

APPLICATIONS



OF DATA SCIENCE

Tidy Data Wrangling - Part B

Applications of Data Science - Class 3

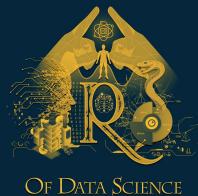
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Joining Tables

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Detour: The Starwars Dataset(s)

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The Starwars Dataset(s)

planets		characters		films	
character_id	int	name	varchar	film_id	int
name	varchar	gender	varchar	episode_id	int
diameter	double	height	varchar	title	varchar
climate	varchar	eye_color	varchar	release_date	date
gravity	varchar	film_id	int	director	varchar
population	double	homeworld_id	int	producer	varchar

```
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, 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, 1, 1, 8, 8, 8, 8, 8,
## $ height <dbl> 172, 172, 172, 172, 172, 167, 167, 167, 167, 167, 167, 167, 167,
## $ mass <dbl> 77, 77, 77, 77, 77, 75, 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", "y
## $ 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.co
## $ vehicles <list> <"http://swapi.co/api/vehicles/14/", "http://swapi.co
## $ starships <list> <"http://swapi.co/api/starships/12/", "http://swap
```

```
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
```

```
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 Marquand"
## $ 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

APPLICATIONS



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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>
## 1           1 Luke Skywalker 1 A New Hope George Lucas
## 2           1 Luke Skywalker 2 The Empire Strikes Back Irvin Kershner
## 3           1 Luke Skywalker 3 Return of the Jedi Richard Marquand
## 4           1 Luke Skywalker 6 Revenge of the Sith George Lucas
## 5           1 Luke Skywalker 7 The Force Awakens J. J. Abrams
## 6           2 C-3PO          1 A New Hope George Lucas
## 7           2 C-3PO          2 The Empire Strikes Back Irvin Kershner
```

(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 Skywalker     1 A New Hope George Lucas Tatoo...
## 2             1 Luke Skywalker     2 The Empire St~ Irvin Kersh~ Tatoo...
## 3             1 Luke Skywalker     3 Return of the~ Richard Mar~ Tatoo...
## 4             1 Luke Skywalker     6 Revenge of th~ George Lucas Tatoo...
## 5             1 Luke Skywalker     7 The Force Awa~ J. J. Abrams Tatoo...
## 6             2 C-3PO            1 A New Hope George Lucas Tatoo...
## 7             2 C-3PO            2 The Empire St~ Irvin Kersh~ Tatoo...
```

(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
##       <dbl>     <dbl>      <dbl>        <dbl> <chr>
## 1         1         1          1            1  blah
## 2         1         1          1            2 something
## 3         1         1          1            2 something
## 4         1         1          1            3 <NA>
## 5         1         1          1            3 <NA>
## 6         1         1          1            4 whatever
```

 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!

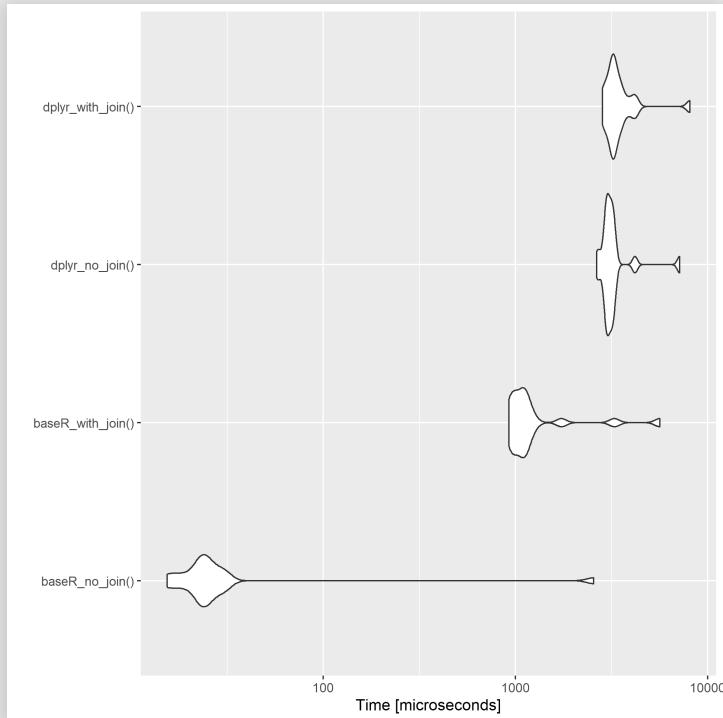
```
baseR_no_join <- function() {
  unique(characters$name[characters$film_id %in% films$film_id[fi]
}

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 = "j"
    pull(name) %>%
    unique()
}
```

```
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

A	B	C
a	t	1
b	u	2
c	v	3



A	B	D
b	u	3
c	v	2
d	w	1



A	B	C	D
b	u	2	3
c	v	3	2

inner_join()

A	B	C
a	t	1
b	u	2
c	v	3



A	B	D
b	u	3
c	v	2
d	w	1



A	B	C	D
a	t	1	NA
b	u	2	3
c	v	3	2

left_join()

A	B	C
a	t	1
b	u	2
c	v	3



A	B	D
b	u	3
c	v	2
d	w	1



A	B	C	D
b	u	2	3
c	v	3	2
d	w	NA	1

right_join()

All Joins

A	B	C
a	t	1
b	u	2
c	v	3



A	B	D
b	u	3
c	v	2
d	w	1



A	B	C	D
a	t	1	NA
b	u	2	3
c	v	3	2
d	w	NA	1

full_join()

A	B	C
a	t	1
b	u	2
c	v	3



A	B	D
b	u	3
c	v	2
d	w	1



A	B	C
b	u	2
c	v	3

semi_join()

A	B	C
a	t	1
b	u	2
c	v	3



A	B	D
b	u	3
c	v	2
d	w	1



A	B	C
a	t	1

anti_join()

Tidying Tables

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Detour: The Migration Dataset

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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!

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	1990	1990001	WORLD	900	153,011,473	6,548,526	2,366,800	6,823,350	180,284	921,727	2,041	3,792		
2	1990	1990002	UN development groups			
3	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	
4	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	
5	1990	1990005	Least developed countries	d	941	11,060,221	482,753	239,756	0	0	5,622	0	0	
6	1990	1990006	Less developed regions, excluding least developed countries	e	934	59,184,036	2,680,670	1,045,855	6,703,964	2,298	49,090	1,014	55	
7	1990	1990007	World Bank income groups		
8	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	
9	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	
10	1990	1990010	Upper-middle-income countries	e	1502	33,285,549	957,059	376,006	3,152,957	49,298	4,719	1,954	42	
11	1990	1990011	Lower-middle-income countries	e	1501	31,938,817	920,619	61,463	3,391,375	538	25,794	19	2	
12	1990	1990012	Low-income countries	e	1500	9,790,238	850,549	145,493	8,485	0	4,370	0	0	
13	1990	1990013	No income group available	e	294,001	16,702	10,593	0	0	255	0	0	0	
14	1990	1990014	Geographic regions		
15	1990	1990015	Africa	903	15,689,666	807,899	258,638	1,037	504	31,807	0	0	0	
16	1990	1990016	Asia	935	48,209,949	2,005,398	961,154	6,702,778	1,291	20,924	0	0	0	
17	1990	1990017	Europe	908	49,608,231	432,964	871,477	82,736	170,977	857,978	963	3,404		
18	1990	1990018	Latin America and the Caribbean	904	7,161,371	344,362	64,989	199	503	863	0	55		
19	1990	1990019	Northern America	905	27,610,408	2,923,653	199,963	33,765	6,025	8,372	0	0	0	
20	1990	1990020	Oceania	909	4,731,848	34,250	11,579	2,885	984	1,783	1,078	333		
21	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-Z a-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

```
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 <dbl>,
## # 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 <dbl>,
## # bermuda <dbl>, bhutan <dbl>, bolivia_plurinational_state_of <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, gender == "men")
  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



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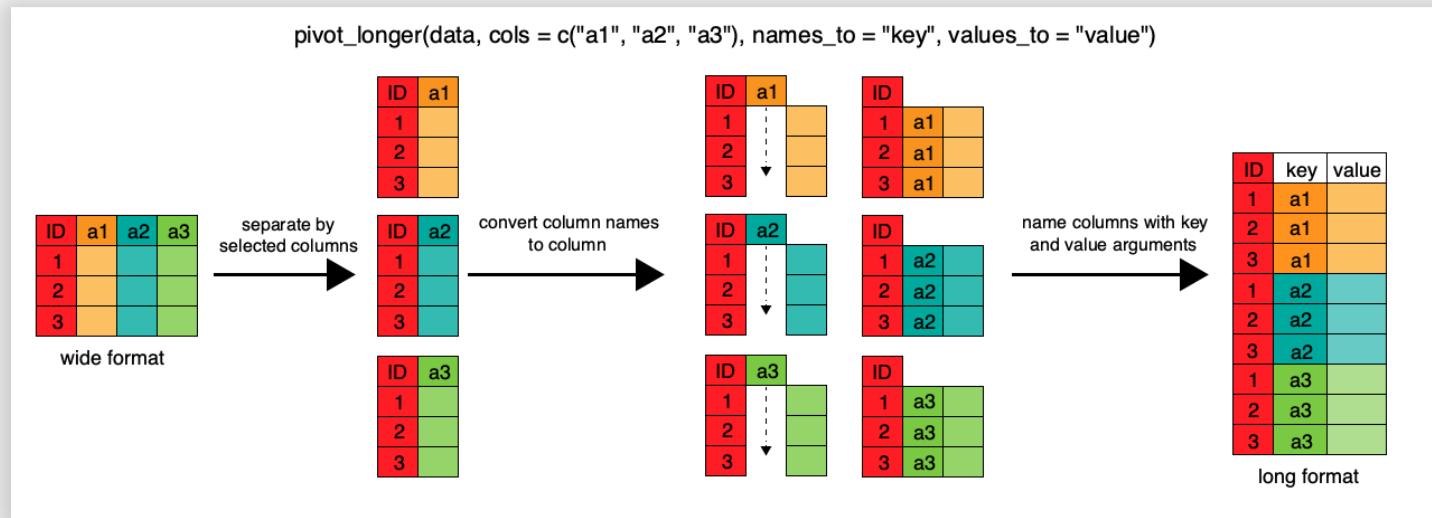
pivot_longer()

```
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()

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

migration wide

```

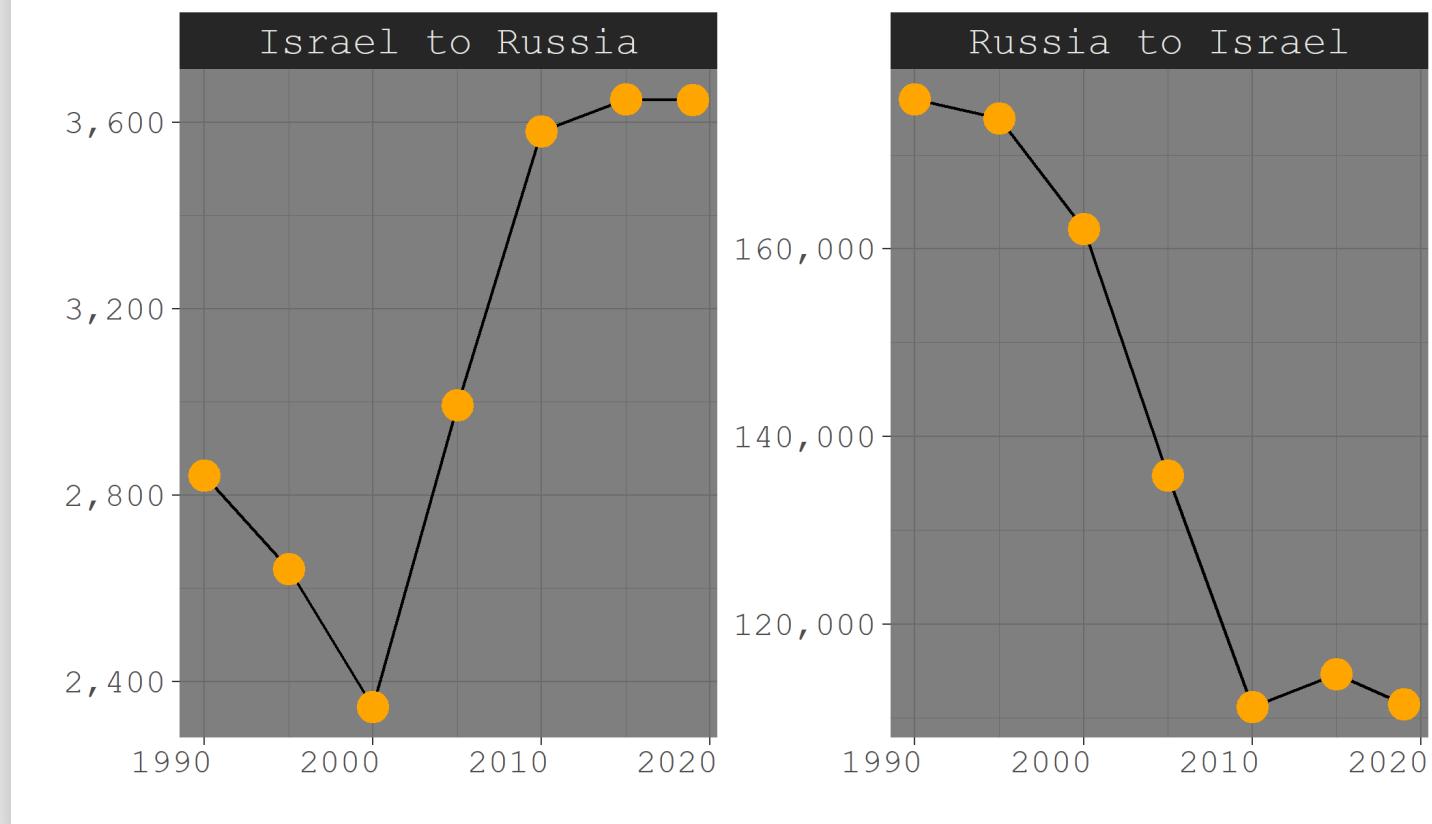
## # A tibble: 3,248 x 236
##   gender year code country_dest afghanistan albania algeria american_...
##   <chr>  <dbl> <dbl> <chr>                <dbl>    <dbl>    <dbl>
## 1 men     1990    108 burundi                 0        0        0
## 2 men     1990    174 comoros                 0        0        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 <dbl>,
## # armenia <dbl>, aruba <dbl>, australia <dbl>, austria <dbl>,

```

Where is this going to?

```
get_1way_migration <- function(.country_dest, .country_orig) {  
  migration_long %>%  
    filter(country_dest == .country_dest, country_orig == .country_orig)  
    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 immigrants") +  
  theme_dark() +  
  facet_wrap(~direction, scales = "free", labeller = labeller(direction =  
    scale_y_continuous(labels = scales::comma_format()) +  
    theme(axis.text = element_text(size = 12, hjust=0.9, family = "mono"),  
          strip.text.x = element_text(size = 14, family = "mono")),  
    plot.title = element_text(hjust = 0.5, size = 18, family = "mono"))
```

Israel-Russia Yearly No. of immigrants



Some more useful Tidying up verbs

Remember?

```
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

APPLICATIONS



OF DATA SCIENCE

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() 1900 2000 43623    2000 2100 4153700    100
##  nchar_vectorized()   300   300 11247     400   400 1086000    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)

Example 1: 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 and  
## 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:

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

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

```
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_height))  
  
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         160. FALSE  
## 2 f         155. FALSE  
## 3 f         160. FALSE  
## 4 m         188. TRUE  
## 5 m         168. FALSE  
## 6 m         175. FALSE
```

Example2: You could even supply args

```
is_above_average_height <- function(sex, height_cm, men_avg, women_avg)
  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_height,
                           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        163. FALSE
## 2 f        170. TRUE
## 3 f        165. TRUE
## 4 m        170. FALSE
## 5 m        190. TRUE
## 6 m        185. TRUE
```

Example2: Anonymous Functions

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

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 undetectable 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
##   <chr>   <chr>   <chr>   <chr>   <chr>   <chr>   <chr>   <chr>
## 1 "about~ "curre~ "makin~ "the w~ "books~ "food.~ dualit~ "tryin~ "i am
## 2 "i am ~ "dedic~ "being~ <NA>   "i am ~ "delic~ <NA>     <NA>   "i am
## 3 "i'm n~ "i mak~ "impro~ "my la~ "okay ~ "movem~ <NA>     "viewi~ "when
## # ... with 10 more variables: essay0_len <int>, essay1_len <int>,
## #   essay2_len <int>, essay3_len <int>, essay4_len <int>, essay5_len <int>
## #   essay6_len <int>, essay7_len <int>, essay8_len <int>, essay9_len <int>
```

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 essays:

```
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  
##   <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      essay3  
##   <chr>                   <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_height))
```

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"))
```

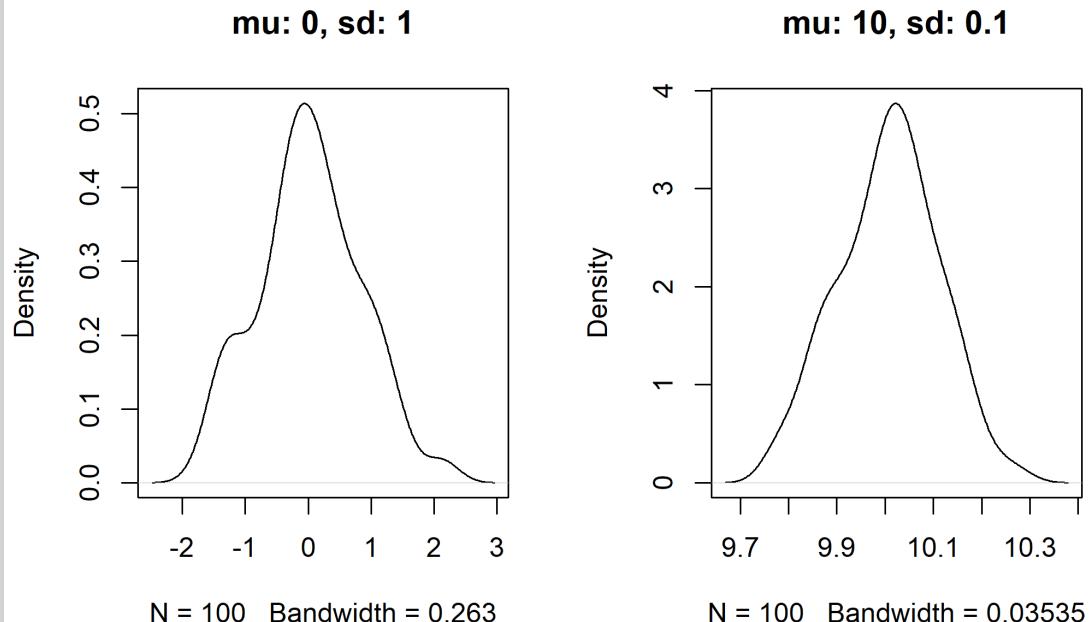
```
## [1] "Hey Girrrl"
```

```

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!