Applications

Of Data Science

Tidy Data Wrangling - Part B

Applications of Data Science - Class 3

Giora Simchoni

`gsimchoni@gmail.com and add #dsapps in subject`

Stat. and OR Department, TAU

2021-03-14

Applications

Of Data Science

Joining Tables

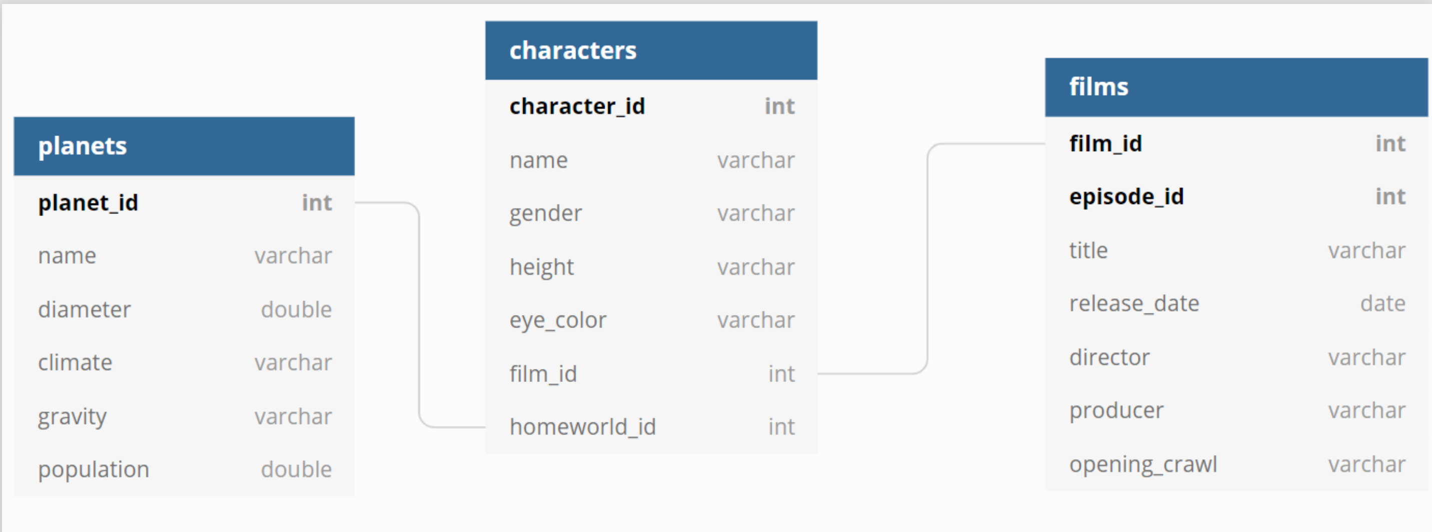
Applications of Data Science

Detour: The Starwars Dataset(s)

Applications

Of Data Science

The Starwars Dataset(s)




```r
sw_tables <- read_rds("../data/sw_tables.rds")
characters <- sw_tables$characters
planets <- sw_tables$planets
films <- sw_tables$films
```

> 💡 What are the advantages/disadvantages of storing data in such a way?

```
glimpse(characters)
```

```
## Rows: 173
## Columns: 14
## $ character_id <int> 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3,
## $ name         <chr> "Luke Skywalker", "Luke Skywalker", "Luke Skywalker
## $ gender       <chr> "male", "male", "male", "male", "male", NA, NA, NA,
## $ homeworld_id <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 8, 8, 8, 8, 8, 8,
## $ height       <dbl> 172, 172, 172, 172, 172, 167, 167, 167, 167, 167, 1
## $ mass         <dbl> 77, 77, 77, 77, 77, 75, 75, 75, 75, 75, 75, 32, 32,
## $ hair_color   <chr> "blond", "blond", "blond", "blond", "blond", NA, NA
## $ skin_color   <chr> "fair", "fair", "fair", "fair", "fair", "gold", "go
## $ eye_color    <chr> "blue", "blue", "blue", "blue", "blue", "yellow", "
## $ birth_year   <dbl> 19.0, 19.0, 19.0, 19.0, 19.0, 112.0, 112.0, 112.0,
## $ film_id      <dbl> 1, 2, 3, 6, 7, 1, 2, 3, 4, 5, 6, 1, 2, 3, 4, 5, 6,
## $ species      <list> ["http://swapi.co/api/species/1/", "http://swapi.c
## $ vehicles     <list> [<"http://swapi.co/api/vehicles/14/", "http://swap
## $ starships    <list> [<"http://swapi.co/api/starships/12/", "http://swa
```

```r
glimpse(planets)
```

```
## Rows: 61
## Columns: 10
## $ planet_id       <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 1
## $ name            <chr> "Tatooine", "Alderaan", "Yavin IV", "Hoth", "Dag
## $ rotation_period <dbl> 23, 24, 24, 23, 23, 12, 18, 26, 24, 27, 30, 27,
## $ orbital_period  <dbl> 304, 364, 4818, 549, 341, 5110, 402, 312, 368, 4
## $ diameter        <dbl> 10465, 12500, 10200, 7200, 8900, 118000, 4900, 1
## $ climate         <chr> "arid", "temperate", "temperate, tropical", "fro
## $ gravity         <chr> "1 standard", "1 standard", "1 standard", "1.1 s
## $ terrain         <chr> "desert", "grasslands, mountains", "jungle, rain
## $ surface_water   <dbl> 1.0, 40.0, 8.0, 100.0, 8.0, 0.0, 8.0, 12.0, NA,
## $ population      <dbl> 2.0e+05, 2.0e+09, 1.0e+03, NA, NA, 6.0e+06, 3.0e
```

```r
glimpse(films)
```

```
## Rows: 7
## Columns: 7
## $ film_id       <dbl> 1, 2, 3, 4, 5, 6, 7
## $ title         <chr> "A New Hope", "The Empire Strikes Back", "Return o
## $ episode_id    <int> 4, 5, 6, 1, 2, 3, 7
## $ opening_crawl <chr> "It is a period of civil war.\r\nRebel spaceships,
## $ director      <chr> "George Lucas", "Irvin Kershner", "Richard Marquan
## $ producer      <chr> "Gary Kurtz, Rick McCallum", "Gary Kutz, Rick McCa
## $ release_date  <chr> "1977-05-25", "1980-05-17", "1983-05-25", "1999-05
```

End of Detour

Q: Which characters appear in SW films directed by George Lucas?

```
unique(
  characters$name[
    characters$film_id %in%
      films$film_id[films$director == "George Lucas"]
    ]
  )

# or dplyr approach:
characters %>%
    filter(film_id %in% (films %>%
                             filter(director=="George Lucas") %>%
                             pull(film_id))) %>%
    pull(name) %>%
    unique()
```

First problem with this approach: code gets messier and messier, prone to bugs and hard to debug.

Q: Which characters, whose homeworld is Alderaan, appear in SW films directed by George Lucas?

```
unique(
  characters$name[
    characters$film_id %in%
      films$film_id[films$director == "George Lucas"] &
    characters$homeworld_id ==
      planets$planet_id[planets$name == "Alderaan"]
  ]
)

# or dplyr approach:
characters %>%
    filter(film_id %in% (films %>%
                           filter(director=="George Lucas") %>%
                           pull(film_id)),
           homeworld_id == (planets %>%
                              filter(name == "Alderaan") %>%
                              pull(planet_id))) %>%
    pull(name) %>%
    unique()

# [1] "Leia Organa"         "Bail Prestor Organa" "Raymus Antilles
```

Now imagine these two tables

`lines`: each film, each scene, each minute, each character, the line

```
lines <- tibble::tribble(
  ~film_id, ~scene_id, ~minute_id, ~character_id,
         1,         1,          1,            23,            "
         1,         1,          2,            15,          "somet
         1,         1,          2,            23, "something somet
         1,         1,          3,            15,
         1,         1,          3,            23,
         1,         1,          4,             8,            "wha
  )
```

`locations`: for each film, each scene, each minute, its location

```
locations <- tibble::tribble(
  ~film_id, ~scene_id, ~minute_id,             ~location,
         1,         1,          1,           "spaceship",
         1,         1,          2, "Alderaan, outdoors",
         1,         1,          3,           "spaceship",
         1,         1,          4,                 "bar"
  )
```

Q: Which characters say "something" in a bar?

- filter only `lines` which contain "something"
- filter only "bar" `locations` and then...
- if the two filtered tables match on film, scene and minute...
- we take the unique characters
- but how do we match? `for` loop*?

→ Clearly, second problem with this approach: it doesn't generalize well to more complex scenarios, where we need to match on multiple criteria

And third problem: speed (but only in a complex scenario!)

* There *is* a way without using a for loop, without joining, still not recommended.

inner_join()

(Inner) Joining two tables:

```
characters %>%
  inner_join(films) %>%
  select(character_id, name, film_id, title, director) %>%
  head(7)
```

```
## Joining, by = "film_id"

## # A tibble: 7 x 5
##   character_id name               film_id title                   director
##          <int> <chr>                <dbl> <chr>                   <chr>
## 1            1 Luke Skywalker           1 A New Hope              George Luc
## 2            1 Luke Skywalker           2 The Empire Strikes Back Irvin Kers
## 3            1 Luke Skywalker           3 Return of the Jedi      Richard Ma
## 4            1 Luke Skywalker           6 Revenge of the Sith     George Luc
## 5            1 Luke Skywalker           7 The Force Awakens       J. J. Abra
## 6            2 C-3PO                    1 A New Hope              George Luc
## 7            2 C-3PO                    2 The Empire Strikes Back Irvin Kers
```

(Inner) Joining multiple tables:

```
characters %>%
  inner_join(films) %>%
  inner_join(planets, by = c("homeworld_id" = "planet_id")) %>%
  select(character_id, name.x, film_id, title, director, name.y, c
```

```
## Joining, by = "film_id"
```

```
## # A tibble: 7 x 7
##   character_id name.x      film_id title              director     name.y
##          <int> <chr>         <dbl> <chr>              <chr>        <chr>
## 1            1 Luke Skywa~       1 A New Hope         George Lucas Tatooi~
## 2            1 Luke Skywa~       2 The Empire Stri~   Irvin Kersh~ Tatooi~
## 3            1 Luke Skywa~       3 Return of the J~   Richard Mar~ Tatooi~
## 4            1 Luke Skywa~       6 Revenge of the ~   George Lucas Tatooi~
## 5            1 Luke Skywa~       7 The Force Awake~   J. J. Abrams Tatooi~
## 6            2 C-3PO             1 A New Hope         George Lucas Tatooi~
## 7            2 C-3PO             2 The Empire Stri~   Irvin Kersh~ Tatooi~
```

(Inner) Joining on multiple keys:

```
lines %>%
  inner_join(locations, by = c("film_id", "scene_id", "minute_id")
```

```
## # A tibble: 6 x 6
##   film_id scene_id minute_id character_id line                  locatio
##     <dbl>    <dbl>     <dbl>        <dbl> <chr>                 <chr>
## 1       1        1         1           23 blah blah blah        spacesh
## 2       1        1         2           15 something something   Alderaa
## 3       1        1         2           23 something something t~ Alderaa
## 4       1        1         3           15 <NA>                  spacesh
## 5       1        1         3           23 <NA>                  spacesh
## 6       1        1         4            8 whatever whatever     bar
```

💡 The base R function for joining is `merge()` which tends to be slower.

What would `inner_join()` do?

Q: Which characters appear in SW films directed by George Lucas?

```
# naive
characters %>%
  inner_join(films, by = "film_id") %>%
  filter(director == "George Lucas") %>%
  pull(name) %>%
  unique()

# smarter
characters %>%
  inner_join(films %>% filter(director == "George Lucas"),
             by = "film_id") %>%
  pull(name) %>%
  unique()
```

> 💡 What else could you do to make `inner_join`'s life easier?

What would `inner_join()` do?

Q: Which characters, whose homeworld is Alderaan, appear in SW films directed by George Lucas?

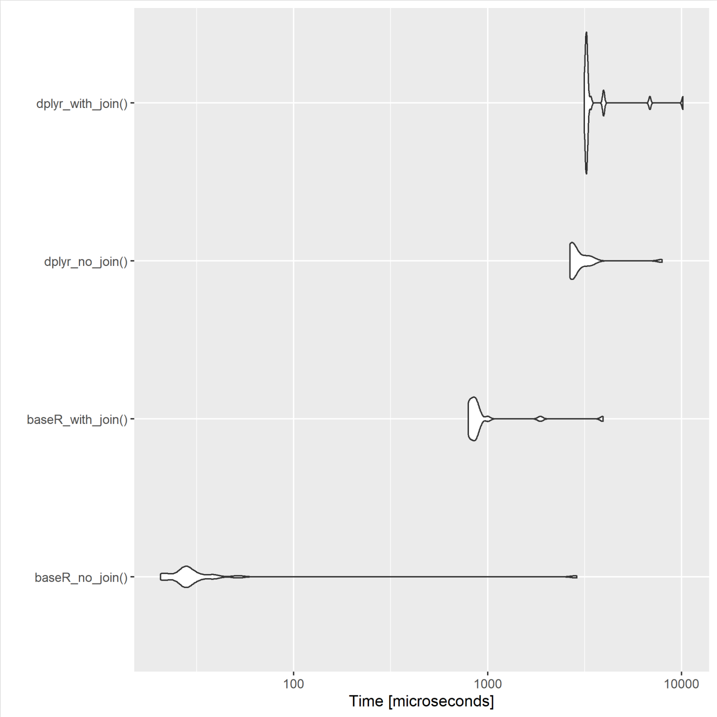
```
characters %>%
  inner_join(films %>% filter(director == "George Lucas"),
             by = "film_id") %>%
  inner_join(planets %>% filter(name == "Alderaan"),
             by = c("homeworld_id" = "planet_id"),
                    suffix = c("_char", "_planet")) %>%
  pull(name_char) %>%
  unique()
```

```
## [1] "Leia Organa"         "Bail Prestor Organa" "Raymus Antilles"
```

Note of caution: Join is not always faster!

```
baseR_no_join <- function() {
  unique(characters$name[characters$film_id %in% films$film_id[fil
}

baseR_with_join <- function() {
  unique(merge(characters, films[films$director == "George Lucas",
}

dplyr_no_join <- function() {
  characters %>%
    filter(film_id %in% (films %>%
                           filter(director=="George Lucas") %>%
                           pull(film_id))) %>%
    pull(name) %>%
    unique()
}

dplyr_with_join <- function() {
  characters %>%
    inner_join(films %>% filter(director=="George Lucas"), by = "f
    pull(name) %>%
    unique()
}
```

```r
library(microbenchmark)
res <- microbenchmark(baseR_no_join(), baseR_with_join(),
                      dplyr_no_join(), dplyr_with_join(), times =
autoplot(res)
```



So when does it shine?

- See this StackOverflow question and answer for a good example*
- But in general: when data gets bigger, when multiple keys are involved

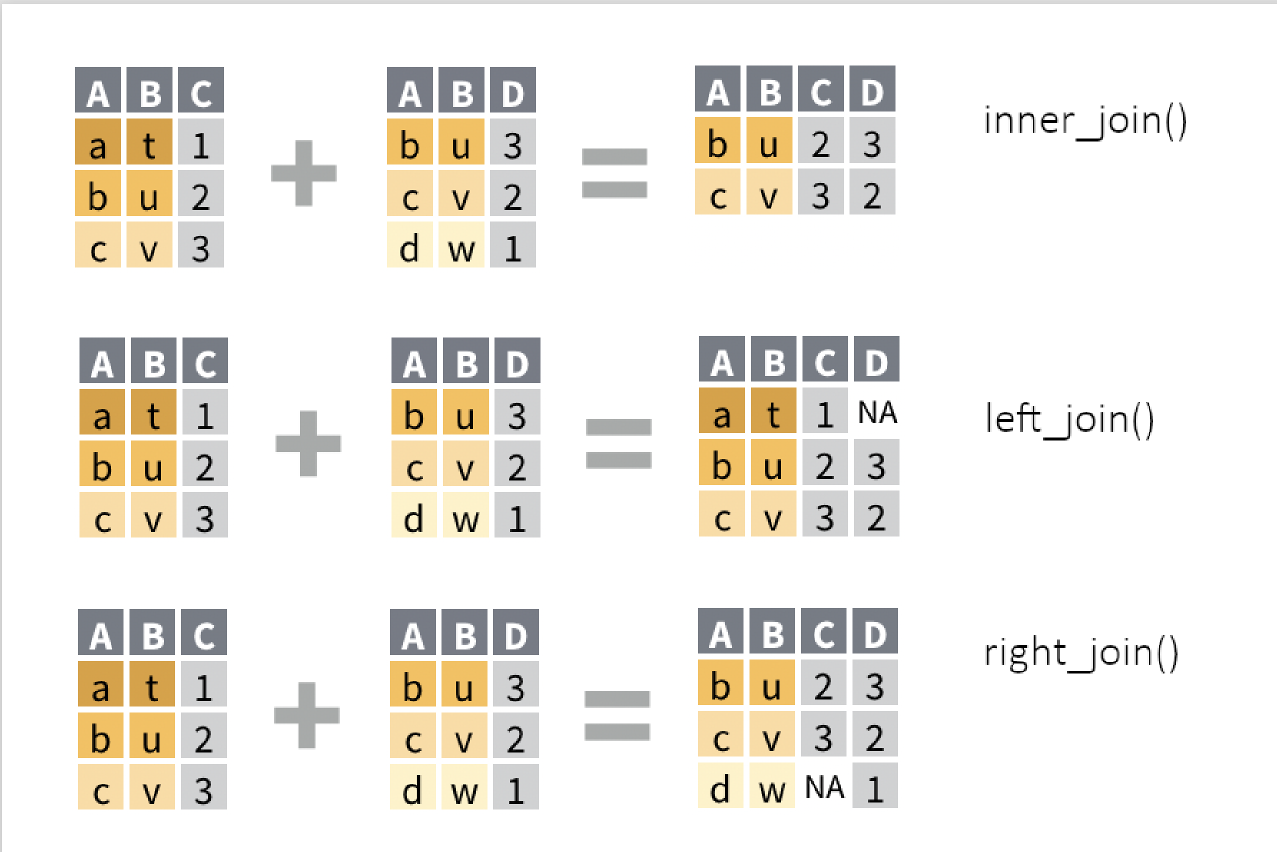
* Yes, I know, I answered my own question, 🤦‍♀️

Other types of Joins?

Definitely, read here, here and here about:

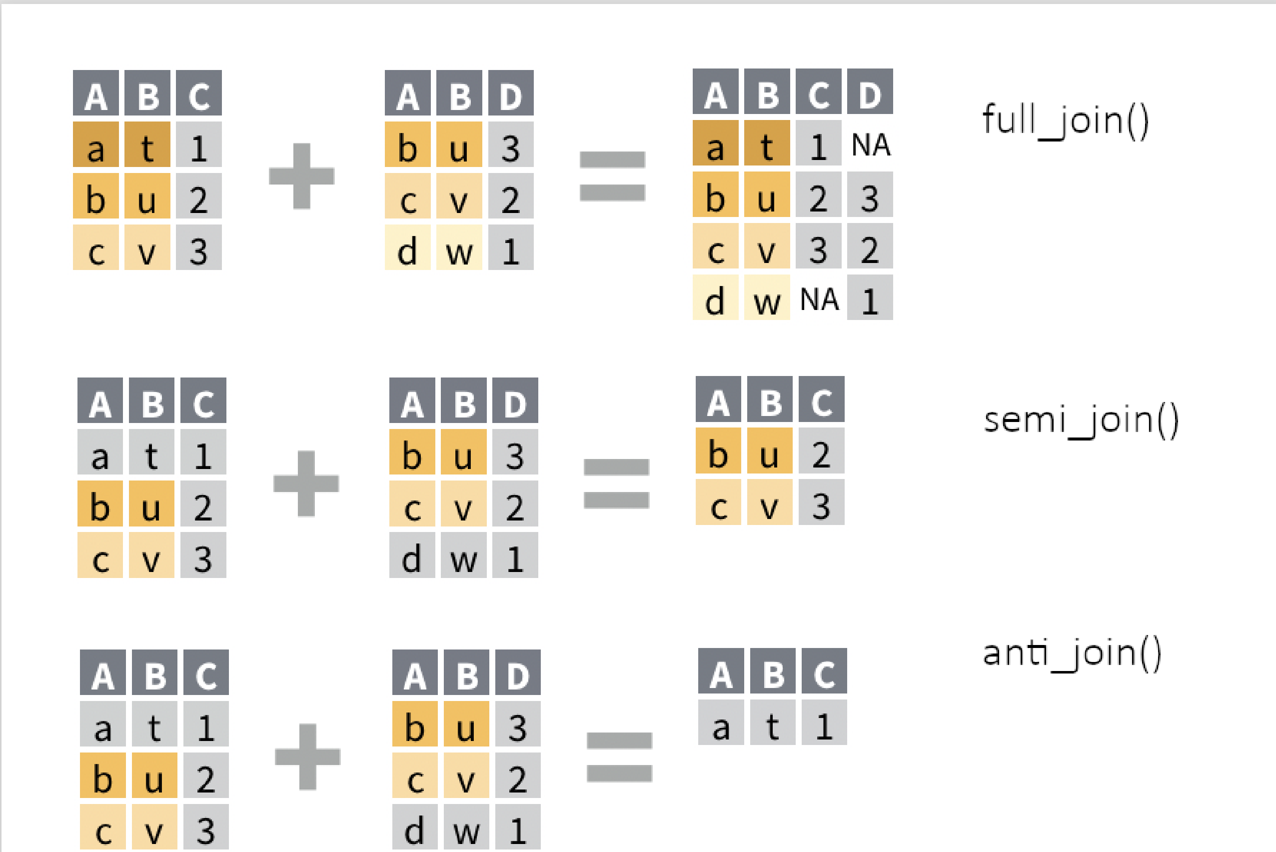
- `left_join()`
- `right_join()`
- `full_join()`
- `anti_join()`
- `semi_join()`

All Joins



Source: [The Tidyverse Cookbook]

All Joins



Source: [The Tidyverse Cookbook]

Tidying Tables

Applications

Of Data Science

Detour: The Migration Dataset

Applications of Data Science

The Migration Dataset

- Straight from the UN, Dept. of Economic and Social Affairs, Population Division
- "Monitoring global population trends"
- For each country, how many (men, women and total) migrated to each country
- In 1990, 1995, 2000, 2005, 2010, 2015, 2019
- How would *you* give access to these data?

You want dirty data? Well dirty data costs!

United Nations
Population Division
Department of Economic and Social Affairs

Workbook: UN_MigrantStockByOriginAndDestination_2019.xlsx
Table 1. Total migrant stock at mid-year by origin and by major area, region, country or area of destination, 1990-2019

Suggested citation: United Nations, Department of Economic and Social Affairs. Population Division (2019). International Migrant Stock 2019 (United Nations database, POP/DB/MIG/Stock/Rev.2019).

Year	Sort order	Major area, region, country or area of destination	Notes	Code	Type of data (a)	Country or area of origin							
						Total	Other South	Other North	Afghanistan	Albania	Algeria	American Samoa	Andorra
1990	1990001	**WORLD**		900		153,011,473	6,548,526	2,366,800	6,823,350	180,284	921,727	2,041	3,792
1990	1990002	**UN development groups**				..	..	..	..	..	..	..	..
1990	1990003	More developed regions	b	901		82,767,216	3,385,103	1,077,179	119,386	177,986	867,015	1,027	3,737
1990	1990004	Less developed regions	c	902		70,244,257	3,163,423	1,289,621	6,703,964	2,298	54,712	1,014	55
1990	1990005	Least developed countries	d	941		11,060,221	482,753	239,756	0	0	5,622	0	1
1990	1990006	Less developed regions, excluding least developed countries		934		59,184,036	2,680,670	1,049,865	6,703,964	2,298	49,090	1,014	55
1990	1990007	**World Bank income groups**				..	..	..	..	..	..	..	..
1990	1990008	High-income countries	e	1503		77,802,868	3,803,597	1,223,239	269,933	131,448	886,589	68	3,748
1990	1990009	Middle-income countries	e	1517		65,124,366	1,877,678	987,475	6,544,932	48,836	30,513	1,973	44
1990	1990010	Upper-middle-income countries	e	1502		33,285,549	957,059	376,006	3,152,957	48,298	4,719	1,954	42
1990	1990011	Lower-middle-income countries	e	1501		31,838,817	920,619	611,469	3,391,975	538	25,794	19	2
1990	1990012	Low-income countries	e	1500		9,790,238	850,549	145,493	8,485	0	4,370	0	0
1990	1990013	No income group available	e			294,001	16,702	10,593	0	0	255	0	0
1990	1990014	**Geographic regions**				..	..	..	..	..	..	..	..
1990	1990015	Africa		903		15,689,666	807,899	258,638	1,037	504	31,807	0	0
1990	1990016	Asia		935		48,209,949	2,005,398	961,154	6,702,728	1,291	20,924	0	0
1990	1990017	Europe		908		49,608,231	432,964	871,477	82,736	170,977	857,978	963	3,404
1990	1990018	Latin America and the Caribbean		904		7,161,371	344,362	64,989	199	503	863	0	55
1990	1990019	Northern America		905		27,610,408	2,923,653	198,963	33,765	6,025	8,372	0	0
1990	1990020	Oceania		909		4,731,848	34,250	11,579	2,885	984	1,783	1,078	333
1990	1990021	**Sustainable Development Goal (SDG) regions**	f										

CONTENTS | Table 1 | Table 2 | Table 3 | ANNEX | NOTES

What's untidy about the migration Excel file?

- It's an Excel file 😠
- Multiple sheets
- Color coded, font coded (bold), space coded!
- Logo, free text in header lines
- Merged cells
- French letters (anything but [A-Za-z] can break code)
- Spaces, parentheses in column names
- Different `NA` values: "..", "-"
- Variable "country_dest" contains sub-total and totals for categories, continents...
- Variable "country_orig" violates Tidy rule no. 1: not in its own column

"Today Only, The Landlord Went Nuts!"

- ~~It's an Excel file 😠~~
- ~~Multiple sheets~~
- ~~Color coded, font coded (bold), space coded!~~
- ~~Logo, free text in header lines~~
- ~~Merged cells~~
- ~~French letters (anything but [A-Za-z] can break code)~~
- ~~Spaces, parentheses in column names~~
- ~~Different `NA` values: "..", "-"~~
- ~~Variable "country_dest" contains sub-total and totals for categories, continents...~~
- Variable "country_orig" violates Tidy rule no. 1: not in its own column

The much nicer `migration` table

```r
migration <- read_rds("../data/migration.rds")

migration
```

```
## # A tibble: 3,248 x 236
##    gender  year  code country_dest afghanistan albania algeria american_
##    <chr>  <dbl> <dbl> <chr>              <dbl>   <dbl>   <dbl>         
##  1 men     1990   108 burundi                0       0       0
##  2 men     1990   174 comoros                0       0       0
##  3 men     1990   262 djibouti               0       0       0
##  4 men     1990   232 eritrea                0       0       0
##  5 men     1990   231 ethiopia               0       0       0
##  6 men     1990   404 kenya                  0       0       0
##  7 men     1990   450 madagascar             0       0       0
##  8 men     1990   454 malawi                 0       0       0
##  9 men     1990   480 mauritius              0       0       0
## 10 men     1990   175 mayotte                0       0       0
## # ... with 3,238 more rows, and 228 more variables: andorra <dbl>,
## #   angola <dbl>, anguilla <dbl>, antigua_and_barbuda <dbl>, argentina <
## #   armenia <dbl>, aruba <dbl>, australia <dbl>, austria <dbl>,
## #   azerbaijan <dbl>, bahamas <dbl>, bahrain <dbl>, bangladesh <dbl>,
## #   barbados <dbl>, belarus <dbl>, belgium <dbl>, belize <dbl>, benin <d
## #   bermuda <dbl>, bhutan <dbl>, bolivia_plurinational_state_of <dbl>,
## #   bonaire_sint_eustatius_and_saba <dbl>, bosnia_and_herzegovina <dbl>,
```

It's not right, but it's Ok:

- How many men immigrated from Russia to Israel in 1990?

```
migration %>%
  filter(country_dest == "israel", year == 1990, gender == "men")
  pull(russian_federation)
```

```
## [1] 80450
```

- How many men immigrated from Israel to Russia in 1990?

```
migration %>%
  filter(country_dest == "russian_federation", year == 1990, gende
  pull(israel)
```

```
## [1] 1395
```

It would have been much nicer to have:

```
migration %>%
  filter(country_orig == "israel", country_dest == "russian_fedrat
         year == 1990, gender == "men") %>%
  pull(n_migrants)
```

Then we could put in a (simpler) function and call the opposite:

```
get_1way_migration <- function(orig, dest, gen, .year) {
  migration %>%
  filter(country_orig == orig, country_dest == dest,
         year == .year, gender == gen) %>%
  pull(n_migrants)
}

get_1way_migration("russian_federation", "israel")
```

End of Detour

Applications

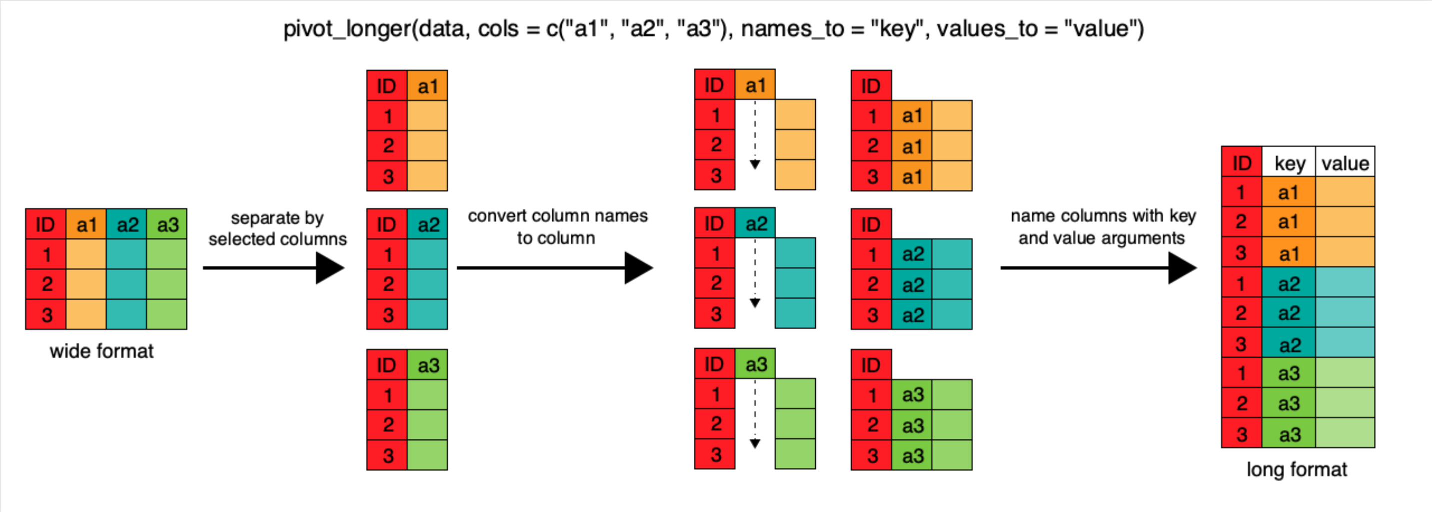
Of Data Science

pivot_longer()

```
migration_long <- migration %>%
  pivot_longer(cols = -c(1:4),
               names_to = "country_orig",
               values_to = "n_migrants")

migration_long
```

```
## # A tibble: 753,536 x 6
##    gender  year  code country_dest country_orig        n_migrants
##    <chr>  <dbl> <dbl> <chr>        <chr>                    <dbl>
##  1 men     1990   108 burundi      afghanistan                  0
##  2 men     1990   108 burundi      albania                      0
##  3 men     1990   108 burundi      algeria                      0
##  4 men     1990   108 burundi      american_samoa               0
##  5 men     1990   108 burundi      andorra                      0
##  6 men     1990   108 burundi      angola                       0
##  7 men     1990   108 burundi      anguilla                     0
##  8 men     1990   108 burundi      antigua_and_barbuda          0
##  9 men     1990   108 burundi      argentina                    0
## 10 men     1990   108 burundi      armenia                      0
## # ... with 753,526 more rows
```

What sorcery is this?



Source: [The Carpentries]()

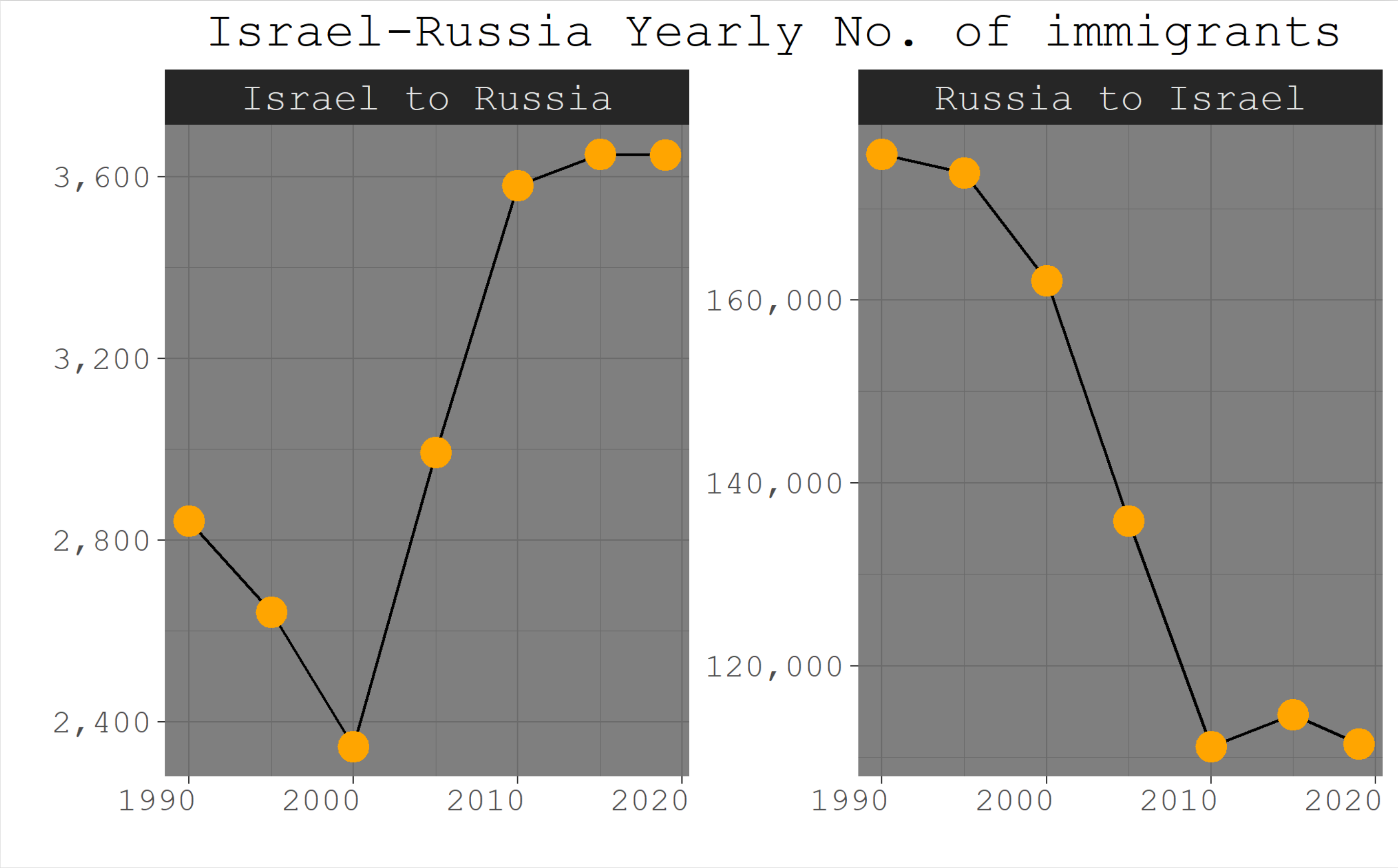
`pivot_wider()`

```r
migration_wide <- migration_long %>%
  pivot_wider(id_cols = 1:4,
              names_from = country_orig,
              values_from = n_migrants)

migration_wide
```

```
## # A tibble: 3,248 x 236
##    gender  year  code country_dest afghanistan albania algeria american_
##    <chr>  <dbl> <dbl> <chr>              <dbl>   <dbl>   <dbl>
##  1 men     1990   108 burundi                0       0       0
##  2 men     1990   174 comoros                0       0       0
##  3 men     1990   262 djibouti               0       0       0
##  4 men     1990   232 eritrea                0       0       0
##  5 men     1990   231 ethiopia               0       0       0
##  6 men     1990   404 kenya                  0       0       0
##  7 men     1990   450 madagascar             0       0       0
##  8 men     1990   454 malawi                 0       0       0
##  9 men     1990   480 mauritius              0       0       0
## 10 men     1990   175 mayotte                0       0       0
## # ... with 3,238 more rows, and 228 more variables: andorra <dbl>,
## #   angola <dbl>, anguilla <dbl>, antigua_and_barbuda <dbl>, argentina <
## #   armenia <dbl>, aruba <dbl>, australia <dbl>, austria <dbl>,
## #   azerbaijan <dbl>, bahamas <dbl>, bahrain <dbl>, bangladesh <dbl>,
```

Where is this going to?

```
get_1way_migration <- function(.country_dest, .country_orig) {
  migration_long %>%
    filter(country_dest == .country_dest, country_orig == .country
    group_by(year) %>%
    tally(n_migrants) %>%
    mutate(direction = str_c(.country_orig, " to ", .country_dest)
}
get_2way_migration <- function(country_a, country_b) {
  a2b <- get_1way_migration(country_b, country_a)
  b2a <- get_1way_migration(country_a, country_b)
  bind_rows(a2b, b2a)
}

get_2way_migration("israel", "russian_federation") %>%
  ggplot(aes(year, n)) + geom_line() +
  geom_point(color = "orange", size = 5) +
  labs(x = "", y = "", title = "Israel-Russia Yearly No. of immigr
  theme_dark() +
  facet_wrap(~direction, scales = "free", labeller = labeller(dire
  scale_y_continuous(labels = scales::comma_format()) +
  theme(axis.text = element_text(size = 12, hjust=0.9, family = "r
        strip.text.x = element_text(size = 14, family = "mono"),
        plot.title = element_text(hjust = 0.5, size = 18, family =
```



Israel-Russia Yearly No. of immigrants
Israel to Russia
Russia to Israel
3,600
3,200
2,800
2,400
160,000
140,000
120,000
1990
2000
2010
2020

Some more useful Tidying up verbs

Remember?

```r
table3 <- read_rds("../data/tidy_tables.rds")$table3

table3
```

```
## # A tibble: 315 x 3
##    religion      yob pct_straight
##    <chr>       <dbl> <chr>
##  1 atheist      1950 26/29
##  2 buddhist     1950 6/6
##  3 christian    1950 28/32
##  4 hindu        1950 0/0
##  5 jewish       1950 21/24
##  6 muslim       1950 0/0
##  7 unspecified  1950 71/76
##  8 atheist      1951 31/33
##  9 buddhist     1951 11/11
## 10 christian    1951 23/24
## # ... with 305 more rows
```

separate()

```
table3_tidy <- table3 %>%
  separate(pct_straight, into = c("straight", "total"), sep = "/")

table3_tidy
```

```
## # A tibble: 315 x 4
##    religion      yob straight total
##    <chr>       <dbl> <chr>    <chr>
##  1 atheist      1950 26       29
##  2 buddhist     1950 6        6
##  3 christian    1950 28       32
##  4 hindu        1950 0        0
##  5 jewish       1950 21       24
##  6 muslim       1950 0        0
##  7 unspecified  1950 71       76
##  8 atheist      1951 31       33
##  9 buddhist     1951 11       11
## 10 christian    1951 23       24
## # ... with 305 more rows
```

unite()

(Though see a much more generalizable approach with `purrr`)

```
table3_tidy %>%
  unite(col = "pct_straight", straight, total, sep = "/")
```

```
## # A tibble: 315 x 3
##    religion      yob pct_straight
##    <chr>       <dbl> <chr>
##  1 atheist      1950 26/29
##  2 buddhist     1950 6/6
##  3 christian    1950 28/32
##  4 hindu        1950 0/0
##  5 jewish       1950 21/24
##  6 muslim       1950 0/0
##  7 unspecified  1950 71/76
##  8 atheist      1951 31/33
##  9 buddhist     1951 11/11
## 10 christian    1951 23/24
## # ... with 305 more rows
```

Iteration without looping

Fun fact: you're already not-looping!

- Say you want the lengths of all of these strings:

```
strings_vec <- c("I'm feeling fine", "I'm perfectly OK",
                 "Nothing is wrong!")
```

- Do you `for` loop?

```
strings_len <- numeric(length(strings_vec))
for (i in seq_along(strings_vec)) {
  strings_len[i] <- nchar(strings_vec[i])
}
strings_len
```

```
## [1] 16 16 17
```

- No, you use R's vectorized functions nature:

```
nchar(strings_vec)
```

```
## [1] 16 16 17
```

- In case you were wondering:

```
microbenchmark(nchar_loop(), nchar_vectorized())
```

```
## Unit: nanoseconds
##                expr  min   lq  mean median   uq     max neval
##        nchar_loop() 3100 3200 50770   3300 3400 4745200   100
##  nchar_vectorized()  900 1000 14494   1100 1100 1338700   100
```

- So why should iterating through a `data.frame` columns or rows be any different?

The problem:

```
okcupid <- read_csv("~/okcupid.csv.zip", col_types = cols())
okcupid %>% select(essay0:essay2) %>% head(3)
```

```
## # A tibble: 3 x 3
##   essay0                           essay1                          essay2
##   <chr>                            <chr>                           <chr>
## 1 "about me:<br />\n<br />\~ "currently working as an~ "making people la
## 2 "i am a chef: this is wha~ "dedicating everyday to ~ "being silly. hav
## 3 "i'm not ashamed of much,~ "i make nerdy software f~ "improvising in d
```

- I want to apply some transformation to one or more columns (say the length of each `essay` question for each user)
- I want to apply some transformation to one or more rows (say the average length of all `essay` questions for each user)
- BTW, you can always use a `for` loop, see how it is done here

The `apply` family

- There *is* a solution in base R
  - `apply()`
  - `sapply()`
  - `lapply()`
  - `tapply()`
  - `vapply()`
  - `mapply()`
- What do you think is the issue with these? See this.

I don't `for`, I `purrr`

The `purrr` package provides a set of functions to make iteration easier:

- No boilerplate code for looping --> less looping bugs
- Focus on the function, the action, not the plumbing
- Generally faster (implemented in C)
- Definitely more clear, concise and elegant code

TBH, I'm addicted 😢

You get a `map()`, you get a `map()`!

Single	Two	Multiple	Returns	Of
`map()`	`map2()`	`pmap()`	`list`	`?`
`map_lgl()`	`map2_lgl()`	`pmap_lgl()`	`vector`	`logical`
`map_chr()`	`map2_chr()`	`pmap_chr()`	`vector`	`character`
`map_int()`	`map2_int()`	`pmap_int()`	`vector`	`integer`
`map_dbl()`	`map2_dbl()`	`pmap_dbl()`	`vector`	`double`
`map_dfr()`	`map2_dfr()`	`pmap_dfr()`	`tibble`	`?`

Where "Single" means "single vector/column input", "Two" means "two vectors/columns input" etc.

(Tip of the iceberg really, I want you to survive this slide)

Example1: Vectorizing a Function

Take a clearly not-vectorized function:

```
my_func <- function(x) {
  if (x %% 2 == 0) return("even")
  "odd"
}

my_func(10)
```

```
## [1] "even"
```

```
my_func(1:5)
```

```
## Warning in if (x%%2 == 0) return("even"): the condition has length > 1 a
## the first element will be used
```

```
## [1] "odd"
```

> 💡 This is a silly example, do you know how to easily vectorize this function?

`map()` will always return a list:

```r
map(1:3, my_func)
```

```
## [[1]]
## [1] "odd"
##
## [[2]]
## [1] "even"
##
## [[3]]
## [1] "odd"
```

```r
1:3 %>% map(my_func)
```

```
## [[1]]
## [1] "odd"
##
## [[2]]
## [1] "even"
##
## [[3]]
## [1] "odd"
```

`map_chr()` will always return a vector of `character`:

```
map_chr(1:3, my_func)
```

```
## [1] "odd"  "even" "odd"
```

```
1:3 %>% map_chr(my_func)
```

```
## [1] "odd"  "even" "odd"
```

But here is the beautiful thing:

```
my_func_vectorized <- function(vec) map_chr(vec, my_func)

my_func_vectorized(1:3)
```

```
## [1] "odd"  "even" "odd"
```

Look Ma, no loops!

Example2: Complex `mutate()`

Manager: Add me a column, for each OkCupid user, whether he/she's above average height.

```
is_above_average_height <- function(sex, height_cm) {
  if (sex == "m") height_cm > 180 else height_cm > 165
}

okcupid <- okcupid %>%
  mutate(is_tall = map2_lgl(sex, height_cm, is_above_average_heigh

okcupid %>% select(sex, height_cm, is_tall) %>%
  group_by(sex) %>% slice_sample(n = 3)
```

```
## # A tibble: 6 x 3
## # Groups:   sex [2]
##   sex   height_cm is_tall
##   <chr>     <dbl> <lgl>
## 1 f          170. TRUE
## 2 f          165. TRUE
## 3 f          165. TRUE
## 4 m          188. TRUE
## 5 m          188. TRUE
## 6 m          173. FALSE
```

Example2: You could even supply args

```
is_above_average_height <- function(sex, height_cm, men_avg, womer
  if(sex == "m") height_cm > men_avg else height_cm > women_avg
}

okcupid <- okcupid %>%
  mutate(is_tall = map2_lgl(sex, height_cm, is_above_average_heigh
                            men_avg = 180, women_avg = 165))

okcupid %>% select(sex, height_cm, is_tall) %>% group_by(sex) %>%
```

```
## # A tibble: 6 x 3
## # Groups:   sex [2]
##   sex   height_cm is_tall
##   <chr>     <dbl> <lgl>
## 1 f          155. FALSE
## 2 f          173. TRUE
## 3 f          165. TRUE
## 4 m          180. TRUE
## 5 m          173. FALSE
## 6 m          170. FALSE
```

Example2: Anonymous Functions

```
okcupid <- okcupid %>%
  mutate(is_tall = map2_lgl(sex, height_cm,
                            function(x, y) if(x == "m") y > 180 el
```

Heck, you can even:

```
okcupid <- okcupid %>%
  mutate(is_tall = map2_lgl(sex, height_cm,
                            ~{if(.x == "m") .y > 180 else .y > 165
```

There's a thin line between elegance and unreadable undebuggable bragging.

Example 3: Remember our problem?

For each `essay` column, add a column with its length:

```
okcupid %>%
  mutate(across(essay0:essay9, list("len" = str_length))) %>%
  select(starts_with("essay")) %>%
  head(3)
```

```
## # A tibble: 3 x 20
##   essay0 essay1 essay2 essay3 essay4 essay5 essay6 essay7 essay8 essay9
##   <chr>  <chr>  <chr>  <chr>  <chr>  <chr>  <chr>  <chr>  <chr>  <chr>
## 1 "abou~ "curr~ "maki~ "the ~ "book~ "food~ duali~ "tryi~ "i am~ "you ~
## 2 "i am~ "dedi~ "bein~  <NA>  "i am~ "deli~ <NA>    <NA>  "i am~  <NA>
## 3 "i'm ~ "i ma~ "impr~ "my l~ "okay~ "move~ <NA>   "view~ "when~ "you ~
## # ... with 10 more variables: essay0_len <int>, essay1_len <int>,
## #   essay2_len <int>, essay3_len <int>, essay4_len <int>, essay5_len <in
## #   essay6_len <int>, essay7_len <int>, essay8_len <int>, essay9_len <in
```

`purrr` not needed, like I said, you've already been non-looping!

Example 3: Input multiple columns

~~For each user, compute the average `essay` length:~~

Wait, before that, for each user compute the average of the 3 first `essay`s:

```
mean_length_3essay <- function(x, y, z) {
  mean(str_length(c(x, y, z)), na.rm = TRUE)
}

okcupid %>%
  mutate(essay3_avglen = pmap_dbl(
    list(essay0, essay1, essay2),
    mean_length_3essay)) %>%
  select(essay0:essay2, essay3_avglen) %>%
  head(2)
```

```
## # A tibble: 2 x 4
##   essay0                  essay1                  essay2                  essay
##   <chr>                   <chr>                   <chr>
## 1 "about me:<br />\n<b~ "currently working a~ "making people laug~
## 2 "i am a chef: this i~ "dedicating everyday~ "being silly. havin~
```

OK now, for each user, compute the average `essay` length:

```
mean_length_essay <- function(...) {
  mean(str_length(c(...)), na.rm = TRUE)
}

okcupid %>%
  mutate(essay_avglen = pmap_dbl(
    across(starts_with("essay")),
    mean_length_essay)) %>%
  select(essay0:essay2, essay_avglen) %>%
  head(3)
```

```
## # A tibble: 3 x 4
##   essay0                      essay1                      essay2                      essa
##   <chr>                       <chr>                       <chr>
## 1 "about me:<br />\n<b~ "currently working a~ "making people laugh~
## 2 "i am a chef: this i~ "dedicating everyday~ "being silly. having~
## 3 "i'm not ashamed of ~ "i make nerdy softwa~ "improvising in diff~
```

Example4: Output multiple columns

```
essay0_features <- function(essay0) {
 contains_love <- str_detect(essay0, "love")
 contains_obama <- str_detect(essay0, "obama")
 contains_rel <- str_detect(essay0, "relationship")
 list(
   essay0_love = contains_love,
   essay0_obama = contains_obama,
   essay0_ser_rel = contains_rel
 )
}

okcupid %>% select(essay0) %>% map_dfc(essay0_features)
```

```
## # A tibble: 59,946 x 3
##    essay0_love essay0_obama essay0_ser_rel
##    <lgl>       <lgl>        <lgl>
##  1 TRUE        FALSE        FALSE
##  2 TRUE        FALSE        FALSE
##  3 TRUE        FALSE        FALSE
##  4 FALSE       FALSE        FALSE
##  5 FALSE       FALSE        FALSE
##  6 TRUE        FALSE        FALSE
##  7 TRUE        FALSE        FALSE
##  8 NA          NA           NA
##  9 NA          NA           NA
```

Or if you want those features as additional columns, you could bind them with `bind_cols()`:

```
okcupid %>%
  bind_cols(
    okcupid %>% select(essay0) %>% map_dfc(essay0_features)
  ) %>%
  select(age, sex, starts_with("essay0"))
```

```
## # A tibble: 59,946 x 6
##      age sex   essay0                         essay0_love essay0_obama essay0_
##    <dbl> <chr> <chr>                          <lgl>       <lgl>        <lgl>
##  1    22 m     "about me:<br />\n<br />~ TRUE        FALSE        FALSE
##  2    35 m     "i am a chef: this is wh~ TRUE        FALSE        FALSE
##  3    38 m     "i'm not ashamed of much~ TRUE        FALSE        FALSE
##  4    23 m     "i work in a library and~ FALSE       FALSE        FALSE
##  5    29 m     "hey how's it going? cur~ FALSE       FALSE        FALSE
##  6    29 m     "i'm an australian livin~ TRUE        FALSE        FALSE
##  7    32 f     "life is about the littl~ TRUE        FALSE        FALSE
##  8    31 f      <NA>                     NA          NA           NA
##  9    24 f      <NA>                     NA          NA           NA
## 10    37 m     "my names jake.<br />\ni~ TRUE        FALSE        FALSE
## # ... with 59,936 more rows
```

```
# or: okcupid %>% mutate(as_tibble(essay0_features(essay0)))
```

`rowwise()` and `c_across()`

The Tidyverse dev team recently acknowledged that the `purrr` lingo might be a bit much for many users. Enter `rowwise()`:

Before:

```
is_above_average_height <- function(sex, height_cm) {
  if (sex == "m") height_cm > 180 else height_cm > 165
}

okcupid %>%
  mutate(is_tall = map2_lgl(sex, height_cm, is_above_average_heigh
```

After:

```
okcupid %>%
  rowwise() %>%
  mutate(is_tall = is_above_average_height(sex, height_cm))
```

rowwise() and c_across()

Before:

```
mean_length_essay <- function(...) {
  mean(str_length(c(...)), na.rm = TRUE)
}

okcupid %>%
  mutate(essay_avglen = pmap_dbl(
    across(starts_with("essay")),
    mean_length_essay))
```

After:

```
okcupid %>%
  rowwise() %>%
  mutate(essay_avglen =
              mean_length_essay(c_across(starts_with("essay"))))
```

Dealing with failure

```
my_func("a")
```

```
## Error in x%%2: non-numeric argument to binary operator
```

Silly example, but:

(a) When dealing with big data expect the unexpected (input)

(b) You don't want your app to crash

Look at: `safely()`, `quietly()` and `possibly()` which wrap your code nicely and protect you from the unexpected (crash).

My favorite: `possibly()`

```
my_func_safe <- possibly(my_func, otherwise = NA)

my_func_safe("a")
```

```
## [1] NA
```

```
map_chr(list(1, 2, "3", 4), my_func_safe)
```

```
## [1] "odd"  "even" NA     "even"
```

💡 See a more realistic example when we talk about Web Scraping

💡 What would `map_chr(c(1, 2, "3", 4), my_func_safe)` return?

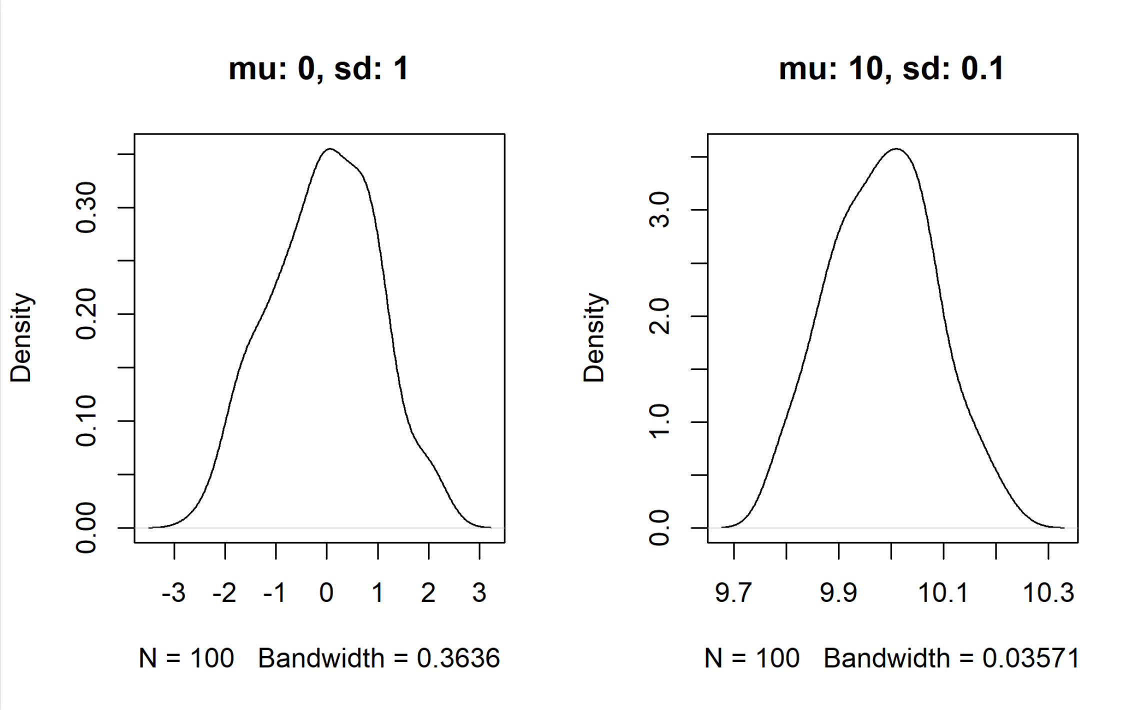
walk(),walk2(),pwalk()

You don't always need to *return* anything, you just wanna loop

```
walk(1:10, ~print("Hey Girrrl"))
```

```
## [1] "Hey Girrrl"
## [1] "Hey Girrrl"
## [1] "Hey Girrrl"
## [1] "Hey Girrrl"
## [1] "Hey Girrrl"
## [1] "Hey Girrrl"
## [1] "Hey Girrrl"
## [1] "Hey Girrrl"
## [1] "Hey Girrrl"
## [1] "Hey Girrrl"
```

```r
plot_norm <- function(mu, sd) {
  plot(density(rnorm(100, mu, sd)),
       main = str_c("mu: ", mu, ", sd: ", sd))
}

par(mfcol = c(1, 2))
walk2(c(0, 10), c(1, 0.1), plot_norm)
```



In the words of Hadley

> Once you master these functions, you'll find it takes much less time to solve iteration problems.

> But you should never feel bad about using a for loop instead of a map function.

> The important thing is that you solve the problem that you're working on, not write the most concise and elegant code.

> Some people will tell you to avoid for loops because they are slow. They're wrong!