

# Week 6: Data Wrangling in R

POP77001 Computer Programming for Social Scientists

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Module website: [tinyurl.com/POP77001](https://tinyurl.com/POP77001)

# Overview

- Data frames in base R
- Alternatives to data frames
- `tidyverse` packages
- Working with tabular data
- Data input and output
- Summary statistics

# Tidy data

- Tidy data is a specific subset of rectangular data, where:
  - Each variable is in a column
  - Each observation is in a row
  - Each value is in a cell

country	year	cases	population
Afghanistan	1999	18145	19987071
Afghanistan	2000	18666	20095360
Brazil	1999	30737	172006362
Brazil	2000	80488	174004898
China	1999	210258	1272015272
China	2000	216766	128062583

variables

country	year	cases	population
Afghanistan	1999	18145	19987071
Afghanistan	2000	18666	20095360
Brazil	1999	30737	172006362
Brazil	2000	80488	174004898
China	1999	210258	1272015272
China	2000	216766	128062583

observations

country	year	cases	population
Afghanistan	1999	18145	19987071
Afghanistan	2000	18666	20095360
Brazil	1999	30737	172006362
Brazil	2000	80488	174004898
China	1999	210258	1272015272
China	2000	216766	128062583

values

Source: [R for Data Science](#)

# Data frames

- Data frame is one of the object types available in base R.
- Despite their matrix-like appearance, data frames are lists of equal-sized vectors.
- Data frames can be created with `data.frame()` function with named vectors as input.

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- Despite their matrix-like appearance, data frames are lists of equal-sized vectors.
- Data frames can be created with `data.frame()` function with named vectors as input.

```
In [2]: df <- data.frame(  
  x = 1:4,  
  y = c("a", "b", "c", "d"),  
  z = c(TRUE, FALSE, FALSE, TRUE)  
)  
df
```

	x	y	z
1	1	a	TRUE
2	2	b	FALSE
3	3	c	FALSE
4	4	d	TRUE

# Data frame example

# Data frame example

```
In [3]: # str() function applied to data frame is useful in determining variable types  
str(df)
```

```
'data.frame':  4 obs. of  3 variables:  
 $ x: int  1 2 3 4  
 $ y: chr  "a" "b" "c" "d"  
 $ z: logi  TRUE FALSE FALSE TRUE
```

# Data frame example

In [3]: *# str() function applied to data frame is useful in determining variable types*  
`str(df)`

```
'data.frame':  4 obs. of  3 variables:  
 $ x: int  1 2 3 4  
 $ y: chr  "a" "b" "c" "d"  
 $ z: logi  TRUE FALSE FALSE TRUE
```

In [4]: *# dim() function behaves similar to matrix, showing N rows and N columns*  
`dim(df)`

```
[1] 4 3
```



# Data frame example

```
In [3]: # str() function applied to data frame is useful in determining variable types
str(df)
```

```
'data.frame':  4 obs. of  3 variables:
 $ x: int  1 2 3 4
 $ y: chr  "a" "b" "c" "d"
 $ z: logi  TRUE FALSE FALSE TRUE
```

```
In [4]: # dim() function behaves similar to matrix, showing N rows and N columns
dim(df)
```

```
[1] 4 3
```

```
In [5]: # In contrast to matrix length() of data frame displays the length of columns
length(df)
```

```
[1] 3
```

# Creating data frame example



# Creating data frame example

```
In [6]: l <- list(x = 1:5, y = letters[1:5], z = rep(c(TRUE, FALSE), length.out  
l
```

```
$x
```

```
[1] 1 2 3 4 5
```

```
$y
```

```
[1] "a" "b" "c" "d" "e"
```

```
$z
```

```
[1] TRUE FALSE TRUE FALSE TRUE
```



# Creating data frame example

```
In [6]: l <- list(x = 1:5, y = letters[1:5], z = rep(c(TRUE, FALSE), length.out = 5))
```

```
$x
[1] 1 2 3 4 5

$y
[1] "a" "b" "c" "d" "e"

$z
[1] TRUE FALSE TRUE FALSE TRUE
```

```
In [7]: df <- data.frame(l)
df
```

```
  x y z
1 1 a TRUE
2 2 b FALSE
3 3 c TRUE
4 4 d FALSE
5 5 e TRUE
```



# Creating data frame example

```
In [6]: l <- list(x = 1:5, y = letters[1:5], z = rep(c(TRUE, FALSE), length.out = 5))
```

```
$x
[1] 1 2 3 4 5

$y
[1] "a" "b" "c" "d" "e"

$z
[1] TRUE FALSE TRUE FALSE TRUE
```

```
In [7]: df <- data.frame(l)
df
```

```
  x y z
1 1 a TRUE
2 2 b FALSE
3 3 c TRUE
4 4 d FALSE
5 5 e TRUE
```

```
In [8]: str(df)
```

```
'data.frame': 5 obs. of 3 variables:
```



```
$ x: int  1 2 3 4 5  
$ y: chr  "a" "b" "c" "d" ...  
$ z: logi  TRUE FALSE TRUE FALSE TRUE
```

# Subsetting data frame

- In subsetting data frames the techniques of subsetting matrices and lists are combined
- If you subset with a single vector, it behaves as a list
- If you subset with two vectors, it behaves as a matrix

# Subsetting data frame example

# Subsetting data frame example

```
In [9]: # Like a list  
df[c("x", "z")]
```

	x	z
1	1	TRUE
2	2	FALSE
3	3	TRUE
4	4	FALSE
5	5	TRUE

# Subsetting data frame example

```
In [9]: # Like a list  
df[c("x", "z")]
```

	x	z
1	1	TRUE
2	2	FALSE
3	3	TRUE
4	4	FALSE
5	5	TRUE

```
In [10]: # Like a matrix  
df[,c("x", "z")]
```

	x	z
1	1	TRUE
2	2	FALSE
3	3	TRUE
4	4	FALSE
5	5	TRUE

# Subsetting data frame example

```
In [9]: # Like a list  
df[c("x", "z")]
```

	x	z
1	1	TRUE
2	2	FALSE
3	3	TRUE
4	4	FALSE
5	5	TRUE

```
In [10]: # Like a matrix  
df[,c("x", "z")]
```

	x	z
1	1	TRUE
2	2	FALSE
3	3	TRUE
4	4	FALSE
5	5	TRUE

```
In [11]: df[df$y == "b",]
```

	x	y	z
2	2	b	FALSE

# Building data frame

- `rbind()` (row bind) - appends a row to data frame
- `cbind()` (column bind) - appends a column to data frame
- Both require compatible sizes (number of rows/columns)

# Building data frame examples

- Adding columns



# Building data frame examples

- Adding columns

In [12]:

```
rand <- rnorm(5)  
rand
```

```
[1] -1.6395385 -0.6401171  1.4880066 -0.4978420 -1.3442429
```

# Building data frame examples

- Adding columns

```
In [12]: rand <- rnorm(5)
rand
```

```
[1] -1.6395385 -0.6401171  1.4880066 -0.4978420 -1.3442429
```

```
In [13]: df <- cbind(df, rand)
df
```

	x	y	z	rand
1	1	a	TRUE	-1.6395385
2	2	b	FALSE	-0.6401171
3	3	c	TRUE	1.4880066
4	4	d	FALSE	-0.4978420
5	5	e	TRUE	-1.3442429

# Building data frame examples continued

- Adding rows



# Building data frame examples continued

- Adding rows

```
In [14]: # Note that a row has to be a list as it contains different data types  
r <- list(6, letters[6], FALSE, rnorm(1))  
r
```

```
[[1]]  
[1] 6
```

```
[[2]]  
[1] "f"
```

```
[[3]]  
[1] FALSE
```

```
[[4]]  
[1] -0.2291225
```



# Building data frame examples continued

- Adding rows

```
In [14]: # Note that a row has to be a list as it contains different data types  
r <- list(6, letters[6], FALSE, rnorm(1))  
r
```

```
[[1]]  
[1] 6
```

```
[[2]]  
[1] "f"
```

```
[[3]]  
[1] FALSE
```

```
[[4]]  
[1] -0.2291225
```

```
In [15]: df <- rbind(df, r)  
df
```

```
  x y z    rand  
1 1 a TRUE -1.6395385  
2 2 b FALSE -0.6401171  
3 3 c TRUE  1.4880066
```

4	4	d	FALSE	-0.4978420
5	5	e	TRUE	-1.3442429
6	6	f	FALSE	-0.2291225



# Issues with data frame

- While very versatile (and available out-of-the-box) data frames have their drawbacks:
  - Individual cells (observations) cannot themselves be lists;
  - Somewhat limited (and inconsistent) data manipulation functions;
  - Memory inefficient (**copy-on-modify** semantics);
  - No parallelisation.

# Alternatives to data frame

- Two major alternatives to/enhanced versions of data frames are:
  - `tibble` from `tibble` package (part of `tidyverse` package ecosystem)
  - `data.table` from `data.table`
- `tibble` provides features enhancing user experience (readability, ease of manipulation)
- `data.table` provides speed

# Data table - fast data frame

- As opposed to data frames, data tables are updated by reference.
- This frees up a lot of RAM for big data!
- It provides low-level parallelism.
- SQL-like operations for data manipulation.
- Has no external dependencies (other than base R itself)

# Data table - fast data frame

- As opposed to data frames, data tables are updated by reference.
- This frees up a lot of RAM for big data!
- It provides low-level parallelism.
- SQL-like operations for data manipulation.
- Has no external dependencies (other than base R itself)

```
In [16]: dt <- data.table::data.table(  
  x = 1:4,  
  y = c("a", "b", "c", "d"),  
  z = c(TRUE, FALSE, FALSE, TRUE)  
)  
dt
```

	x	y	z
1	1	a	TRUE
2	2	b	FALSE
3	3	c	FALSE
4	4	d	TRUE

# tidyverse packages

- tidyverse [package ecosystem](#) - rich collection of data science packages
- Designed with consistent interfaces and generally higher usability than base R function
- Notable packages:
  - readr - data input/output (also readxl for spreadsheets, haven for SPSS/Stata)
  - dplyr - data manipulation (also tidyr for pivoting)
  - ggplot2 - data visualisation
  - lubridate - working with dates and time
  - tibble - enhanced data frame

```
install.packages("tidyverse")
```

# Tibble - user-friendly data frame

- Tibbles are designed to be backward compatible with base R data frames
- Console printing of tibbles is cleaner (prettified, only first 10 rows by default)
- Tibbles can have columns that themselves contain lists as elements
- Tibbles can be created with `tibble::tibble()` function
- Or objects can be coerced into a tibble using `tibble::as_tibble()` function

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- Tibbles can have columns that themselves contain lists as elements
- Tibbles can be created with `tibble::tibble()` function
- Or objects can be coerced into a tibble using `tibble::as_tibble()` function

```
In [17]: tb <- tibble::tibble(  
  x = 1:4,  
  y = c("a", "b", "c", "d"),  
  z = c(TRUE, FALSE, FALSE, TRUE)  
)  
tb
```

	x	y	z
1	1	a	TRUE
2	2	b	FALSE
3	3	c	FALSE
4	4	d	TRUE

Tibbles work (mostly) like data frames



# Tibbles work (mostly) like data frames

In [18]: `str(tb)`

```
tibble [4 × 3] (S3: tbl_df/tbl/data.frame)
 $ x: int [1:4] 1 2 3 4
 $ y: chr [1:4] "a" "b" "c" "d"
 $ z: logi [1:4] TRUE FALSE FALSE TRUE
```

# Tibbles work (mostly) like data frames

In [18]: `str(tb)`

```
tibble [4 × 3] (S3: tbl_df/tbl/data.frame)
 $ x: int [1:4] 1 2 3 4
 $ y: chr [1:4] "a" "b" "c" "d"
 $ z: logi [1:4] TRUE FALSE FALSE TRUE
```

In [19]: `dim(tb)`

```
[1] 4 3
```

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In [18]: `str(tb)`

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tibble [4 × 3] (S3: tbl_df/tbl/data.frame)
 $ x: int [1:4] 1 2 3 4
 $ y: chr [1:4] "a" "b" "c" "d"
 $ z: logi [1:4] TRUE FALSE FALSE TRUE
```

In [19]: `dim(tb)`

```
[1] 4 3
```

In [20]: `tb[c("x", "z")]`

```
  x z
1 1 TRUE
2 2 FALSE
3 3 FALSE
4 4 TRUE
```

# Tibbles work (mostly) like data frames

In [18]: `str(tb)`

```
tibble [4 × 3] (S3: tbl_df/tbl/data.frame)
 $ x: int [1:4] 1 2 3 4
 $ y: chr [1:4] "a" "b" "c" "d"
 $ z: logi [1:4] TRUE FALSE FALSE TRUE
```

In [19]: `dim(tb)`

```
[1] 4 3
```

In [20]: `tb[c("x", "z")]`

```
  x z
1 1 TRUE
2 2 FALSE
3 3 FALSE
4 4 TRUE
```

In [21]: `tb[tb$y == "b",]`

```
  x y z
1 2 b FALSE
```

# Manipulating columns in base R

- Adding/modifying columns

# Manipulating columns in base R

- Adding/modifying columns

```
In [22]: # New columns can also be created/modified by assignment (if the RHS of  
tb["r"] <- rnorm(4)  
tb
```

	x	y	z	r
1	1	a	TRUE	-0.63905096
2	2	b	FALSE	-0.40466580
3	3	c	FALSE	0.49230918
4	4	d	TRUE	0.09646717

# Manipulating columns in base R

- Adding/modifying columns

```
In [22]: # New columns can also be created/modified by assignment (if the RHS of  
tb["r"] <- rnorm(4)  
tb
```

	x	y	z	r
1	1	a	TRUE	-0.63905096
2	2	b	FALSE	-0.40466580
3	3	c	FALSE	0.49230918
4	4	d	TRUE	0.09646717

```
In [23]: # Individual columns can also be selected with $ operator  
tb$r <- tb$r + 5  
tb
```

	x	y	z	r
1	1	a	TRUE	4.360949
2	2	b	FALSE	4.595334
3	3	c	FALSE	5.492309
4	4	d	TRUE	5.096467

# Manipulating columns in base R continued

- Renaming columns



# Manipulating columns in base R continued

- Renaming columns

```
In [24]: # names() attribute for data frames/tibbles contains column names  
names(tb)
```

```
[1] "x" "y" "z" "r"
```

# Manipulating columns in base R continued

- Renaming columns

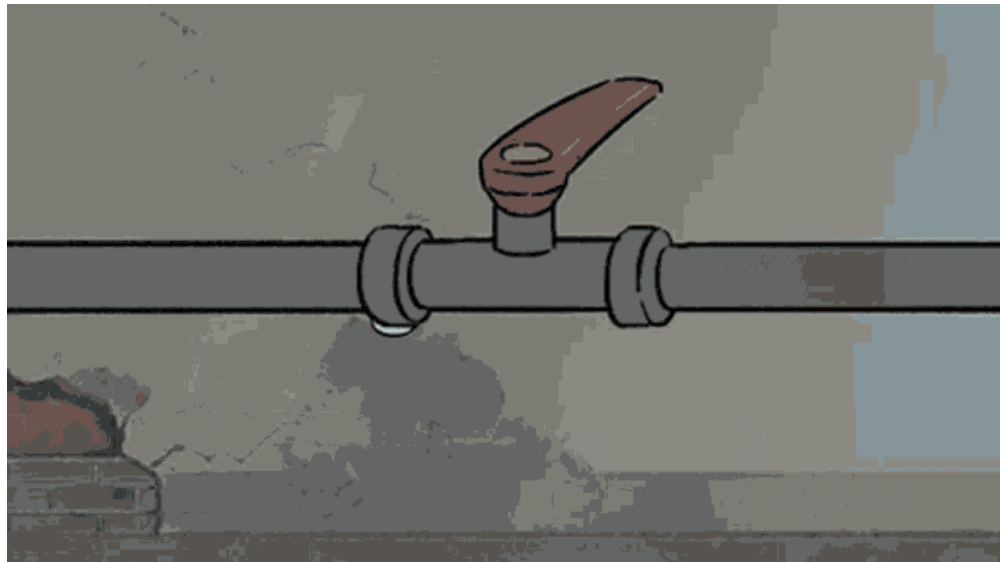
```
In [24]: # names() attribute for data frames/tibbles contains column names  
names(tb)
```

```
[1] "x" "y" "z" "r"
```

```
In [25]: names(tb)[4] <- "rand"  
tb
```

	x	y	z	rand
1	1	a	TRUE	4.360949
2	2	b	FALSE	4.595334
3	3	c	FALSE	5.492309
4	4	d	TRUE	5.096467

# Data preparation



Source: [Tenor](#)

# Data manipulation with `dplyr`

- `dplyr` - is one of the core packages for data manipulation in `tidyverse`
- Its principal functions are:
  - `filter()` - subset rows from data
  - `mutate()` - add new/modify existing variables
  - `rename()` - rename existing variable
  - `select()` - subset columns from data
  - `arrange()` - order data by some variable
- For data summary:
  - `group_by()` - aggregate data by some variable
  - `summarise()` - create a summary of aggregated variables



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- Its principal functions are:
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  - `rename()` - rename existing variable
  - `select()` - subset columns from data
  - `arrange()` - order data by some variable
- For data summary:
  - `group_by()` - aggregate data by some variable
  - `summarise()` - create a summary of aggregated variables

```
In [26]: library("dplyr")
```

```
Attaching package: 'dplyr'
```

```
The following objects are masked from 'package:stats':
```

`filter, lag`

The following objects are masked from 'package:base':

`intersect, setdiff, setequal, union`

# Data manipulation with `dplyr` examples

- Subsetting



# Data manipulation with `dplyr` examples

- Subsetting

```
In [27]: dplyr::filter(tb, y == 'b', z == FALSE)
```

```
  x y z    rand
1 2 b FALSE 4.595334
```

# Data manipulation with `dplyr` examples

- Subsetting

```
In [27]: dplyr::filter(tb, y == 'b', z == FALSE)
```

	x	y	z	rand
1	2	b	FALSE	4.595334

```
In [28]: # Note that dplyr functions do not require enquoted variable names  
dplyr::select(tb, x, z)
```

	x	z
1	1	TRUE
2	2	FALSE
3	3	FALSE
4	4	TRUE

# Data manipulation with `dplyr` examples

- Subsetting

```
In [27]: dplyr::filter(tb, y == 'b', z == FALSE)
```

```
  x y z    rand
1 2 b FALSE 4.595334
```

```
In [28]: # Note that dplyr functions do not require enquoted variable names
dplyr::select(tb, x, z)
```

```
  x z
1 1 TRUE
2 2 FALSE
3 3 FALSE
4 4 TRUE
```

```
In [29]: # We can also use helpful tidyselect functions for more complex rules
dplyr::select(tb, tidyselect::starts_with('r'))
```

```
  rand
1 4.360949
2 4.595334
3 5.492309
4 5.096467
```

# Data manipulation with `dplyr` examples continued

- Renaming/modifying columns

## Data manipulation with `dplyr` examples continued

- Renaming/modifying columns

```
In [30]: # Data is not modified in-place, you need to re-assign the results  
tb <- dplyr::rename(tb, random = rand)
```

# Data manipulation with `dplyr` examples continued

- Renaming/modifying columns

```
In [30]: # Data is not modified in-place, you need to re-assign the results  
tb <- dplyr::rename(tb, random = rand)
```

```
In [31]: dplyr::mutate(tb, random_8plus = ifelse(random >= 8, TRUE, FALSE))
```

	x	y	z	random	random_8plus
1	1	a	TRUE	4.360949	FALSE
2	2	b	FALSE	4.595334	FALSE
3	3	c	FALSE	5.492309	FALSE
4	4	d	TRUE	5.096467	FALSE

## %>% operator

- Users of `tidyverse` packages are encouraged to use pipe operator `%>%`
- It allows to chain data transformations without creating intermediate variables
- It passes the result of the previous operation as a first argument to the next
- Base R now also includes its own pipe operator `|>` but it is still relatively uncommon

```
<result> <- <input> %>%  
  <function_name>(. , arg_1, arg_2, ..., arg_n)  
  
<result> <- <input> %>%  
  <function_name>(arg_1, arg_2, ..., arg_n)
```

`%>%` operator examples



## %>% operator examples

In [32]:

tb

	x	y	z	random
1	1	a	TRUE	4.360949
2	2	b	FALSE	4.595334
3	3	c	FALSE	5.492309
4	4	d	TRUE	5.096467

## %>% operator examples

In [32]:

tb

	x	y	z	random
1	1	a	TRUE	4.360949
2	2	b	FALSE	4.595334
3	3	c	FALSE	5.492309
4	4	d	TRUE	5.096467

In [33]:

```
tb <- tb %>%  
  dplyr::mutate(random_2 = rnorm(4)) %>%  
  dplyr::filter(z == FALSE)
```

## %>% operator examples

In [32]:

tb

	x	y	z		random
1	1	a	TRUE		4.360949
2	2	b	FALSE		4.595334
3	3	c	FALSE		5.492309
4	4	d	TRUE		5.096467

In [33]:

```
tb <- tb %>%  
  dplyr::mutate(random_2 = rnorm(4)) %>%  
  dplyr::filter(z == FALSE)
```

In [34]:

tb

	x	y	z		random	random_2
1	2	b	FALSE		4.595334	-0.9099916
2	3	c	FALSE		5.492309	-0.1632015

## `%>%` operator vs built-in `|>` operator

- Since R version 4.1.0 (mid-2021), there is a built-in `|>` pipe operator

## %>% operator vs built-in |> operator

- Since R version 4.1.0 (mid-2021), there is a built-in |> pipe operator

```
In [35]: # Pipe %>% can also be used with non-dplyr functions
tb$x %>% .[2]

[1] 3
```

## %>% operator vs built-in |> operator

- Since R version 4.1.0 (mid-2021), there is a built-in |> pipe operator

```
In [35]: # Pipe %>% can also be used with non-dplyr functions
tb$x %>% .[2]
```

```
[1] 3
```

```
In [36]: # Base R pipe operator |> is more restrictive (e.g. tb$x |> `[`(2) does
tb |> nrow()
```

```
[1] 2
```

# Pivoting data

- Sometimes you want to pivot you data by:
  - Spreading some variable across columns (`tidyr::pivot_wider()`)
  - Gathering some columns in a variable pair (`tidyr::pivot_longer()`)

country	year	key	value
Afghanistan	1999	cases	745
Afghanistan	1999	population	19987071
Afghanistan	2000	cases	2666
Afghanistan	2000	population	20595360
Brazil	1999	cases	37737
Brazil	1999	population	172006362
Brazil	2000	cases	80488
Brazil	2000	population	174504898
China	1999	cases	212258
China	1999	population	1272915272
China	2000	cases	213766
China	2000	population	1280428583

table2

country	year	cases
Afghanistan	1999	745
Afghanistan	2000	2666
Brazil	1999	37737
Brazil	2000	80488
China	1999	212258
China	2000	213766

table4

`pivot_wider()`

`pivot_longer()`

Source: [R for Data Science](#)

# Pivoting data example





# Pivoting data example

```
In [37]: tb2 <- tibble::tibble(  
  country = c("Afghanistan", "Brazil"),  
  `1999` = c(745, 2666),  
  `2000` = c(37737, 80488)  
)  
tb2
```

	country	1999	2000
1	Afghanistan	745	37737
2	Brazil	2666	80488



# Pivoting data example

```
In [37]: tb2 <- tibble::tibble(  
  country = c("Afghanistan", "Brazil"),  
  `1999` = c(745, 2666),  
  `2000` = c(37737, 80488)  
)  
tb2
```

	country	1999	2000
1	Afghanistan	745	37737
2	Brazil	2666	80488

```
In [38]: tb2 <- tb2 %>%  
  # Note that pivoting functions come 'tidyr' package  
  tidyr::pivot_longer(cols = c("1999", "2000"), names_to = "year", val  
tb2
```

	country	year	cases
1	Afghanistan	1999	745
2	Afghanistan	2000	37737
3	Brazil	1999	2666
4	Brazil	2000	80488



# Pivoting data example

```
In [37]: tb2 <- tibble::tibble(  
  country = c("Afghanistan", "Brazil"),  
  `1999` = c(745, 2666),  
  `2000` = c(37737, 80488)  
)  
tb2
```

	country	1999	2000
1	Afghanistan	745	37737
2	Brazil	2666	80488

```
In [38]: tb2 <- tb2 %>%  
  # Note that pivoting functions come 'tidyr' package  
  tidyr::pivot_longer(cols = c("1999", "2000"), names_to = "year", values_to = "cases")  
tb2
```

	country	year	cases
1	Afghanistan	1999	745
2	Afghanistan	2000	37737
3	Brazil	1999	2666
4	Brazil	2000	80488

```
In [39]: tb2 <- tb2 %>%  
  tidyr::pivot_wider(names_from = "year", values_from = "cases")  
tb2
```

	country	1999	2000
1	Afghanistan	745	37737
2	Brazil	2666	80488

# Data formats in R

- `.csv` (Comma-separated value) files for storing tabular data
  - Standard file format for storing data that is highly interoperable across systems
  - Human-readable and can be opened in a simple text processor
- `.rds` (R data serialization) files allow to store single R object
  - Can store arbitrary R objects (e.g. fitted model), similar to Python `pickle`
  - Offers data compression
  - Only works within R
- `.rda` (R data) files for saving and loading multiple R objects
  - Offers data compression
  - Compares unfavourably to `rds` and, generally, should be avoided
- `.feather` / `.parquet` - big data formats associated with [Apache Hadoop](#) ecosystem
  - Cutting-edge performance (compression and read/write access)
  - Not human-readable
  - Relatively new, could be an overkill for some tasks



# Functions for data I/O

- `.csv` (Comma-separated value)
  - `read.csv()` / `write.csv()` - base R functions
  - `readr::read_csv()` / `readr::write_csv()` - functions from `readr` package in `tidyverse`
- `.rds` (R data serialization)
  - `readRDS()` / `writeRDS()` - base R functions
  - `readr::read_rds()` / `readr::write_rds()` - functions from `readr` (no default compression)
- `.rda` (R data)
  - `save()` / `load()` - base R functions
- `.feather` / `.parquet`
  - `arrow::read_feather()` / `arrow::write_feather()` - functions from `arrow`
  - `arrow::read_parquet()` / `arrow::write_parquet()` - `arrow` package in [Apache Arrow](#)

# Reading data in R example



# Reading data in R example

```
In [41]: # We are skipping the first row as this dataset has a composite header
kaggle2021 <- readr::read_csv('../data/kaggle_survey_2021_responses.csv')
```

Rows: 25973 Columns: 369

— Column specification —

---

---

---

**Delimiter:** ","

**chr** (360): What is your age (# years)?, What is your gender? -  
Selected Choi...

**dbl** (1): Duration (in seconds)

**lgl** (8): In the next 2 years, do you hope to become more fami  
liar with any...

**i** Use ``spec()`` to retrieve the full column specification for thi  
s data.

**i** Specify the column types or set ``show_col_types = FALSE`` to qu  
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iet this message.

```
In [42]: head(kaggle2021[,1:10])
```

Duration (in seconds)	What is your age (# years)?	What is your gender? - Selected Choice	In which country do you currently reside?	What is the highest level of formal education that you have attained or plan to attain within the next 2 years?	Select the title most similar to your current role (or most recent title if retired): - Selected Choice	For how ma years ha you be writing co and programmin
<dbl>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>
910	50-54	Man	India	Bachelor's degree	Other	5-10 ye
784	50-54	Man	Indonesia	Master's degree	Program/Project Manager	20+ ye
924	22-24	Man	Pakistan	Master's degree	Software Engineer	1-3 ye
575	45-49	Man	Mexico	Doctoral degree	Research Scientist	20+ ye
781	45-49	Man	India	Doctoral degree	Other	< 1 ye

# Summarizing numeric variables







# Summarizing numeric variables

```
In [43]: # Note that summary() as opposed to pandas' describe() gives summary for  
summary(kaggle2021[,1:10])
```

```
Duration (in seconds) What is your age (# years)?  
Min.      :      120      Length:25973  
1st Qu.:      443      Class :character  
Median :      656      Mode  :character  
Mean     :     11055  
3rd Qu.:     1038  
Max.     :    2488653  
What is your gender? - Selected Choice  
Length:25973  
Class :character  
Mode  :character
```

```
In which country do you currently reside?  
Length:25973  
Class :character  
Mode  :character
```

```
What is the highest level of formal education that you have at  
tained or plan to attain within the next 2 years?
```

Length:25973  
Class :character  
Mode :character

Select the title most similar to your current role (or most recent title if retired): - Selected Choice

Length:25973  
Class :character  
Mode :character

For how many years have you been writing code and/or programming?

Length:25973  
Class :character  
Mode :character

What programming languages do you use on a regular basis? (Select all that apply) - Selected Choice - Python

Length:25973  
Class :character  
Mode :character

What programming languages do you use on a regular basis? (Sel

ect all that apply) - Selected Choice - R  
Length:25973  
Class :character  
Mode :character

What programming languages do you use on a regular basis? (Select all that apply) - Selected Choice - SQL  
Length:25973  
Class :character  
Mode :character

---

# Summarizing categorical variables

# Summarizing categorical variables

In [44]: *# table() function is rather flexible in allowing to tabulate a single*  
`table(kaggle2021[3])`

	Man	Nonbinary	Prefer no
t to say			
	20598	88	
355			
Prefer to self-describe		Woman	
	42	4890	

# Summarizing categorical variables

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	Man	Nonbinary	Prefer no
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355			
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		4890	

In [45]: *# Wrapping it inside prop.table() gives proportions of each category*  
`prop.table(table(kaggle2021[3]))`

	Man	Nonbinary	Prefer no
t to say	0.793054326	0.003388134	0.0
13668040			
Prefer to self-describe	0.001617064	Woman	
		0.188272437	



# Summarizing categorical variables

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13668040			
Prefer to self-describe		Woman	
	0.001617064	0.188272437	

In [46]: *# Wrapping it inside sort() gives value sorting, as opposed to alphabetical*  
`sort(table(kaggle2021[3]), decreasing = TRUE)[1]`

**Man: 20598**

# Next

- Tutorial: Working with data in R
- Assignment 2: Due at 12:00 on Monday, 24th October (submission on Blackboard)
- Next week: Reading week
- After reading week: Python 