Data Science for Economists

Lecture 9: Data cleaning & wrangling: Tidyverse

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✱ Slides adapted from Grant McDermott's EC 607 at University of Oregon.

Prologue

What is "tidy" data?

Resources:

- Vignette (from the **tidyr** package)
- Original paper (Hadley Wickham, 2014 JSS)

Key points:

1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

Basically, tidy data is more likely to be long (i.e. narrow) format than wide format.

Checklist

R packages you'll need today

☑ **tidyverse**

☑ **nycflights13**

I'll hold off loading these libraries for now. But you can install/update them both with the following command.

```
install.packages(c('tidyverse', 'nycflights13'), repos = 'https://cran.rstudio.com', c
```

Tip: If you're on Linux, then I *strongly* recommend installing the pre-compiled binary versions of these packages from RSPM instead of CRAN. The exact repo mirror varies by distro (see the link). But on Ubuntu 20.04, for example, you'd use:

```
install.packages(c('tidyverse', 'nycflights13'), repos = 'https://packagemanager.rstu
```

Tidyverse basics

Tidyverse vs. base R

Much digital ink has been spilled over the "tidyverse vs. base R" debate.

I won't delve into this debate here, because I think the answer is clear: We should teach the tidyverse first (or, at least, early).

- The documentation and community support are outstanding.
- Having a consistent philosophy and syntax makes it easier to learn.
- Provides a convenient "front-end" to big data tools that we'll use later in the course.
- For data cleaning, wrangling, and plotting, the tidyverse really is a no-brainer.[1]

But... this certainly shouldn't put you off learning base R alternatives.

- Base R is extremely flexible and powerful (and stable).
- There are some things that you'll have to venture outside of the tidyverse for.
- A combination of tidyverse and base R is often the best solution to a problem.
- Excellent base R data manipulation tutorials: here and here.

Tidyverse vs. base R (cont.)

One point of convenience is that there is often a direct correspondence between a tidyverse command and its base R equivalent.

These generally follow a `tidyverse::snake_case` vs `base::period.case` rule. E.g. Compare:

tidyverse	base
`?readr::read_csv`	`?utils::read.csv`
`?dplyr::if_else`	`?base::ifelse`
`?tibble::tibble`	`?base::data.frame`

Etcetera.

If you call up the above examples, you'll see that the tidyverse alternative typically offers some enhancements or other useful options (and sometimes restrictions) over its base counterpart.

Remember: There are (almost) always multiple ways to achieve a single goal in R.

Tidyverse packages

Let's load the tidyverse meta-package and check the output.

```r
library(tidyverse)
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✔ dplyr     1.1.4     ✔ readr     2.1.5
## ✔ forcats   1.0.0     ✔ stringr   1.5.1
## ✔ ggplot2   3.5.1     ✔ tibble    3.2.1
## ✔ lubridate 1.9.3     ✔ tidyr     1.3.1
## ✔ purrr     1.0.2
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to
```

We see that we have actually loaded a number of packages (which could also be loaded individually): **ggplot2**, **tibble**, **dplyr**, etc.

- We can also see information about the package versions and some namespace conflicts.

Tidyverse packages (cont.)

The tidyverse actually comes with a lot more packages than those that are just loaded automatically.[1]

```
tidyverse_packages()
```

```
##  [1] "broom"         "conflicted"    "cli"           "dbplyr"
##  [5] "dplyr"         "dtplyr"        "forcats"       "ggplot2"
##  [9] "googledrive"   "googlesheets4" "haven"         "hms"
## [13] "httr"          "jsonlite"      "lubridate"     "magrittr"
## [17] "modelr"        "pillar"        "purrr"         "ragg"
## [21] "readr"         "readxl"        "reprex"        "rlang"
## [25] "rstudioapi"    "rvest"         "stringr"       "tibble"
## [29] "tidyr"         "xml2"          "tidyverse"
```

- E.g. The **lubridate** package for working with dates and the **rvest** package for webscraping.
- However, bear in mind that these packages will have to be loaded separately.

[1] It also includes a *lot* of dependencies upon installation. This is a matter of some controversy.

Tidyverse packages (cont.)

I hope to cover most of the tidyverse packages over the length of this course.

Today, however, I'm only really going to focus on two packages:

1. **dplyr**
2. **tidyr**

These are the workhorse packages for cleaning and wrangling data. They are thus the ones that you will likely make the most use of (alongside **ggplot2**, which we already met back in Lecture 1).

- Data cleaning and wrangling occupies an inordinate amount of time, no matter where you are in your research career.

We're in (New) Pipe-land Now

The `tidyverse` uses a pipe `▷` (|>) which lets you send (i.e. "pipe") intermediate output to another command. Shortcut: **Ctrl/Command+Shift+M**

In other words, it allows us to chain together a sequence of simple operations and thereby implement a more complex operation.

I want to reiterate how cool pipes are, and how using them can dramatically improve the experience of reading and writing code. Compare:

```
## These next two lines of code do exactly the same thing.
mpg ▷ filter(manufacturer=="audi") ▷ group_by(model) ▷ summarize(hwy_mean = mean(hw
summarize(group_by(filter(mpg, manufacturer=="audi"), model), hwy_mean = mean(hwy))
```

The first line reads from left to right, exactly how I thought of the operations in my head.

- Take this object (`mpg`), do this (`filter`), then do this (`group_by`), etc.

The second line totally inverts this logical order (the final operation comes first!)

- Who wants to read things inside out?

An aside on pipes: |> (cont.)

The piped version of the code is even more readable if we write it over several lines. Here it is again and, this time, I'll run it for good measure so you can see the output:

```
mpg |>
  filter(manufacturer=="audi") |>
  group_by(model) |>
  summarize(hwy_mean = mean(hwy))
```

```
## # A tibble: 3 × 2
##   model      hwy_mean
##   <chr>         <dbl>
## 1 a4             28.3
## 2 a4 quattro     25.8
## 3 a6 quattro     24
```

Remember: Using vertical space costs nothing and makes for much more readable/writeable code than cramming things horizontally.

PS — The pipe is originally from the **magrittr** package, which can do some other cool things if you're inclined to explore. It's been so popular that even SQL is adopting a pipe syntax. SQL!

dplyr

Aside: dplyr 1.0.0 release

Some of the **dplyr** features that we'll cover today were introduced in version 1.0.0 of the package.

- Version 1.0.0 is a big deal since it marks a stable code base for the package going forward.
- Please make sure that you are running at least **dplyr** 1.0.0 before continuing.

```
packageVersion('dplyr')
```

```
## [1] '1.1.4'
```

```
# install.packages('dplyr') ## install updated version if < 1.0.0
```

Note: **dplyr** 1.0.0 also notifies you about grouping variables every time you do operations on or with them. YMMV, but, personally, I find these messages annoying. You can switch them off.

```
options(dplyr.summarize.inform = FALSE) ## Add to .Rprofile to make permanent
```

Key dplyr verbs

There are five key dplyr verbs that you need to learn.

1. `filter`: Filter (i.e. subset) rows based on their values.
2. `arrange`: Arrange (i.e. reorder) rows based on their values.
3. `select`: Select (i.e. subset) columns by their names:
4. `mutate`: Create new columns.
5. `summarize`: Collapse multiple rows into a single summary value.[1]

Let's practice these commands together using the `starwars` data frame that comes pre-packaged with dplyr.

[1] `summarise` with a "s" works too.

1) dplyr::filter

We can chain multiple filter commands with the pipe (`▷`), or just separate them within a single filter command using commas.

```
starwars ▷
  filter(
    species == "Human",
    height ⩾ 190
    )
```

```
## # A tibble: 4 × 14
##   name      height  mass hair_color skin_color eye_color birth_year sex   gender
##   <chr>      <int> <dbl> <chr>      <chr>      <chr>          <dbl> <chr> <chr>
## 1 Darth Va…    202   136 none       white      yellow          41.9 male  mascu…
## 2 Qui-Gon …    193    89 brown      fair       blue            92   male  mascu…
## 3 Dooku        193    80 white      fair       brown          102   male  mascu…
## 4 Bail Pre…    191    NA black      tan        brown           67   male  mascu…
## # ℹ 5 more variables: homeworld <chr>, species <chr>, films <list>,
## #   vehicles <list>, starships <list>
```

What's the base R equivalent of this code?

1) dplyr::filter *cont.*

Regular expressions work well too.

```
starwars |>
  filter(grepl("Skywalker", name))
```

```
## # A tibble: 3 × 14
##   name      height  mass hair_color skin_color eye_color birth_year sex    gender
##   <chr>      <int> <dbl> <chr>      <chr>      <chr>          <dbl> <chr>  <chr>
## 1 Luke Sky…    172    77 blond      fair       blue            19   male   mascu…
## 2 Anakin S…    188    84 blond      fair       blue            41.9 male   mascu…
## 3 Shmi Sky…    163    NA black      fair       brown           72   fema… femin…
## # ℹ 5 more variables: homeworld <chr>, species <chr>, films <list>,
## #   vehicles <list>, starships <list>
```

1) dplyr::filter *cont.*

A very common `filter` use case is identifying (or removing) missing data cases.

```
starwars ▷
  filter(is.na(height))
```

```
## # A tibble: 6 × 14
##   name      height  mass hair_color skin_color eye_color birth_year sex   gender
##   <chr>      <int> <dbl> <chr>      <chr>      <chr>          <dbl> <chr> <chr>
## 1 Arvel Cr…     NA    NA brown      fair       brown             NA male  mascu…
## 2 Finn          NA    NA black      dark       dark              NA male  mascu…
## 3 Rey           NA    NA brown      light      hazel             NA fema… femin…
## 4 Poe Dame…     NA    NA brown      light      brown             NA male  mascu…
## 5 BB8           NA    NA none       none       black             NA none  mascu…
## 6 Captain …     NA    NA none       none       unknown           NA fema… femin…
## # ℹ 5 more variables: homeworld <chr>, species <chr>, films <list>,
## #   vehicles <list>, starships <list>
```

To remove missing observations, simply use negation: `filter(!is.na(height))`. Try this yourself.

2) dplyr::arrange

```
starwars ▷
  arrange(birth_year)
```

```
## # A tibble: 87 × 14
##    name     height  mass hair_color skin_color eye_color birth_year sex   gender
##    <chr>     <int> <dbl> <chr>      <chr>      <chr>          <dbl> <chr> <chr>
##  1 Wicket …     88  20   brown      brown      brown            8   male  mascu…
##  2 IG-88       200 140   none       metal      red             15   none  mascu…
##  3 Luke Sk…    172  77   blond      fair       blue            19   male  mascu…
##  4 Leia Or…    150  49   brown      light      brown           19   fema… femin…
##  5 Wedge A…    170  77   brown      fair       hazel           21   male  mascu…
##  6 Plo Koon    188  80   none       orange     black           22   male  mascu…
##  7 Biggs D…    183  84   black      light      brown           24   male  mascu…
##  8 Han Solo    180  80   brown      fair       brown           29   male  mascu…
##  9 Lando C…    177  79   black      dark       brown           31   male  mascu…
## 10 Boba Fe…    183  78.2 black      fair       brown           31.5 male  mascu…
## # ℹ 77 more rows
## # ℹ 5 more variables: homeworld <chr>, species <chr>, films <list>,
## #   vehicles <list>, starships <list>
```

Note: Arranging on a character-based column (i.e. strings) will sort alphabetically. Try this yourself by arranging according to the "name" column.

2) dplyr::arrange *cont.*

We can also arrange items in descending order using `arrange(desc())`.

```
starwars ▷
  arrange(desc(birth_year))
```

```
## # A tibble: 87 × 14
##    name     height  mass hair_color skin_color eye_color birth_year sex   gender
##    <chr>     <int> <dbl> <chr>      <chr>      <chr>          <dbl> <chr> <chr>
##  1 Yoda         66    17 white      green      brown            896 male  mascu…
##  2 Jabba D…    175  1358 <NA>       green-tan… orange           600 herm… mascu…
##  3 Chewbac…    228   112 brown      unknown    blue             200 male  mascu…
##  4 C-3PO       167    75 <NA>       gold       yellow           112 none  mascu…
##  5 Dooku       193    80 white      fair       brown            102 male  mascu…
##  6 Qui-Gon…    193    89 brown      fair       blue              92 male  mascu…
##  7 Ki-Adi-…    198    82 white      pale       yellow            92 male  mascu…
##  8 Finis V…    170    NA blond      fair       blue              91 male  mascu…
##  9 Palpati…    170    75 grey       pale       yellow            82 male  mascu…
## 10 Cliegg …    183    NA brown      fair       blue              82 male  mascu…
## # ℹ 77 more rows
## # ℹ 5 more variables: homeworld <chr>, species <chr>, films <list>,
## #   vehicles <list>, starships <list>
```

3) dplyr::select

Use commas to select multiple columns out of a data frame. (You can also use "first:last" for consecutive columns). Deselect a column with "-".

```
starwars ▷
  select(name:skin_color, species, -height)
```

```
## # A tibble: 87 × 5
##    name                mass hair_color    skin_color  species
##    <chr>              <dbl> <chr>         <chr>       <chr>
##  1 Luke Skywalker        77 blond         fair        Human
##  2 C-3PO                 75 <NA>          gold        Droid
##  3 R2-D2                 32 <NA>          white, blue Droid
##  4 Darth Vader          136 none          white       Human
##  5 Leia Organa           49 brown         light       Human
##  6 Owen Lars            120 brown, grey   light       Human
##  7 Beru Whitesun Lars    75 brown         light       Human
##  8 R5-D4                 32 <NA>          white, red  Droid
##  9 Biggs Darklighter     84 black         light       Human
## 10 Obi-Wan Kenobi        77 auburn, white fair        Human
## # ℹ 77 more rows
```

3) dplyr::select *cont.*

You can also rename some (or all) of your selected variables in place.

```
starwars |>
  select(alias=name, crib=homeworld, sex=gender)
```

```
## # A tibble: 87 × 3
##    alias              crib     sex
##    <chr>              <chr>    <chr>
##  1 Luke Skywalker     Tatooine masculine
##  2 C-3PO              Tatooine masculine
##  3 R2-D2              Naboo    masculine
##  4 Darth Vader        Tatooine masculine
##  5 Leia Organa        Alderaan feminine
##  6 Owen Lars          Tatooine masculine
##  7 Beru Whitesun Lars Tatooine feminine
##  8 R5-D4              Tatooine masculine
##  9 Biggs Darklighter  Tatooine masculine
## 10 Obi-Wan Kenobi     Stewjon  masculine
## # ℹ 77 more rows
```

If you just want to rename columns without subsetting them, you can use `rename`. Try this now by replacing `select( ... )` in the above code chunk with `rename( ... )`.

3) dplyr::select *cont.*

The `select(contains(PATTERN))` option provides a nice shortcut in relevant cases.

```
starwars ▷
  select(name, contains("color"))
```

```
## # A tibble: 87 × 4
##    name               hair_color    skin_color  eye_color
##    <chr>              <chr>         <chr>       <chr>
##  1 Luke Skywalker     blond         fair        blue
##  2 C-3PO              <NA>          gold        yellow
##  3 R2-D2              <NA>          white, blue red
##  4 Darth Vader        none          white       yellow
##  5 Leia Organa        brown         light       brown
##  6 Owen Lars          brown, grey   light       blue
##  7 Beru Whitesun Lars brown         light       blue
##  8 R5-D4              <NA>          white, red  red
##  9 Biggs Darklighter  black         light       brown
## 10 Obi-Wan Kenobi     auburn, white fair        blue-gray
## # ℹ 77 more rows
```

3) dplyr::select *cont.*

The `select( ... , everything())` option is another useful shortcut if you only want to bring some variable(s) to the "front" of a data frame.

```
starwars ▷
  select(species, homeworld, everything()) ▷
  head(5)
```

```
## # A tibble: 5 × 14
##   species homeworld name           height  mass hair_color skin_color  eye_color
##   <chr>   <chr>     <chr>           <int> <dbl> <chr>      <chr>       <chr>
## 1 Human   Tatooine  Luke Skywalker    172    77 blond      fair        blue
## 2 Droid   Tatooine  C-3PO             167    75 <NA>       gold        yellow
## 3 Droid   Naboo     R2-D2              96    32 <NA>       white, blue red
## 4 Human   Tatooine  Darth Vader       202   136 none       white       yellow
## 5 Human   Alderaan  Leia Organa       150    49 brown      light       brown
## # ℹ 6 more variables: birth_year <dbl>, sex <chr>, gender <chr>, films <list>,
## #   vehicles <list>, starships <list>
```

Note: The `relocate` function available in dplyr 1.0.0 has brought a lot more functionality to ordering of columns. See here.

4) dplyr::mutate

You can create new columns from scratch, or (more commonly) as transformations of existing columns.

```r
starwars ▷
  select(name, birth_year) ▷
  mutate(dog_years = birth_year * 7) ▷
  mutate(comment = paste0(name, " is ", dog_years, " in dog years."))
```

```
## # A tibble: 87 × 4
##    name               birth_year dog_years comment
##    <chr>                   <dbl>     <dbl> <chr>
##  1 Luke Skywalker           19         133  Luke Skywalker is 133 in dog years.
##  2 C-3PO                   112         784  C-3PO is 784 in dog years.
##  3 R2-D2                    33         231  R2-D2 is 231 in dog years.
##  4 Darth Vader              41.9       293. Darth Vader is 293.3 in dog years.
##  5 Leia Organa              19         133  Leia Organa is 133 in dog years.
##  6 Owen Lars                52         364  Owen Lars is 364 in dog years.
##  7 Beru Whitesun Lars       47         329  Beru Whitesun Lars is 329 in dog yea…
##  8 R5-D4                    NA          NA  R5-D4 is NA in dog years.
##  9 Biggs Darklighter        24         168  Biggs Darklighter is 168 in dog year…
## 10 Obi-Wan Kenobi           57         399  Obi-Wan Kenobi is 399 in dog years.
## # ℹ 77 more rows
```

4) dplyr::mutate *cont.*

Note: `mutate` is order aware. So you can chain multiple mutates in a single call.

```
starwars ▷
  select(name, birth_year) ▷
  mutate(
    dog_years = birth_year * 7, ## Separate with a comma
    comment = paste0(name, " is ", dog_years, " in dog years.")
    )
```

```
## # A tibble: 87 × 4
##    name               birth_year dog_years comment
##    <chr>                   <dbl>     <dbl> <chr>
##  1 Luke Skywalker           19       133   Luke Skywalker is 133 in dog years.
##  2 C-3PO                   112       784   C-3PO is 784 in dog years.
##  3 R2-D2                    33       231   R2-D2 is 231 in dog years.
##  4 Darth Vader              41.9     293.  Darth Vader is 293.3 in dog years.
##  5 Leia Organa              19       133   Leia Organa is 133 in dog years.
##  6 Owen Lars                52       364   Owen Lars is 364 in dog years.
##  7 Beru Whitesun Lars       47       329   Beru Whitesun Lars is 329 in dog yea…
##  8 R5-D4                    NA        NA   R5-D4 is NA in dog years.
##  9 Biggs Darklighter        24       168   Biggs Darklighter is 168 in dog year…
## 10 Obi-Wan Kenobi           57       399   Obi-Wan Kenobi is 399 in dog years.
## # ℹ 77 more rows
```

4) dplyr::mutate *cont.*

Boolean, logical and conditional operators all work well with `mutate` too.

```
starwars ▷
  select(name, height) ▷
  filter(name %in% c("Luke Skywalker", "Anakin Skywalker")) ▷
  mutate(tall1 = height > 180) ▷
  mutate(tall2 = ifelse(height > 180, "Tall", "Short")) ## Same effect, but can choos
```

```
## # A tibble: 2 × 4
##   name             height tall1 tall2
##   <chr>             <int> <lgl> <chr>
## 1 Luke Skywalker      172 FALSE Short
## 2 Anakin Skywalker    188 TRUE  Tall
```

4) dplyr::mutate *cont.*

Lastly, combining `mutate` with the `across` feature in dplyr 1.0.0+ allows you to easily work on a subset of variables. For example:

```
starwars ▷
  select(name:eye_color) ▷
  mutate(across(where(is.character), toupper)) ▷
  head(5)
```

```
## # A tibble: 5 × 6
##   name               height  mass hair_color skin_color  eye_color
##   <chr>               <int> <dbl> <chr>      <chr>       <chr>
## 1 LUKE SKYWALKER        172    77 BLOND      FAIR        BLUE
## 2 C-3PO                 167    75 <NA>       GOLD        YELLOW
## 3 R2-D2                  96    32 <NA>       WHITE, BLUE RED
## 4 DARTH VADER           202   136 NONE       WHITE       YELLOW
## 5 LEIA ORGANA           150    49 BROWN      LIGHT       BROWN
```

Note: This workflow (i.e. combining `mutate` and `across`) supersedes the old "scoped" variants of `mutate` that you might have used previously. More details here and here.

5) dplyr::summarize

Particularly useful in combination with the `group_by` command.

```
starwars |>
  group_by(species, gender) |>
  summarize(mean_height = mean(height, na.rm = TRUE))
```

```
## summarise() has grouped output by 'species'. You can override using the
## .groups argument.

## # A tibble: 42 × 3
## # Groups:   species [38]
##    species   gender    mean_height
##    <chr>     <chr>           <dbl>
##  1 Aleena    masculine          79
##  2 Besalisk  masculine         198
##  3 Cerean    masculine         198
##  4 Chagrian  masculine         196
##  5 Clawdite  feminine          168
##  6 Droid     feminine           96
##  7 Droid     masculine         140
##  8 Dug       masculine         112
##  9 Ewok      masculine          88
## 10 Geonosian masculine         183
## # ℹ 32 more rows
```

5) dplyr::summarize *cont.*

Note that including "na.rm = TRUE" (or, its alias "na.rm = T") is usually a good idea with summarize functions. Otherwise, any missing value will propogate to the summarized value too.

```
## Probably not what we want
starwars ▷
  summarize(mean_height = mean(height))
```

```
## # A tibble: 1 × 1
##   mean_height
##         <dbl>
## 1          NA
```

```
## Much better
starwars ▷
  summarize(mean_height = mean(height, na.rm = TRUE))
```

```
## # A tibble: 1 × 1
##   mean_height
##         <dbl>
## 1        175.
```

5) dplyr::summarize *cont.*

The same `across`-based workflow that we saw with `mutate` a few slides back also works with `summarize`. For example:

```
starwars ▷
  group_by(species) ▷
  summarize(across(where(is.numeric), function(x) mean(x, na.rm=T))) ▷
  head(5)
```

```
## # A tibble: 5 × 4
##   species  height  mass birth_year
##   <chr>     <dbl> <dbl>      <dbl>
## 1 Aleena       79    15        NaN
## 2 Besalisk    198   102        NaN
## 3 Cerean      198    82         92
## 4 Chagrian    196   NaN        NaN
## 5 Clawdite    168    55        NaN
```

Note: Again, this functionality supersedes the old "scoped" variants of `summarize` that you used prior to dplyr 1.0.0. Details here and here.

Other dplyr goodies

`group_by` and `ungroup`: For (un)grouping.

- Particularly useful with the `summarize` and `mutate` commands, as we've already seen.

`slice`: Subset rows by position rather than filtering by values.

- E.g. `starwars ▷ slice(c(1, 5))`

`pull`: Extract a column from as a data frame as a vector or scalar.

- E.g. `starwars ▷ filter(gender=="female") ▷ pull(height)`

`count` and `distinct`: Number and isolate unique observations.

- E.g. `starwars ▷ count(species)`, or `starwars ▷ distinct(species)`
- You could also use a combination of `mutate`, `group_by`, and `n()`, e.g. `starwars ▷ group_by(species) ▷ mutate(num = n())`.

Other dplyr goodies (cont.)

There are also a whole class of window functions for getting leads and lags, ranking, creating cumulative aggregates, etc.

- See `vignette("window-functions")`.

The final set of dplyr "goodies" are the family of join operations. However, these are important enough that I want to go over some concepts in a bit more depth...

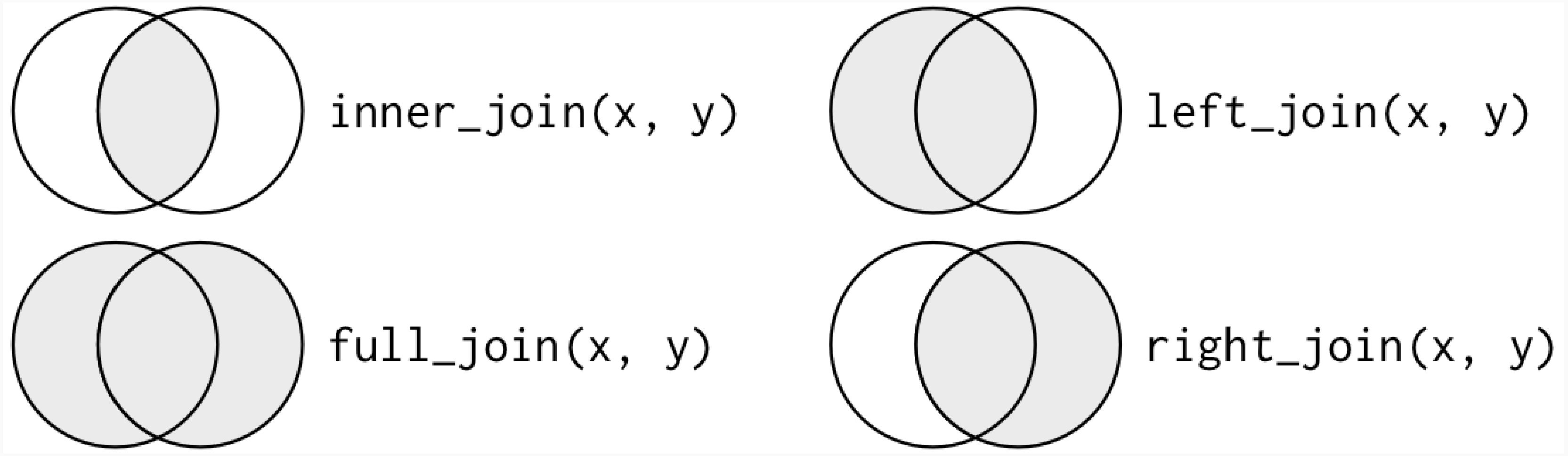
- We will encounter and practice these many more times as the course progresses.

Joins

One of the mainstays of the dplyr package is merging data with the family join operations.

- `inner_join(df1, df2)`
- `left_join(df1, df2)`
- `right_join(df1, df2)`
- `full_join(df1, df2)`
- `semi_join(df1, df2)`
- `anti_join(df1, df2)`

Visualizing Joins



For the simple examples that I'm going to show here, we'll need some data sets that come bundled with the **nycflights13** package.

- Load it now and then inspect these data frames in your own console.

```
library(nycflights13)
flights
planes
```

Joins (cont.)

Let's perform a left join on the flights and planes datasets.

- *Note*: I'm going subset columns after the join, but only to keep text on the slide.

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

```
## Joining with by = join_by(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>
##  8  2013     1     1      557      709 EV        5708 N829AS  <NA>  <NA>
##  9  2013     1     1      557      838 B6          79 N593JB  <NA>  <NA>
## 10  2013     1     1      558      753 AA         301 N3ALAA  <NA>  <NA>
## # ℹ 336,766 more rows
```

Joins (cont.)

(*continued from previous slide*)

Note that dplyr made a reasonable guess about which columns to join on (i.e. columns that share the same name). It also told us its choices:

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

However, there's an obvious problem here: the variable "year" does not have a consistent meaning across our joining datasets!

- In one it refers to the *year of flight*, in the other it refers to *year of construction*.

Luckily, there's an easy way to avoid this problem.

- See if you can figure it out before turning to the next slide.
- Try `?dplyr::join`.

Joins (cont.)

(*continued from previous slide*)

You just need to be more explicit in your join call by using the `by =` argument.

- You can also rename any ambiguous columns to avoid confusion.

```
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, t
  head(3) ## Just to save vertical space on the slide
```

```
## # A tibble: 3 × 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…
## # ℹ 1 more variable: model <chr>
```

Joins (cont.)

(*continued from previous slide*)

Last thing I'll mention for now; note what happens if we again specify the join column... but don't rename the ambiguous "year" column in at least one of the given data frames.

```
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, t
  head(3)
```

```
## # A tibble: 3 × 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-…
```

Make sure you know what "year.x" and "year.y" are. Again, it pays to be specific.

tidyr

Key tidyr verbs

1. `pivot_longer`: Pivot wide data into long format (i.e. "melt").[1]
2. `pivot_wider`: Pivot long data into wide format (i.e. "cast").[2]
3. `separate`: Separate (i.e. split) one column into multiple columns.
4. `unite`: Unite (i.e. combine) multiple columns into one.

Let's practice these verbs together in class.

- Side question: Which of `pivot_longer` vs `pivot_wider` produces "tidy" data?

[1] Updated version of `tidyr::gather`.

[2] Updated version of `tidyr::spread`.

1) tidyr::pivot_longer

```
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 1.944249 -1.613529 -7.097121
## 2 2009-01-02 1.561860  1.395649  2.988417
```

```
stocks ▷ pivot_longer(-time, names_to="stock", values_to="price")
```

```
## # A tibble: 6 × 3
##   time       stock price
##   <date>     <chr> <dbl>
## 1 2009-01-01 X      1.94
## 2 2009-01-01 Y     -1.61
## 3 2009-01-01 Z     -7.10
## 4 2009-01-02 X      1.56
## 5 2009-01-02 Y      1.40
## 6 2009-01-02 Z      2.99
```

1) tidyr::pivot_longer *cont.*

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

```
## Write out the argument names this time: i.e. "names_to=" and "values_to="
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  1.94 -1.61 -7.10
## 2 2009-01-02  1.56  1.40  2.99
```

```
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             1.94         1.56
## 2 Y            -1.61         1.40
## 3 Z            -7.10         2.99
```

Note that the second example — which has combined different pivoting arguments — has effectively transposed the data.

Aside: Remembering the pivot_* syntax

There's a long-running joke about no-one being able to remember Stata's "reshape" command. (Exhibit A.)

It's easy to see this happening with the `pivot_*` functions too. However, I find that easier to remember the commands as long as I remember the argument order is *"names"* then *"values"*.

3) tidyr::separate

```r
economists = data.frame(name = c("Adam.Smith", "Paul.Samuelson", "Milton.Friedman"))
economists
```

```
##              name
## 1      Adam.Smith
## 2  Paul.Samuelson
## 3 Milton.Friedman
```

```r
economists |> separate(name, c("first_name", "last_name"))
```

```
##   first_name last_name
## 1       Adam     Smith
## 2       Paul Samuelson
## 3     Milton  Friedman
```

This command is pretty smart. But to avoid ambiguity, you can also specify the separation character with `separate( ... , sep=".")`.

3) tidyr::separate *cont.*

A related function is `separate_rows`, for splitting up cells that contain multiple fields or observations (a frustratingly common occurence with survey data).

```
jobs = data.frame(
  name = c("Jack", "Jill"),
  occupation = c("Homemaker", "Philosopher, Philanthropist, Troublemaker")
  )
jobs
```

```
##   name                                occupation
## 1 Jack                                 Homemaker
## 2 Jill Philosopher, Philanthropist, Troublemaker
```

```
## Now split out Jill's various occupations into different rows
jobs ▷ separate_rows(occupation)
```

```
## # A tibble: 4 × 2
##   name  occupation
##   <chr> <chr>
## 1 Jack  Homemaker
## 2 Jill  Philosopher
## 3 Jill  Philanthropist
## 4 Jill  Troublemaker
```

4) tidyr::unite

```r
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 99.28177
## 2 2016    1  2 96.99765
## 3 2016    1  3 99.16636
## 4 2016    1  4 97.02445
```

```r
## Combine "yr", "mnth", and "dy" into one "date" column
gdp ▷ unite(date, c("yr", "mnth", "dy"), sep = "-")
```

```
##       date      gdp
## 1 2016-1-1 99.28177
## 2 2016-1-2 96.99765
## 3 2016-1-3 99.16636
## 4 2016-1-4 97.02445
```

4) tidyr::unite *cont.*

Note that `unite` will automatically create a character variable. You can see this better if we convert it to a tibble.

```
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    99.3
## 2 2016-1-2    97.0
## 3 2016-1-3    99.2
## 4 2016-1-4    97.0
```

If you want to convert it to something else (e.g. date or numeric) then you will need to modify it using `mutate`. See the next slide for an example, using the lubridate package's super helpful date conversion functions.

4) tidyr::unite *cont.*

(continued from previous slide)

```
library(lubridate)
gdp_u ▷ mutate(date = ymd(date))
```

```
## # A tibble: 4 × 2
##   date         gdp
##   <date>     <dbl>
## 1 2016-01-01  99.3
## 2 2016-01-02  97.0
## 3 2016-01-03  99.2
## 4 2016-01-04  97.0
```

Other tidyr goodies

Use `crossing` to get the full combination of a group of variables.[1]

```r
crossing(side=c("left", "right"), height=c("top", "bottom"))
```

```
## # A tibble: 4 × 2
##   side  height
##   <chr> <chr>
## 1 left  bottom
## 2 left  top
## 3 right bottom
## 4 right top
```

See `?expand` and `?complete` for more specialised functions that allow you to fill in (implicit) missing data or variable combinations in existing data frames.

- You'll encounter this during your next assignment.

[1] Base R alternative: `expand.grid`.

Summary

Key verbs

dplyr

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

tidyr

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

Other useful items include: pipes (`▷`), grouping (`group_by`), joining functions (`left_join`, `inner_join`, etc.).

Next lecture: Data cleaning and wrangling: (2) data.table