Lab 02: Data and Reproducibility

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❗ Due date

This lab is due on **Monday, September 22 at 11:59pm**. To be considered on time, the following must be done by the due date:

- Final `.pdf` file submitted on Gradescope

Introduction

The main goal is to learn data processsing using tidyverse and introduce you to version control using Github.

Learning goals

By the end of the lab, you will learn:

1. Tidyverse basics
2. Data wrangling with dplyr
3. Data tidying with tidyr

The tidyverse

A whole "universe" of functions within R

- The most powerful, intuitive, and popular approach to data cleaning, wrangling, and visualization in R

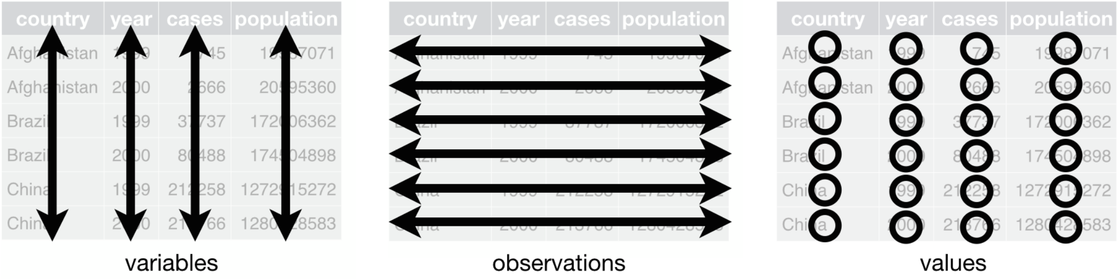
Advantages:

- Consistent philosophy and syntax
- "Verb" based approach makes it more familiar to users of Stata/SAS/SPSS
- Serves as the front-end for many other big data and ML tools

Tidying Data

The two most important properties of tidy data are:

1. Each column is a unique variable.
2. Each row is a single observation.



[Image is from "R for Data Science" by Hadley Wickham & Garrett Grolemund, used under CC BY-NC-ND 3.0]

Tidy data is easier to work with, because you have a consistent way of referring to variables and observations. It then becomes easy to manipulate, visualize, and model.

Wide vs. Long Formats

Both of these data sets display information on heart rate observed in individuals across 3 different time periods:

```
     name time1 time2 time3
1  Wilbur    67    56    70
2 Petunia    80    90    67
3 Gregory    64    50   101
```

```
     name time heartrate
1  Wilbur    1        67
2 Petunia    1        80
3 Gregory    1        64
```

```
4  Wilbur    2        56
5 Petunia    2        90
6 Gregory    2        50
7  Wilbur    3        70
8 Petunia    3        67
9 Gregory    3        10
```

Which dataframe is in *tidy* format?

Wide data:

- Row = patient. Columns = repeated observations over time.
- Often easier to take in at a glance (as in a spreadsheet).

Long data:

- Row = one observation. Columns = ID variables + observed variable.
- Usually easier to clean, merge with other data, and avoid errors.

Tidy data is more likely to be **long**.

- Most R packages have been written assuming your data is in long format.

"Tidy datasets are all alike but every messy dataset is messy in its own way."
– Hadley Wickham

Tidyverse packages

We need to install and load a couple of packages. Run these preliminaries:

```r
# load and install package if necessary
if (!require("pacman")) install.packages("pacman")
pacman::p_load(
  tidyverse,
  nycflights13
  )
```

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.

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

```r
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"    
```

All of these are super useful

- **lubridate** helps us work with dates
- **rvest** is for webscraping

This labs will focus on two that are automatically loaded: **dplyr** and **tidyr**.

Pipes: |> or %>%

Pipes take the **output** of one function and feed it into the **first argument** of the next (which you then skip).

`dataframe |> filter(condition)` is equivalent to `filter(dataframe, condition)`.

Note: `|>` on these slides is generated by the two characters `| >`, without the space.

Older version of the pipe: `%>%` * From the `magrittr` package loaded with the tidyverse * Works identically to `|>` in most situations.

Keyboard shortcut: Ctl/Cmd + Shift + M

- Have to turn on a setting in RStudio options to make `|>` the default

Pipes can dramatically improve the experience of reading and writing code. Compare:

```r
## These next two lines of code do exactly the same thing.

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

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

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

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

The first line reads from left to right, exactly how you think about the operations.

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

Best practice is to put each function on its own line and indent. Look how much more readable this is:

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

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

Vertical space costs nothing and makes for much more readable/writable code than cramming things horizontally.

All together, this multi-line line of code is called a **pipeline**.

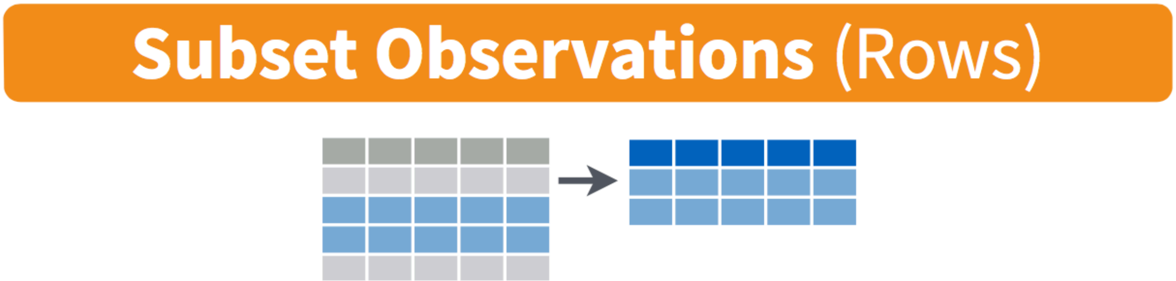
Key dplyr verbs

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.

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

Exercise 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 x 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>
```

Regular expressions work well too.

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

```
# A tibble: 3 x 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>
```

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

```
starwars |>
  filter(is.na(height))
```

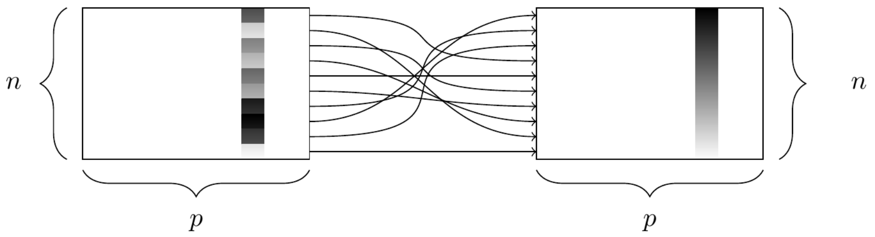
```
# A tibble: 6 x 14
  name      height  mass hair_color skin_color eye_color birth_year sex   gender
  <chr>      <int> <dbl> <chr>      <chr>      <chr>          <dbl> <chr> <chr>
1 Arvel Cr~     NA    NA brown      fair       brown             NA male  mascu~
2 Finn          NA    NA black      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.

```
clean_starwars<-starwars |>
  filter(!is.na(height))
clean_starwars
```

```
# A tibble: 81 x 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 Sk~    172    77 blond      fair       blue            19   male  mascu~
 2 C-3PO       167    75 <NA>       gold       yellow         112   none  mascu~
 3 R2-D2        96    32 <NA>       white, bl~ red             33   none  mascu~
 4 Darth V~    202   136 none       white      yellow          41.9 male  mascu~
 5 Leia Or~    150    49 brown      light      brown           19   fema~ femin~
 6 Owen La~    178   120 brown, gr~ light      blue            52   male  mascu~
 7 Beru Wh~    165    75 brown      light      blue            47   fema~ femin~
 8 R5-D4        97    32 <NA>       white, red red             NA   none  mascu~
 9 Biggs D~    183    84 black      light      brown           24   male  mascu~
10 Obi-Wan~    182    77 auburn, w~ fair       blue-gray       57   male  mascu~
# i 71 more rows
# i 5 more variables: homeworld <chr>, species <chr>, films <list>,
#   vehicles <list>, starships <list>
```

Exercise 2: dplyr::arrange



`arrange` sorts your data frame by a particular column (numerically, or alphabetically)

```
starwars |>
  arrange(birth_year)
```

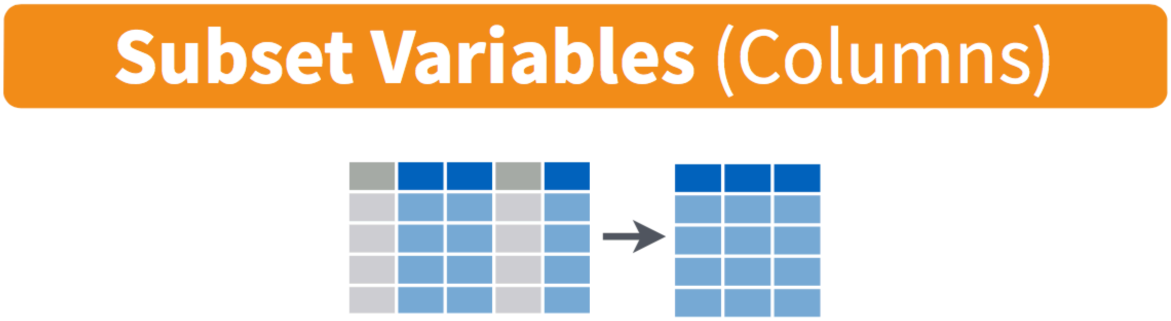
```
# A tibble: 87 x 14
   name     height  mass hair_color skin_color eye_color birth_year sex   gender
   <chr>     <int> <dbl> <chr>      <chr>      <chr>          <dbl> <chr> <chr>
 1 Wicket ~     88  20   brown      brown      brown              8 male  mascu~
 2 IG-88       200 140   none       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>
```

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

```r
starwars |>
  arrange(desc(birth_year))
```

```
# A tibble: 87 x 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>
```

Exercise 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 x 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
```

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

```
starwars |>
  select(alias=name, planet=homeworld)
```

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

If you just want to rename columns without subsetting them, you can use `rename`. Try this!

```
starwars_rename<-starwars |>
  rename(alias=name)
names(starwars_rename)
```

```
 [1] "alias"      "height"     "mass"       "hair_color" "skin_color"
 [6] "eye_color"  "birth_year" "sex"        "gender"     "homeworld" 
[11] "species"    "films"      "vehicles"   "starships" 
```

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

```
starwars |>
  select(name, contains("color"))
```

```
# A tibble: 87 x 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
```

Some other selection helpers: `starts_with()`, `ends_with()`, `all_of(c("name1", "name2"))`, `matches()`.

Exercise 4: dplyr::mutate

Make New Variables

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

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

```
# A tibble: 87 x 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
```

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 x 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
```

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

```r
starwars |>
  select(name, height) |>
  filter(name %in% c("Luke Skywalker", "Anakin Skywalker")) |>
  mutate(tall1 = height > 180) |>
  mutate(tall2 = if_else(height > 180, "Tall", "Short"))
```

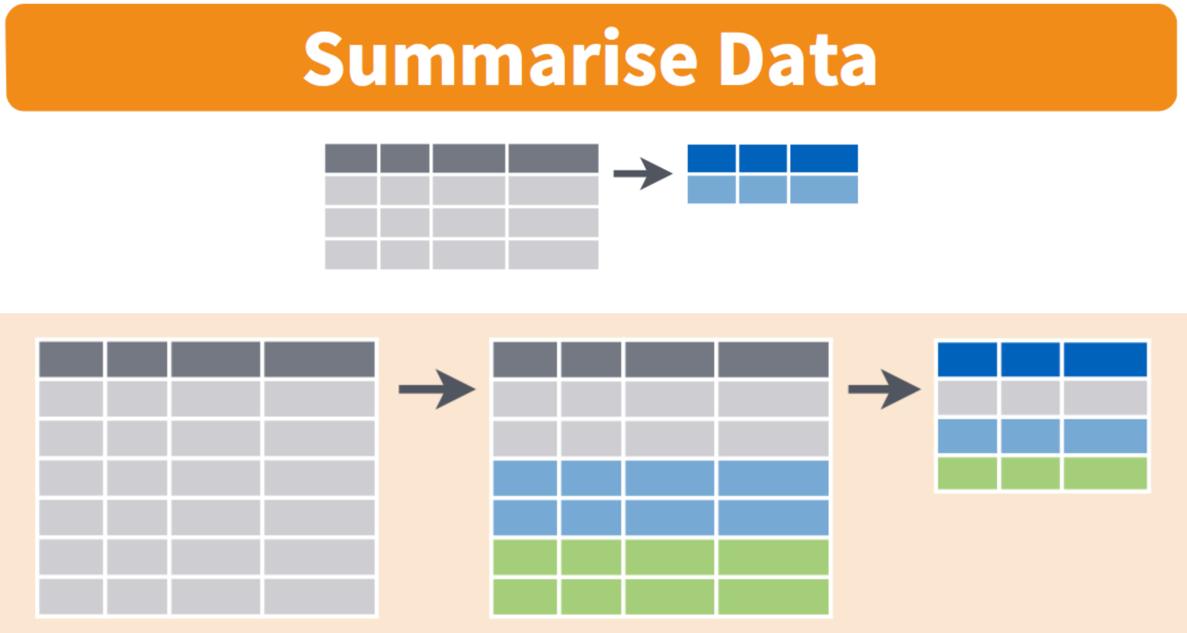
```
# A tibble: 2 x 4
  name             height tall1 tall2
  <chr>             <int> <lgl> <chr>
1 Luke Skywalker      172 FALSE Short
2 Anakin Skywalker    188 TRUE  Tall
```

Lastly, combining `mutate` with `across` allows you to easily perform the same operation on a subset of variables.

```r
starwars |>
  select(name:eye_color) |>
  mutate(across(where(is.character), toupper))
```

```
# A tibble: 87 x 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
 6 OWEN LARS             178   120 BROWN, GREY   LIGHT       BLUE
 7 BERU WHITESUN LARS    165    75 BROWN         LIGHT       BLUE
 8 R5-D4                  97    32 <NA>          WHITE, RED  RED
 9 BIGGS DARKLIGHTER     183    84 BLACK         LIGHT       BROWN
10 OBI-WAN KENOBI        182    77 AUBURN, WHITE FAIR        BLUE-GRAY
# i 77 more rows
```

Exercise 5: dplyr::summarize



Particularly useful in combination with the `group_by` command.

```
starwars |>
  group_by(species) |>
  summarize(mean_height = mean(height))
```

```
# A tibble: 38 x 2
   species   mean_height
   <chr>           <dbl>
 1 Aleena            79
 2 Besalisk         198
 3 Cerean           198
 4 Chagrian         196
 5 Clawdite         168
 6 Droid             NA
 7 Dug              112
 8 Ewok              88
 9 Geonosian        183
10 Gungan           209.
# i 28 more rows
```

Notice that some of these summarized values are missing. If we want to ignore missing values, use `na.rm = T`:

```r
## Much better
starwars |>
  group_by(species) |>
  summarize(mean_height = mean(height, na.rm = T))
```

```
# A tibble: 38 x 2
   species   mean_height
   <chr>           <dbl>
 1 Aleena             79
 2 Besalisk         198
 3 Cerean           198
 4 Chagrian         196
 5 Clawdite         168
 6 Droid            131.
 7 Dug              112
 8 Ewok              88
 9 Geonosian        183
10 Gungan           209.
# i 28 more rows
```

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

```r
starwars |>
  group_by(species) |>
  summarize(across(where(is.numeric), mean))
```

```
# A tibble: 38 x 4
   species   height  mass birth_year
   <chr>      <dbl> <dbl>      <dbl>
 1 Aleena       79     15         NA
 2 Besalisk    198    102         NA
 3 Cerean      198     82         92
 4 Chagrian    196     NA         NA
 5 Clawdite    168     55         NA
 6 Droid        NA     NA         NA
 7 Dug         112     40         NA
 8 Ewok         88     20          8
 9 Geonosian   183     80         NA
10 Gungan      209.    NA         NA
# i 28 more rows
```

The same `across`-based workflow that we saw with `mutate` a few slides back also works with `summarize`. Though to add arguments, we have to use an **anonymous function:**

```r
starwars |>
  group_by(species) |>
  summarize(across(where(is.numeric), ~ mean(.x, na.rm=T)))
```

```
# A tibble: 38 x 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
 6 Droid       131.  69.8         53.3
 7 Dug         112   40          NaN
 8 Ewok         88   20            8
 9 Geonosian   183   80          NaN
10 Gungan      209.  74           52
# i 28 more rows
```

Other dplyr goodies

`ungroup`: For ungrouping after using `group_by`. - Use after doing your grouped `summarize` or `mutate` operation, or everything else you do will be super slow.

`slice`: Subset rows by position rather than filtering by values. - E.g. `starwars |> slice(1:10)`

`pull`: Extract a column from as a data frame as a vector or scalar. - E.g. `starwars |> filter(sex=="female") |> pull(height)`

`distinct` and `count`: List unique values, with or without their number of appearances. - E.g. `starwars |> distinct(species)`, or `starwars |> count(species)` - `count` is equivalent to `group_by` and `summarize` with `n()`:

```r
starwars |> group_by(species) |> summarize(n = n())
```

```
# A tibble: 38 x 2
   species       n
   <chr>     <int>
 1 Aleena        1
 2 Besalisk      1
 3 Cerean        1
 4 Chagrian      1
 5 Clawdite      1
 6 Droid         6
 7 Dug           1
 8 Ewok          1
 9 Geonosian     1
10 Gungan        3
# i 28 more rows
```

Challenge 1

List the most common eye colors among female Star Wars characters in descending order of frequency.

As usual, there are multiple solutions.

```r
starwars |>
  filter(sex == "female") |>
  count(eye_color) |>
  arrange(desc(n))
```

```
# A tibble: 6 x 2
  eye_color     n
  <chr>     <int>
1 blue          6
2 brown         4
3 black         2
4 hazel         2
5 unknown       1
6 yellow        1
```

```r
starwars |>
  filter(sex == "female") |>
  group_by(eye_color) |>
  summarize(n = n()) |>
  arrange(desc(n))
```

```
# A tibble: 6 x 2
  eye_color     n
  <chr>     <int>
1 blue          6
2 brown         4
3 black         2
4 hazel         2
5 unknown       1
6 yellow        1
```

Explain what each line in the codes do:

Answer: In the first code, line 1 is used to explain that the code should be played or executed as R code. Line 2 starts with starwars which refers to the starwars dataset and is followed by the pipe operator which chains together the multiple functions by feeding an output of the first function into the argument of the left, it passes these results left to right. Line 3 uses the filter() function to subset specific data, and then sex == female to only pick rows whose sex clumns equals female, removing nonfemale characters from the dataset, it is followed by our pipe. Line 4 count(eye_color) counts the number of female characters who have a unique or specific eye color. The pipe brings us down to line 5 which sorts these results by the count n, our number place holder, and orders them in descending order. Doing this orders our rows so that the most common eye color is first.

In the second code, lines 1-3 are the same. Line 4 uses a different function, group_by(eye_color) which groups our data by the eye color column. The pipe brings use to line 5 which is summarize (n = n()) which counts how many characters there are in each of these eye color groups. Then it puts our count into a new column n and is followed by a pipe. Line 6 arrange(desc(n)) is the same and it sorts our data into a descending order based on n which, again, puts the most common eye color first.

Storing results in memory

So far we haven't been saving the dataframes that result from our code in memory. Usually, we will want to use them for the next task. Create a new object each time you write a pipeline.

```r
women = starwars |> filter(sex == "female")
brown_eyed_women = women |> filter(eye_color == "brown")
```

Resist the temptation to use the same object name. This is called **clobbering** since it overwrites the previous version. It ruins your ability to easily go back to previous steps.

```r
# DON'T do this
starwars = starwars |> filter(sex == "female")
```

By keeping multiple copies of very similar dataframes, will you waste your computer's memory? Usually, no – R is smart and stores only the changes between objects.

Key tidyr verbs

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

Which of `pivot_longer` vs `pivot_wider` produces "tidy" data?

pivot_longer() would produce tidy data because it turns wide-format data into a long format, so each variable is in its own column and each observation is in its own row. pivot_wider() is better suited for situations that specifically require or look better with a wide format.

Exercise 6: 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, 10, 1),
  Y = rnorm(2, 10, 2),
  Z = rnorm(2, 10, 5)
  )
stocks
```

```
        time        X         Y        Z
1 2009-01-01 10.23962 12.105597 15.21728
2 2009-01-02 10.23920  8.389373 12.49788
```

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

```
# A tibble: 6 x 3
  time       stock price
  <date>     <chr> <dbl>
1 2009-01-01 X     10.2
2 2009-01-01 Y     12.1
3 2009-01-01 Z     15.2
4 2009-01-02 X     10.2
5 2009-01-02 Y      8.39
6 2009-01-02 Z     12.5
```

Exercise 7: tidyr::pivot_wider

Now we can use pivot_wider to go back to the original dataframe:

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

```
# A tibble: 2 x 4
  time           X     Y     Z
  <date>     <dbl> <dbl> <dbl>
1 2009-01-01  10.2 12.1   15.2
2 2009-01-02  10.2  8.39  12.5
```

Or, we can put it into a new (“transposed”) format, in which the observations are stocks and the columns are dates:

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

```
# A tibble: 3 x 3
  stock `2009-01-01` `2009-01-02`
  <chr>        <dbl>        <dbl>
1 X             10.2        10.2 
2 Y             12.1         8.39
3 Z             15.2        12.5 
```

Exercise 8: tidyr::separate

`separate` helps when you have more than one value in a single column:

```
economists = data.frame(name = c("Adam_Smith", "Paul_Samuelson", "Milton_Friedman"))
economists
```

```
             name
1      Adam_Smith
2  Paul_Samuelson
3 Milton_Friedman
```

```
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 the `sep` argument:

```
economists |> separate(name, c("first_name", "last_name"), sep = "_")
```

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

Exercise 9: tidyr::separate

Related is `separate_rows`, for splitting cells with multiple values into multiple rows:

```r
jobs = data.frame(
  name = c("Joe", "Jill"),
  occupation = c("President", "First Lady, Professor, Grandmother")
  )
jobs
```

```
  name                           occupation
1  Joe                            President
2 Jill First Lady, Professor, Grandmother
```

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

```
# A tibble: 5 x 2
  name  occupation
  <chr> <chr>
1 Joe   President
2 Jill  First
3 Jill  Lady
4 Jill  Professor
5 Jill  Grandmother
```

Related is `separate_rows`, for splitting cells with multiple values into multiple rows:

```r
jobs = data.frame(
  name = c("Joe", "Jill"),
  occupation = c("President", "First Lady, Professor, Grandmother")
  )
jobs
```

```
  name                           occupation
1  Joe                            President
2 Jill First Lady, Professor, Grandmother
```

```r
# Now split out Jill's various occupations into different rows
jobs |> separate_rows(occupation, sep = ", ")
```

```
# A tibble: 4 x 2
  name  occupation
  <chr> <chr>
1 Joe   President
2 Jill  First Lady
3 Jill  Professor
4 Jill  Grandmother
```

Exercise 10: 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  1 101.14254
2 2016    1  2  94.71021
3 2016    1  3  97.46583
4 2016    1  4 102.15085
```

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

```
      date       gdp
1 2016-1-1 101.14254
2 2016-1-2  94.71021
3 2016-1-3  97.46583
4 2016-1-4 102.15085
```

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

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

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

```
library(lubridate)
gdp_u |> mutate(date = ymd(date))
```

```
        date       gdp
1 2016-01-01 101.14254
2 2016-01-02  94.71021
3 2016-01-03  97.46583
4 2016-01-04 102.15085
```

Challenge 2

Using `nycflights13`, create a table of average arrival delay (in minutes) by day (in rows) and carrier (in columns).

Hint: Recall that you can tabulate summary statistics using `group_by` and `summarize`:

```
flights |>
  group_by(carrier) |>
  summarize(avg_late = mean(arr_delay, na.rm=T)) |>
  pivot_wider(names_from = carrier, values_from = avg_late)
```

```
# A tibble: 1 x 16
   `9E`    AA    AS    B6    DL    EV    F9    FL    HA    MQ    OO    UA    US
  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1  7.38 0.364 -9.93  9.46  1.64  15.8  21.9  20.1 -6.92  10.8  11.9  3.56  2.13
# i 3 more variables: VX <dbl>, WN <dbl>, YV <dbl>
```

Solution:

```
delay_long = flights |>
  group_by(carrier, day) |>
  summarize(avg_late = mean(arr_delay, na.rm=T))
delay_wide = delay_long |>
  pivot_wider(names_from=carrier, values_from=avg_late)
head(delay_wide, 4)
```

```
# A tibble: 4 x 17
    day  `9E`     AA     AS      B6     DL    EV    F9    FL    HA    MQ    OO
  <int> <dbl>  <dbl>  <dbl>   <dbl>  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1     1  7.21 -1.23   -5.96 11.9     0.866 21.3  21.7  22.7  -15.4 12.9    NA
2     2  7.35 -0.905 -13.7   9.90    3.05  18.0   7.71 20.9  -16.1  9.04 NaN
3     3  5.80 -3.09  -20.8   5.26   -0.204 15.3  18.0  19.6  -16.8 13.7    0.5
4     4 -2.11 -5.80  -22.3  -0.0939 -6.24   3.87 14.5   4.38 -15.2  3.82 -12
# i 5 more variables: UA <dbl>, US <dbl>, VX <dbl>, WN <dbl>, YV <dbl>
```

Explain what each line in the codes do:

Answer: For code 1, line 1 with {r} identifies us being in r code. Line 2, flights |> refers to the flights dataset and passes the operation along with the pipe operator. Line 3, group_by(carrier) |> groups the flights dataset by the carrier column, meaning following code will be separate for each specific or individual carrier. Line 4, summarize(avg_late = mean(arr_delay, na.rm=T)) |:> means that we calculate the average delays for each carrier using the arr_delay column. na.rm = T means that NA missing values are ignored durinng this, and the new calculated average is put into the new column avg_late. Our pipe operator carriers us to line 5 pivot_wider(names_from = carrier, values_from = avg_late) moves the data to wide format from the long format, so each carrier becomes its own column and in the columns is the average delay for each carrier.

For code 2, we know the {r} refers to r code. Line 2 means we are assigning the flights dataset to the new variable delay_long, with the following operations from the code. The pipe takes us to line 3 which groups the flights datset by the 2 variables carrier and day so following operations will happen in both of those categories separately. Line 4 calculates the average arrival delay (avg_late) for each group by the carrier and day. na.rm = T means we ginore missing NA values when computing the mean and putting it into our new avg_late column. Line 5 takes our calculated delay_long dataset and stores it and calculatiosn that happen to it going forward in delay_wide. Line 6 then has the data be reshaped from long to wide format. name_from = carrier means the specific values in the carrier column will become the new column names in the wide format. values_from = avg_late means that the values in the new columns will come from the avg_late column which has the average arrival delays. Finally, in lien 7 the head() function gives back the first few rows from a dataset, so head(delay_wide, 4) will give us back the first 4 rows of the delay_wide dataset.

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Grading

Component	Points
Replicating Ex 1-10	85
Challenge	5
Creating Github Account	5
Workflow & formatting	5

The "Workflow & formatting" grade is to assess the reproducible workflow and document format.