10
##     year month   day dep_time arr_time carrier flight tailnum type  model
##    <int> <int> <int>    <int>    <int> <chr>    <int> <chr>   <chr> <chr>
##  1  2013     1     1      517      830 UA        1545 N14228  <NA>  <NA>
##  2  2013     1     1      533      850 UA        1714 N24211  <NA>  <NA>
##  3  2013     1     1      542      923 AA        1141 N619AA  <NA>  <NA>
##  4  2013     1     1      544     1004 B6         725 N804JB  <NA>  <NA>
##  5  2013     1     1      554      812 DL         461 N668DN  <NA>  <NA>
##  6  2013     1     1      554      740 UA        1696 N39463  <NA>  <NA>
##  7  2013     1     1      555      913 B6         507 N516JB  <NA>  <NA>
```

More on joins

As before, `dplyr` guessed which columns to join on

It uses columns with the same name:

```
## Joining, by = c("year", "tailnum")
```

Does anyone see a potential problem here?

The variable `year` does not have a consistent meaning across the datasets

In `flights` it refers to the *year of flight*, in `planes` it refers to *year of construction*

Luckily we can avoid this by using the `by =` argument

More on joins

We just need to be more explicit in the join call by using the `by =` argument

```
left_join(flights,
          planes %>% rename(year_built = year), # not necessary w/ below line, but helpful
          by = "tailnum" # be specific about the joining column
          ) %>%
  select(year, month, day, dep_time, arr_time, carrier, flight, tailnum, year_built, type, model) %>
  head(5) # just to save vertical space on the slide
```

```
## # A tibble: 5 × 11
##    year month   day dep_time arr_time carrier flight tailnum year_built type
##   <int> <int> <int>    <int>    <int> <chr>    <int> <chr>         <int> <chr>
## 1  2013     1     1      517      830 UA        1545 N14228         1999 Fixed w…
## 2  2013     1     1      533      850 UA        1714 N24211         1998 Fixed w…
## 3  2013     1     1      542      923 AA        1141 N619AA         1990 Fixed w…
## 4  2013     1     1      544     1004 B6         725 N804JB         2012 Fixed w…
## 5  2013     1     1      554      812 DL         461 N668DN         1991 Fixed w…
## # … with 1 more variable: model <chr>
```

More on joins

What happens if we don't rename `year` before this join?

```
left_join(flights,
          planes, # not renaming "year" to "year_built" this time
          by = "tailnum") %>%
  select(contains("year"), month, day, dep_time, arr_time, carrier, flight, tailnum, type, model) %>
  head(5) # just to save vertical space on the slide
```

```
## # A tibble: 5 × 11
##   year.x year.y month   day dep_time arr_time carrier flight tailnum type  model
##    <int>  <int> <int> <int>    <int>    <int> <chr>    <int> <chr>   <chr> <chr>
## 1   2013   1999     1     1      517      830 UA        1545 N14228  Fixe… 737-…
## 2   2013   1998     1     1      533      850 UA        1714 N24211  Fixe… 737-…
## 3   2013   1990     1     1      542      923 AA        1141 N619AA  Fixe… 757-…
## 4   2013   2012     1     1      544     1004 B6         725 N804JB  Fixe… A320…
## 5   2013   1991     1     1      554      812 DL         461 N668DN  Fixe… 757-…
```

What is `year.x`? What is `year.y`?

Summary

Key verbs

Import

readr

1. `read_csv`
2. `write_csv`

readxl

1. `read_excel`

Tidy

tidyr

1. `pivot_longer`
2. `pivot_wider`
3. `separate`
4. `unite`

Join

dplyr

1. `left_join`
2. `right_join`
3. `inner_join`
4. `full_join`
5. `semi_join`
6. `anti_join`

Transform

dplyr

1. `filter`
2. `arrange`
3. `select`
4. `mutate`
5. `summarize`