05 - Importation et jointure de données

PRO1036 - Analyse de données scientifiques en R

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Importation de données

Présentations

`readr`

- `read_csv()` - fichiers CSV
  - CSV: comma-separated values - valeurs séparées par des virgules
- `read_csv2()` - fichiers CSV mais où le séparateur est un point-virgule
  - Commun dans les pays où le séparateur décimal est la virgule
- `read_tsv()` - fichiers TSV
  - TSV: tab-separated values - valeurs séparées par des tabulations
- `read_delim()` - fichiers avec un délimiteur spécifique
  - On peut spécifier le délimiteur avec l'argument `delim`
- …

`readxl`

- `read_excel()` - Permet de lire des fichiers Excel

Lecture de fichiers

```
1 nobel <- read_csv(file = "data/nobel.csv")
2 nobel
```

```
# A tibble: 935 × 26
      id firstname   surname  year category affiliation city  country born_date
   <dbl> <chr>       <chr>   <dbl> <chr>    <chr>       <chr> <chr>   <date>
 1     1 Wilhelm Co… Röntgen  1901 Physics  Munich Uni… Muni… Germany 1845-03-27
 2     2 Hendrik A.  Lorentz  1902 Physics  Leiden Uni… Leid… Nether… 1853-07-18
 3     3 Pieter      Zeeman   1902 Physics  Amsterdam … Amst… Nether… 1865-05-25
 4     4 Henri       Becque…  1903 Physics  École Poly… Paris France  1852-12-15
 5     5 Pierre      Curie    1903 Physics  École muni… Paris France  1859-05-15
 6     6 Marie       Curie    1903 Physics  <NA>        <NA>  <NA>    1867-11-07
 7     6 Marie       Curie    1911 Chemist… Sorbonne U… Paris France  1867-11-07
 8     8 Lord        Raylei…  1904 Physics  Royal Inst… Lond… United… 1842-11-12
 9     9 Philipp     Lenard   1905 Physics  Kiel Unive… Kiel  Germany 1862-06-07
10    10 J.J.        Thomson  1906 Physics  University… Camb… United… 1856-12-18
# ℹ 925 more rows
# ℹ 17 more variables: died_date <date>, gender <chr>, born_city <chr>,
#   born_country <chr>, born_country_code <chr>, died_city <chr>,
#   died_country <chr>, died_country_code <chr>, overall_motivation <chr>,
#   share <dbl>, motivation <chr>, born_country_original <chr>,
#   born_city_original <chr>, died_country_original <chr>,
#   died_city_original <chr>, city_original <chr>, country_original <chr>
```

Noms des varaibles

Le nom des variables n’est pas toujours optimal.

```
1 edibnb_badnames <- read_csv("data/edibnb-badnames.csv")
2 names(edibnb_badnames)
```

```
 [1] "ID"                   "Price"                "neighbourhood"
 [4] "accommodates"         "Number of bathrooms"  "Number of Bedrooms"
 [7] "n beds"               "Review Scores Rating" "Number of reviews"
[10] "listing_url"
```

Et R n’aime pas les noms de variables avec des espaces.

```
1 ggplot(edibnb_badnames, aes(x = Number of bathrooms, y = Price)) +
2   geom_point()
```

```
Error in parse(text = input): <text>:1:40: symbole inattendu
1: ggplot(edibnb_badnames, aes(x = Number of
                                          ^
```

Option 1: Spécifier les noms des variables à l'importation

```
edibnb_col_names <- read_csv("data/edibnb-badnames.csv",
                             col_names = c("id", "price",
                                           "neighbourhood", "accommodates",
                                           "bathroom", "bedroom",
                                           "bed", "review_scores_rating",
                                           "n_reviews", "url"))

names(edibnb_col_names)
```

```
 [1] "id"                  "price"               "neighbourhood"
 [4] "accommodates"        "bathroom"            "bedroom"
 [7] "bed"                 "review_scores_rating" "n_reviews"
[10] "url"
```

Option 2: Utiliser le format snake_case

- Les espaces sont remplacés par des underscores
- Les lettres sont en minuscules

Nous pouvons utiliser la fonction `janitor::clean_names()`

```
edibnb_clean_names <- read_csv("data/edibnb-badnames.csv") %>%
  janitor::clean_names()
names(edibnb_clean_names)
```

```
 [1] "id"                  "price"               "neighbourhood"
 [4] "accommodates"        "number of bathrooms" "number of bedrooms"
 [7] "n_beds"              "review_scores_rating" "number_of_reviews"
[10] "listing_url"
```

Gestion des types de données

x	y	z
1	a	hi
NA	b	hello
3	Not applicable	9999
4	d	ola
5	e	hola
.	f	whatup
7	g	wassup
8	h	sup
9	i	

```
read_csv("data/df-na.csv")
```

```
# A tibble: 9 × 3
  x     y              z
  <chr> <chr>          <chr>
1 1     a              hi
2 <NA>  b              hello
3 3     Not applicable 9999
4 4     d              ola
5 5     e              hola
6 .     f              whatup
7 7     g              wassup
8 8     h              sup
9 9     i              <NA>
```

Spécification des NAs

```
read_csv("data/df-na.csv",
         na = c("", "NA", ".", "9999", "Not applicable"))
```

```
# A tibble: 9 × 3
      x y     z
  <dbl> <chr> <chr>
1     1 a     hi
2    NA b     hello
3     3 <NA>  <NA>
4     4 d     ola
5     5 e     hola
6    NA f     whatup
7     7 g     wassup
8     8 h     sup
9     9 i     <NA>
```

Spécification des types de chaque colonne

```
read_csv("data/df-na.csv", col_types = list(col_double(),
                                            col_character(),
                                            col_character()))
```

```
# A tibble: 9 × 3
      x y              z
  <dbl> <chr>          <chr>
1     1 a              hi
2    NA b              hello
3     3 Not applicable 9999
4     4 d              ola
5     5 e              hola
6    NA f              whatup
7     7 g              wassup
8     8 h              sup
9     9 i              <NA>
```

Les types de colonnes

Fonction	Types de données
`col_character()`	Chaine de caractères
`col_date()`	Date
`col_datetime()`	POSIXct (date-time)
`col_double()`	Double (numeric)
`col_factor()`	Factor
`col_guess()`	Laisse readr deviner (par défaut)
`col_integer()`	Entier
`col_logical()`	Logique
`col_number()`	Nombre et texte mélangés
`col_numeric()`	Double ou entier
`col_skip()`	Ne pas lire la colonne
`col_time()`	Temps

Jointure de données

Kesako

Lorsque nous avons des données dans plusieurs fichiers/tables, il est souvent nécessaire de les combiner.

Données: Les femmes dans la science

Nous avons des informations sur 10 femmes qui ont changé le monde. Les informations sont réparties dans trois fichiers:

- `professions.csv`: Information sur la profession de chacune
- `dates.csv`: date de naissance et de décès de chacune
- `works.csv`: Ce qu'elles ont fait pour changer le monde

professions.csv

```
professions <- read_csv("data/scientists/professions.csv")
professions
```

```
# A tibble: 10 × 2
   name                profession
   <chr>               <chr>
 1 Ada Lovelace        Mathematician
 2 Marie Curie         Physicist and Chemist
 3 Janaki Ammal        Botanist
 4 Chien-Shiung Wu     Physicist
 5 Katherine Johnson   Mathematician
 6 Rosalind Franklin   Chemist
 7 Vera Rubin          Astronomer
 8 Gladys West         Mathematician
 9 Flossie Wong-Staal  Virologist and Molecular Biologist
10 Jennifer Doudna     Biochemist
```

dates.csv

```
1 dates <- read_csv("data/scientists/dates.csv")
2 dates
```

```
# A tibble: 8 × 3
  name                birth_year death_year
  <chr>                    <dbl>      <dbl>
1 Janaki Ammal              1897       1984
2 Chien-Shiung Wu           1912       1997
3 Katherine Johnson         1918       2020
4 Rosalind Franklin         1920       1958
5 Vera Rubin                1928       2016
6 Gladys West               1930         NA
7 Flossie Wong-Staal        1947         NA
8 Jennifer Doudna           1964         NA
```

works.csv

```
1 works <- read_csv("data/scientists/works.csv")
2 works
```

```
# A tibble: 9 × 2
  name                known_for
  <chr>               <chr>
1 Ada Lovelace        first computer algorithm
2 Marie Curie         theory of radioactivity,  discovery of elements polonium a…
3 Janaki Ammal        hybrid species, biodiversity protection
4 Chien-Shiung Wu     confim and refine theory of radioactive beta decy, Wu expe…
5 Katherine Johnson   calculations of orbital mechanics critical to sending the …
6 Vera Rubin          existence of dark matter
7 Gladys West         mathematical modeling of the shape of the Earth which serv…
8 Flossie Wong-Staal  first scientist to clone HIV and create a map of its genes…
9 Jennifer Doudna     one of the primary developers of CRISPR, a ground-breaking…
```

Ce que nous voulons comme output

```
# A tibble: 10 × 5
   name               profession                  birth_year death_year known_for
   <chr>              <chr>                            <dbl>      <dbl> <chr>    
 1 Ada Lovelace       Mathematician                       NA         NA first co…
 2 Marie Curie        Physicist and Chemist               NA         NA theory o…
 3 Janaki Ammal       Botanist                          1897       1984 hybrid s…
 4 Chien-Shiung Wu    Physicist                         1912       1997 confim a…
 5 Katherine Johnson  Mathematician                     1918       2020 calculat…
 6 Rosalind Franklin  Chemist                          1920       1958 <NA>     
 7 Vera Rubin         Astronomer                        1928       2016 existenc…
 8 Gladys West        Mathematician                     1930         NA mathemat…
 9 Flossie Wong-Staal Virologist and Molecular …        1947         NA first sc…
10 Jennifer Doudna    Biochemist                        1964         NA one of t…
```

Types de jointures

- `left_join()`: Retourne toutes les lignes de la première table et les lignes correspondantes de la deuxième table
- `right_join()`: Retourne toutes les lignes de la deuxième table et les lignes correspondantes de la première table
- `inner_join()`: Retourne les lignes qui ont une correspondance dans les deux tables
- `full_join()`: Retourne toutes les lignes des deux tables
- `semi_join()`: Retourne toutes les lignes de la première table qui ont une correspondance dans la deuxième table
- `anti_join()`: Retourne toutes les lignes de la première table qui n'ont pas de correspondance dans la deuxième table

Pour l’exemple...

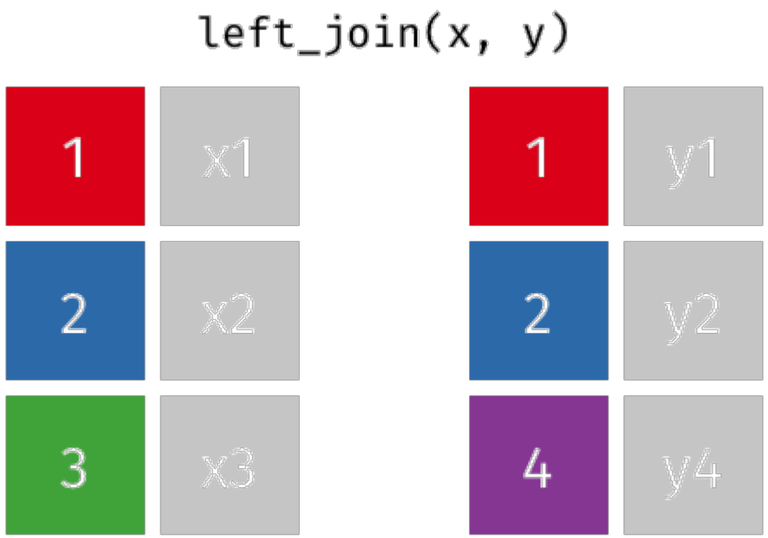
```
          1  x
```

```
# A tibble: 3 × 2
     id value_x
  <dbl> <chr>
1     1 x1
2     2 x2
3     3 x3
```

```
          1  y
```

```
# A tibble: 3 × 2
     id value_y
  <dbl> <chr>
1     1 y1
2     2 y2
3     4 y4
```

left_join()




```
1  left_join(x, y)
```

```
# A tibble: 3 × 3
     id value_x value_y
  <dbl> <chr>   <chr>
1     1 x1      y1
2     2 x2      y2
3     3 x3      <NA>
```

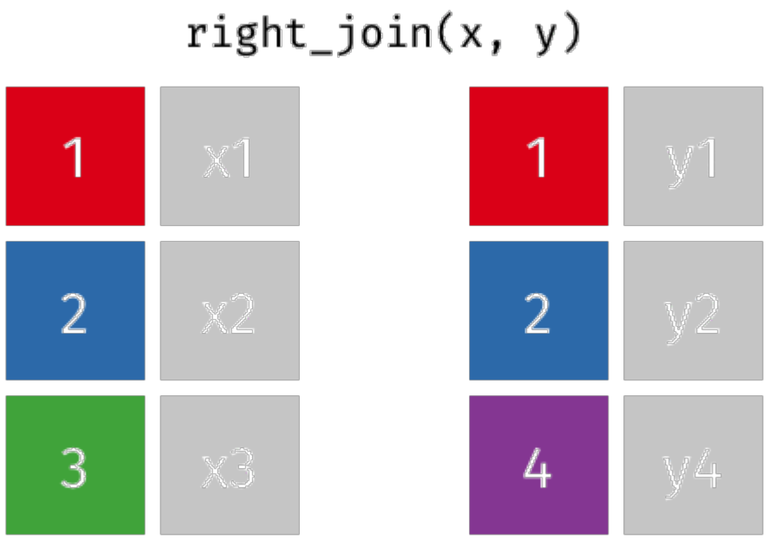
Data Science in a Box

left_join()

```
professions %>%
  left_join(dates)
```

```
# A tibble: 10 × 4
   name                profession                       birth_year death_year
   <chr>               <chr>                                 <dbl>      <dbl>
 1 Ada Lovelace        Mathematician                            NA         NA
 2 Marie Curie         Physicist and Chemist                    NA         NA
 3 Janaki Ammal        Botanist                               1897       1984
 4 Chien-Shiung Wu     Physicist                              1912       1997
 5 Katherine Johnson   Mathematician                          1918       2020
 6 Rosalind Franklin   Chemist                                1920       1958
 7 Vera Rubin          Astronomer                             1928       2016
 8 Gladys West         Mathematician                          1930         NA
 9 Flossie Wong-Staal  Virologist and Molecular Biologist     1947         NA
10 Jennifer Doudna     Biochemist                             1964         NA
```

right_join()




```
1  right_join(x, y)
```

```
# A tibble: 3 × 3
     id value_x value_y
  <dbl> <chr>   <chr>
1     1 x1      y1
2     2 x2      y2
3     4 <NA>    y4
```

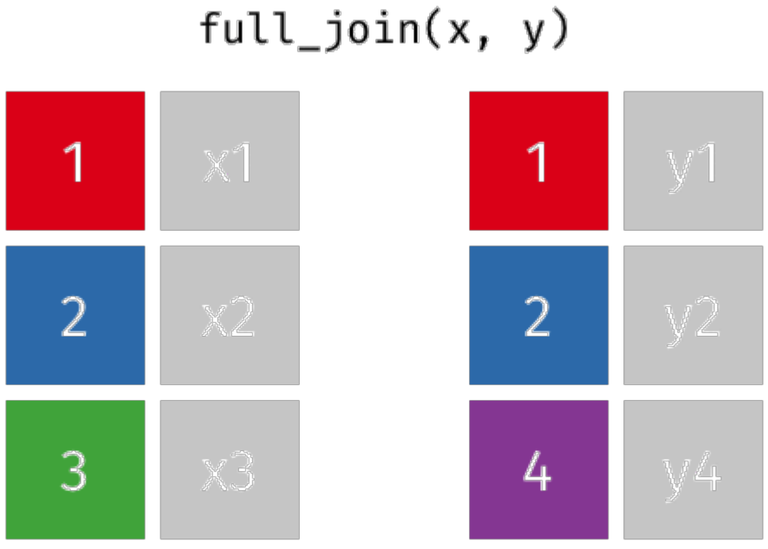
Data Science in a Box

right_join()

```
professions %>%
  right_join(dates)
```

```
# A tibble: 8 × 4
  name               profession                          birth_year death_year
  <chr>              <chr>                                    <dbl>      <dbl>
1 Janaki Ammal       Botanist                                  1897       1984
2 Chien-Shiung Wu    Physicist                                 1912       1997
3 Katherine Johnson  Mathematician                            1918       2020
4 Rosalind Franklin  Chemist                                   1920       1958
5 Vera Rubin         Astronomer                                1928       2016
6 Gladys West        Mathematician                             1930         NA
7 Flossie Wong-Staal Virologist and Molecular Biologist        1947         NA
8 Jennifer Doudna    Biochemist                                1964         NA
```

full_join()




```
full_join(x, y)
```

```
# A tibble: 4 × 3
     id value_x value_y
  <dbl> <chr>   <chr>
1     1 x1      y1
2     2 x2      y2
3     3 x3      <NA>
4     4 <NA>    y4
```

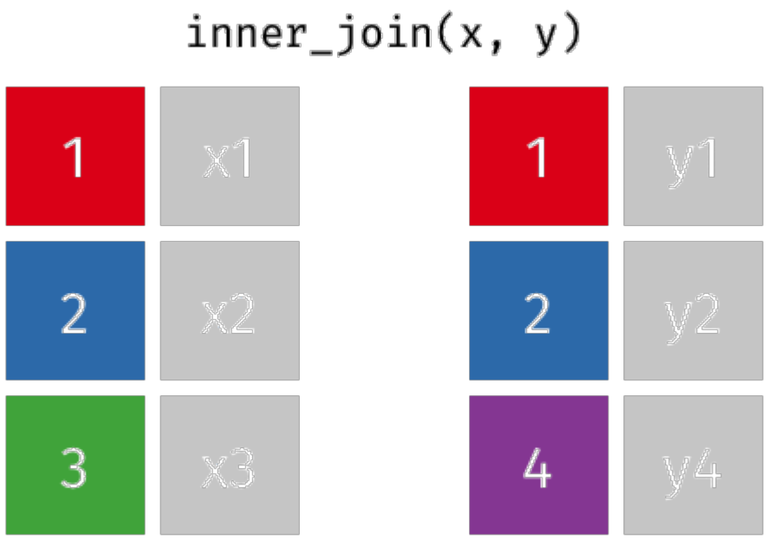
Data Science in a Box

full_join()

```
professions %>%
  full_join(works)
```

```
# A tibble: 10 × 3
   name                profession                    known_for
   <chr>               <chr>                         <chr>
 1 Ada Lovelace        Mathematician                 first computer algorit…
 2 Marie Curie         Physicist and Chemist         theory of radioactivit…
 3 Janaki Ammal        Botanist                      hybrid species, biodiv…
 4 Chien-Shiung Wu     Physicist                     confim and refine theo…
 5 Katherine Johnson   Mathematician                 calculations of orbita…
 6 Rosalind Franklin   Chemist                       <NA>
 7 Vera Rubin          Astronomer                    existence of dark matt…
 8 Gladys West         Mathematician                 mathematical modeling …
 9 Flossie Wong-Staal  Virologist and Molecular Biologist first scientist to clo…
10 Jennifer Doudna     Biochemist                    one of the primary dev…
```

inner_join()




```
1  inner_join(x, y)
```

```
# A tibble: 2 × 3
     id value_x value_y
  <dbl> <chr>   <chr>
1     1 x1      y1
2     2 x2      y2
```

Data Science in a Box

inner_join()

```
professions %>%
  inner_join(dates)
```

```
# A tibble: 8 × 4
  name               profession                          birth_year death_year
  <chr>              <chr>                                    <dbl>      <dbl>
1 Janaki Ammal       Botanist                                  1897       1984
2 Chien-Shiung Wu    Physicist                                 1912       1997
3 Katherine Johnson  Mathematician                            1918       2020
4 Rosalind Franklin  Chemist                                   1920       1958
5 Vera Rubin         Astronomer                                1928       2016
6 Gladys West        Mathematician                             1930         NA
7 Flossie Wong-Staal Virologist and Molecular Biologist        1947         NA
8 Jennifer Doudna    Biochemist                                1964         NA
```

Si on reprend…

```
professions %>%
  left_join(dates) %>%
  left_join(works)
```

```
# A tibble: 10 × 5
   name                profession                    birth_year death_year known_for
   <chr>               <chr>                              <dbl>      <dbl> <chr>
 1 Ada Lovelace        Mathematician                         NA         NA first co…
 2 Marie Curie         Physicist and Chemist                 NA         NA theory o…
 3 Janaki Ammal        Botanist                            1897       1984 hybrid s…
 4 Chien-Shiung Wu     Physicist                           1912       1997 confim a…
 5 Katherine Johnson   Mathematician                       1918       2020 calculat…
 6 Rosalind Franklin   Chemist                             1920       1958 <NA>
 7 Vera Rubin          Astronomer                          1928       2016 existenc…
 8 Gladys West         Mathematician                       1930         NA mathemat…
 9 Flossie Wong-Staal  Virologist and Molecular …         1947         NA first sc…
10 Jennifer Doudna     Biochemist                          1964         NA one of t…
```

Tidy data

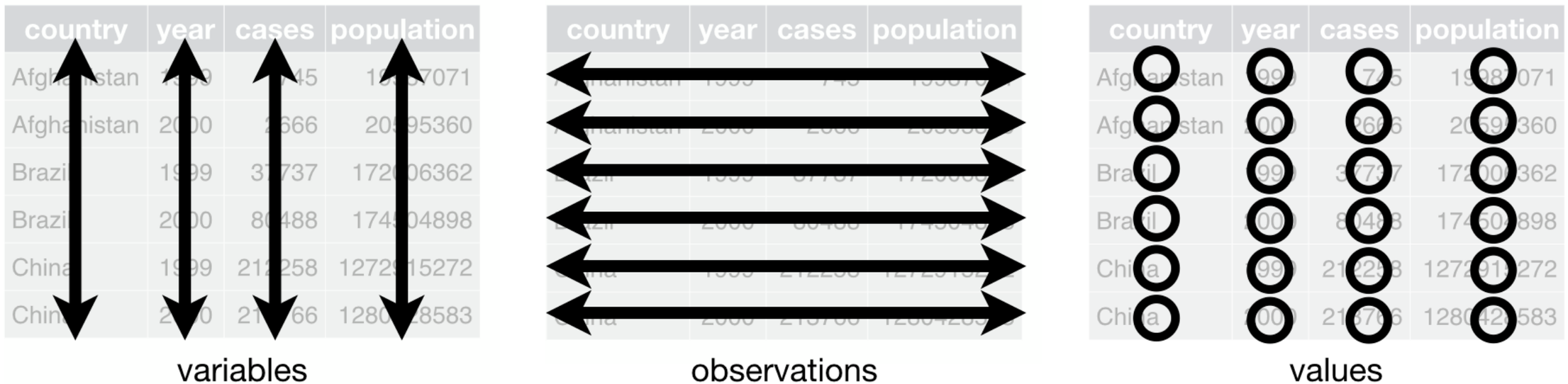
Tidy data

> *Happy families are all alike; every unhappy family is unhappy in its own way. – Leo Tolstoy*

Qu’est ce que des données Tidy ?

- Chaque variable est une colonne
- Chaque observation est une ligne
- Chaque valeur est une cellule

Tidy data



(Wickham et al., 2023, chap. 5)

Exemples

En quoi ces données ne sont pas tidy ?

Airplanes on Hand in the AAF, By Major Type:
Jul 1939 to Aug 1945

End of Month	Total	Very Heavy Bombers	Heavy Bombers	Medium Bombers	Light Bombers	Fighters	Recon-naissance	Transports	Trainers	Communi-cations
1939										
Jul	2,402	-	16	400	276	494	356	118	735	7
Aug	2,440	-	18	414	276	492	359	129	745	7
[Germany invades Poland, 1 Sep 1939]										
Sep	2,473	-	22	428	278	489	359	136	754	7
Oct	2,507	-	27	446	277	490	365	137	758	7
Nov	2,536	-	32	458	275	498	375	136	755	7
Dec	2,546	-	39	464	274	492	378	131	761	7
1940										
Jan	2,588	-	45	466	271	464	409	128	798	7
Feb	2,658	-	49	470	271	458	415	128	860	7
Mar	2,709	-	54	468	267	453	415	125	920	7
Apr	2,806	-	54	468	263	451	416	125	1,022	7
May	2,906	-	54	470	259	459	410	124	1,123	7
Jun	2,966	-	54	478	166	477	414	127	1,243	7
[France surrenders to Germany, 25 Jun 1940] [Battle of Britain begins, 10 July 1940]										
Jul	3,102	-	56	483	161	500	410	128	1,357	7
Aug	3,295	-	65	485	158	539	407	128	1,506	7

Source: Army Air Forces Statistical Digest, WWII

En quoi ces données ne sont pas tidy ?

	A	AA	AB	AC	AD	AE	AF	AG	AH
1	Estimated HIV Prevalence% - (Ages 15-49)	2004	2005	2006	2007	2008	2009	2010	2011
2	Abkhazia								
3	Afghanistan						0.06	0.06	0.06
4	Akrotiri and Dhekelia								
5	Albania								
6	Algeria	0.1	0.1	0.1	0.1	0.1			
7	American Samoa								
8	Andorra								
9	Angola	1.9	1.9	1.9	1.9	2	2.1	2.1	2.1
10	Anguilla								
11	Antigua and Barbuda								
12	Argentina	0.4	0.4	0.4	0.4	0.5	0.4	0.4	0.4
13	Armenia	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2
14	Aruba								
15	Australia	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2
16	Austria	0.2	0.2	0.2	0.3	0.3	0.3	0.4	0.4
17	Azerbaijan	0.06	0.06	0.06	0.1	0.1	0.1	0.1	0.1
18	Bahamas	3	3	3	3.1	3.1	2.9	2.8	2.8

Source: Gapminder, Estimated HIV prevalence among 15-49 year olds

En quoi ces données ne sont pas tidy ?

Subject	United States			
	Estimate	Margin of Error	Percent	Percent Margin of Error
EMPLOYMENT STATUS				
Population 16 years and over	255,797,692	+/-17,051	255,797,692	(X)
In labor force	162,184,325	+/-135,158	63.4%	+/-0.1
Civilian labor force	161,159,470	+/-127,501	63.0%	+/-0.1
Employed	150,599,165	+/-138,066	58.9%	+/-0.1
Unemployed	10,560,305	+/-27,385	4.1%	+/-0.1
Armed Forces	1,024,855	+/-10,363	0.4%	+/-0.1
Not in labor force	93,613,367	+/-126,007	36.6%	+/-0.1
Civilian labor force	161,159,470	+/-127,501	161,159,470	(X)
Unemployment Rate	(X)	(X)	6.6%	+/-0.1
Females 16 years and over	131,092,196	+/-11,187	131,092,196	(X)
In labor force	76,493,327	+/-75,824	58.4%	+/-0.1
Civilian labor force	76,350,498	+/-75,238	58.2%	+/-0.1
Employed	71,451,559	+/-79,007	54.5%	+/-0.1
Own children of the householder under 6 years	22,939,897	+/-14,240	22,939,897	(X)
All parents in family in labor force	14,957,537	+/-36,506	65.2%	+/-0.1
Own children of the householder 6 to 17 years	47,007,147	+/-19,644	47,007,147	(X)
All parents in family in labor force	33,238,793	+/-49,036	70.7%	+/-0.1

Source: US Census Fact Finder, General Economic Characteristics, ACS 2017

Tidying data

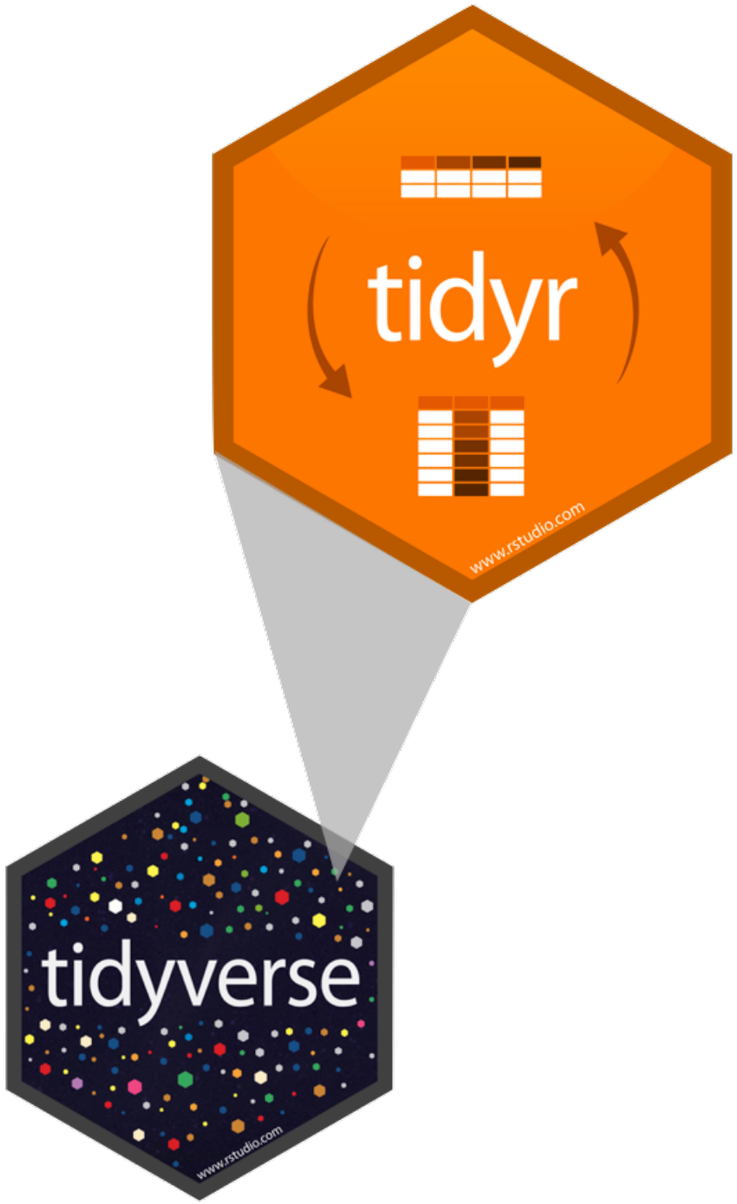
Ce qu'on a...

```
# A tibble: 2 × 4
  customer_id item_1 item_2       item_3
        <dbl> <chr>  <chr>        <chr>
1           1 bread  milk         banana
2           2 milk   toilet paper <NA>
```

Ce qu’on veut…

```
# A tibble: 6 × 3
  customer_id item_no item
        <dbl> <chr>   <chr>
1           1 item_1  bread
2           1 item_2  milk
3           1 item_3  banana
4           2 item_1  milk
5           2 item_2  toilet paper
6           2 item_3  <NA>
```

Pour Tidyer: Tidyr



Tidyr permet de transformer les données pour les Tidy :

- Faire pivoter les données
- Séparer ou combiner des colonnes
- Imbriquer/Désimbriquer des colonnes
- Préciser commenter traiter les NA

Pivoter les données


PIVOT!!!

Wide vs Long

Forme large :

id	bp1	bp2
A	100	120
B	140	115
C	120	125

Forme longue :

id	measurement	value
A	bp1	100
A	bp2	120
B	bp1	140
B	bp2	115
C	bp1	120
C	bp2	125

Source: (Wickham et al., 2023, chap. 5)

Wide vs Long

Wide

Plus de colonnes

```
# A tibble: 2 × 4
  customer_id item_1 item_2       item_3
        <dbl> <chr>  <chr>        <chr>
1           1 bread  milk         banana
2           2 milk   toilet paper <NA>
```

Long

Plus de lignes

```
# A tibble: 6 × 3
  customer_id item_no item
        <dbl> <chr>   <chr>
1           1 item_1  bread
2           1 item_2  milk
3           1 item_3  banana
4           2 item_1  milk
5           2 item_2  toilet paper
6           2 item_3  <NA>
```

pivot_longer()

- `data` : Comme d'habitude
- `cols` : Colonne à pivoter
- `names_to` : Nom de la colonne où les variables vont être envoyées
- `values_to` : Nom de la colonne où les valeurs vont être envoyées

```
pivot_longer(
  data,
  cols,
  names_to = "name",
  values_to = "value"
  )
```

Customer → purchases

```
purchases <- customers %>%
  pivot_longer(
    cols = item_1:item_3,   # variables item_1 à item_3
    names_to = "item_no",   # Noms des colonnes -> dans une nouvelle colonne item_no
    values_to = "item"      # valeurs pour chaque colonne -> dans une nouvelle colonne ite
    )

purchases
```

```
# A tibble: 6 × 3
  customer_id item_no item
        <dbl> <chr>   <chr>
1           1 item_1  bread
2           1 item_2  milk
3           1 item_3  banana
4           2 item_1  milk
5           2 item_2  toilet paper
6           2 item_3  <NA>
```

pivot_wider()

- `data` : Comme d'habitude
- `names_from` : Colonne contenant les noms de colonnes
- `values_from` : Colonne contenant les valeurs

```
purchases %>%
  pivot_wider(
    names_from = item_no,
    values_from = item
  )
```

```
# A tibble: 2 × 4
  customer_id item_1 item_2       item_3
        <dbl> <chr>  <chr>        <chr>
1           1 bread  milk         banana
2           2 milk   toilet paper <NA>
```

Références

Wickham, H., Çetinkaya-Rundel, M. and Grolemund, G. (2023). *R for Data Science* (2nd ed.). O'Reilly Media, Inc.