# An Introduction to Data Wrangling with R (or, an Introduction to R with Data Wrangling)

Rod Alence
International Relations and e-Science
University of the Witwatersrand

Workshop
Introduction to Emerging Methodologies in Social Science Research (IEMeSSR)
10–14 May 2021

# Aims of my sessions

My two sessions aim to introduce R as software for "data science" – understood to include:

1. Data "wrangling" (mainly this session)
   - Importing (possibly "messy") data into R – from text files, spreadsheets, or other statistical programs (SPSS, Stata, SAS, etc.); and
   - "Tidying" data for analysis – getting the data into a rectangular (one-observation-per-row, one-variable-per-column) format.
2. Data analysis (mainly next session)
   - Transforming data (mathematical calculations and recoding);
   - Visualizing data (graphics); and
   - Modeling data (statistics).

# Approach of my sessions

## “Learning by doing” (as much as possible)

- Start with “traditional” slides/lecture format;
- Shift to “live coding” in R/RStudio as soon as possible (technology permitting);
- Recommend options for offline self-study.

## Programming within R

- Give “non-exclusive emphasis” to Base R over Tidyverse.

  (If you have no idea what that means, don’t worry!)

# Expectations for my sessions (beyond attendance!)

## What I do not expect

- Prior experience programming in R (a bonus if you have it!);
- Mathematical expertise beyond high-school algebra.

## What I do expect

- Some prior experience using some statistical software (e.g., SPSS or Stata);
- Basic familiarity with descriptive statistics and statistical models (not beyond least-squares linear regression).

# Outline

- On learning R
- Some R basics
  - Data in R
  - Functions in R
  - Read data into R
- Data “wrangling” with R: the UNDP Human Development Index
  - Read the data into R
  - “Tidy” the data
- Self-study in R/RStudio with `swirl`
- Wrapping up

# Outline

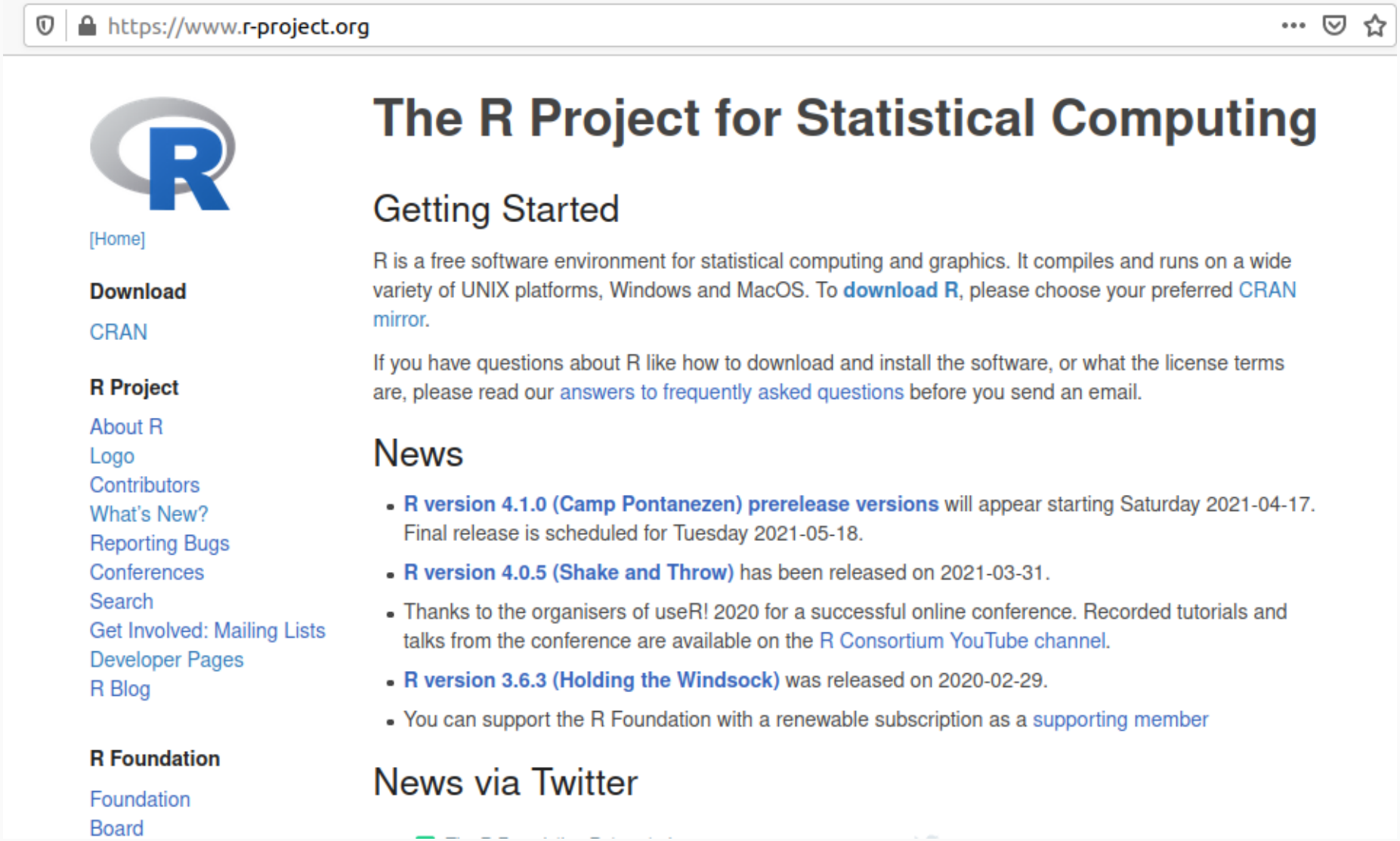
# What is R?

- Free, open-source statistical software that runs on all major operating systems;
- Created in the mid-1990s at the University of Auckland, New Zealand, by Ross Ihaka and Robert Gentleman as an implementation of the S programming language;
- Now maintained by a volunteer Core Development Team, which releases an updated version about twice a year;
- New and updated add-on “packages” appear weekly – more than 17,000 now available;
- For more information: http://www.r-project.org

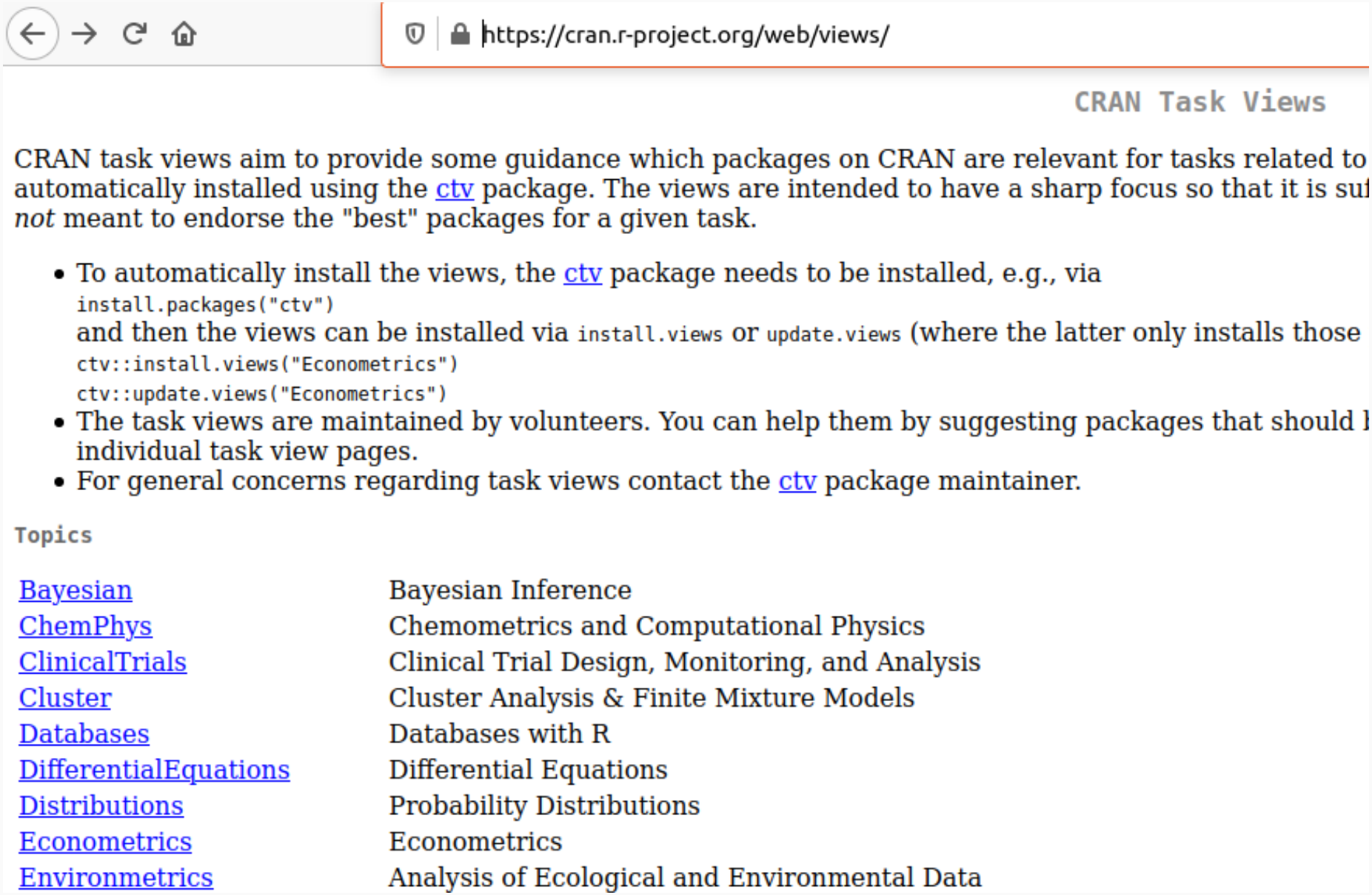
# Why R?

- Is probably the most powerful software for statistical analysis;
- Has the best graphics capabilities;
- Its package system is “going viral” (in a good way);
- Is “free” – as intellectual property and in price.

# The R Project website



# R package “task views”



# If statistics programs/languages were cars...






https://twitter.com/statsepi/status/795574223439876100

# Does R have a “steep learning curve”?

## The two most challenging things about R

1. It is entirely command (“expression”) based – you type commands, and R executes them (no “point-and-click” menus).
2. It allows multiple (unlimited) data “objects” in a session simultaneously.

## But – these features are essential to R’s strengths

- No menu system could ever keep up with software as powerful and dynamic as R.
- Allowing multiple objects is essential to a programming language in which the output of nearly any command can be the input of another.

## And... RStudio makes learning and executing R command syntax

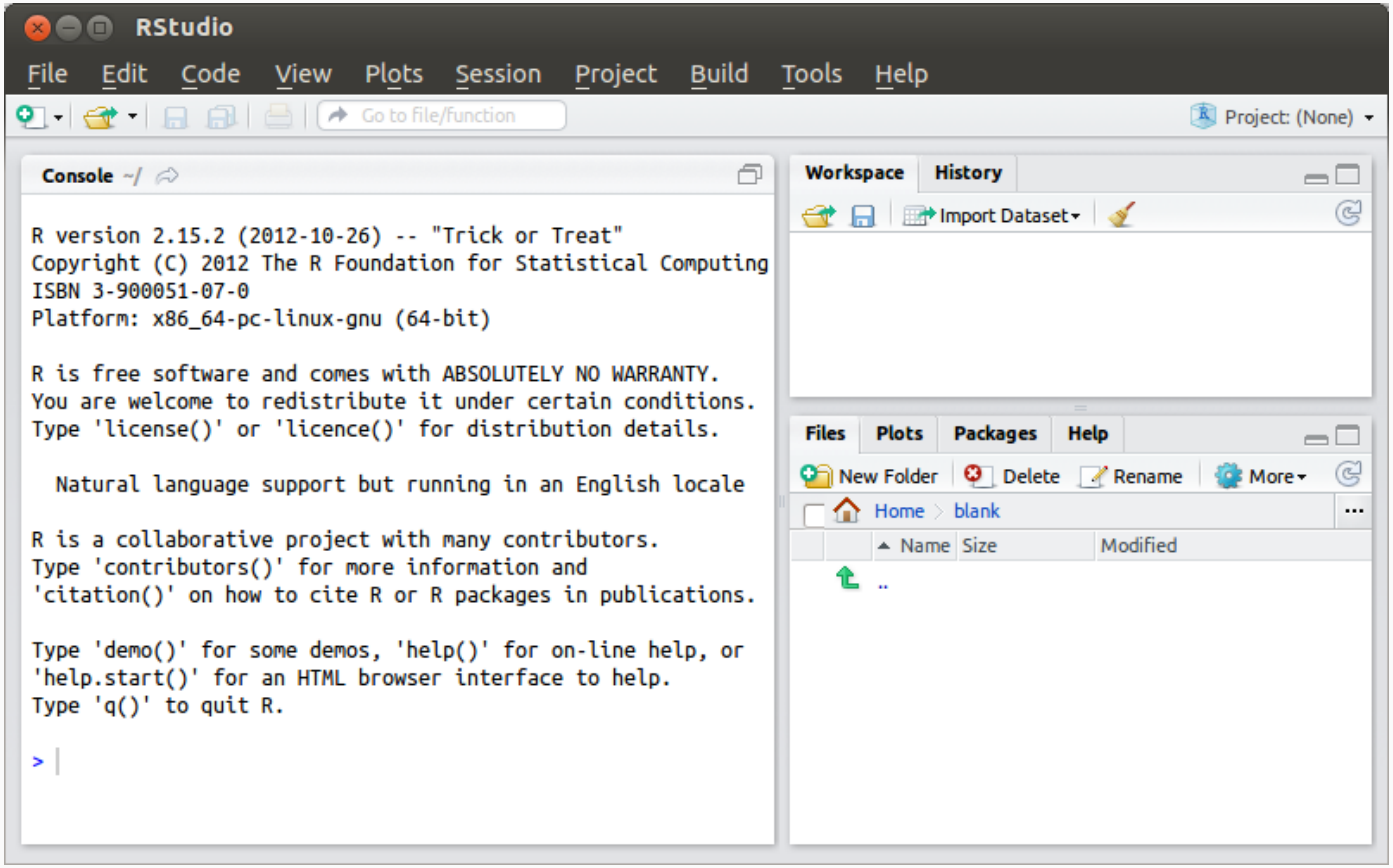
# What is RStudio?

- An “integrated development environment” (IDE) for R (but not a “point-and-click” interface to R commands);
- Launched in 2011;
- Free and open source;
- Available for all major operating systems (Windows, MacOS, and Linux);
- For more information:
  http://www.rstudio.org

# RStudio at first start-up

## Three windows

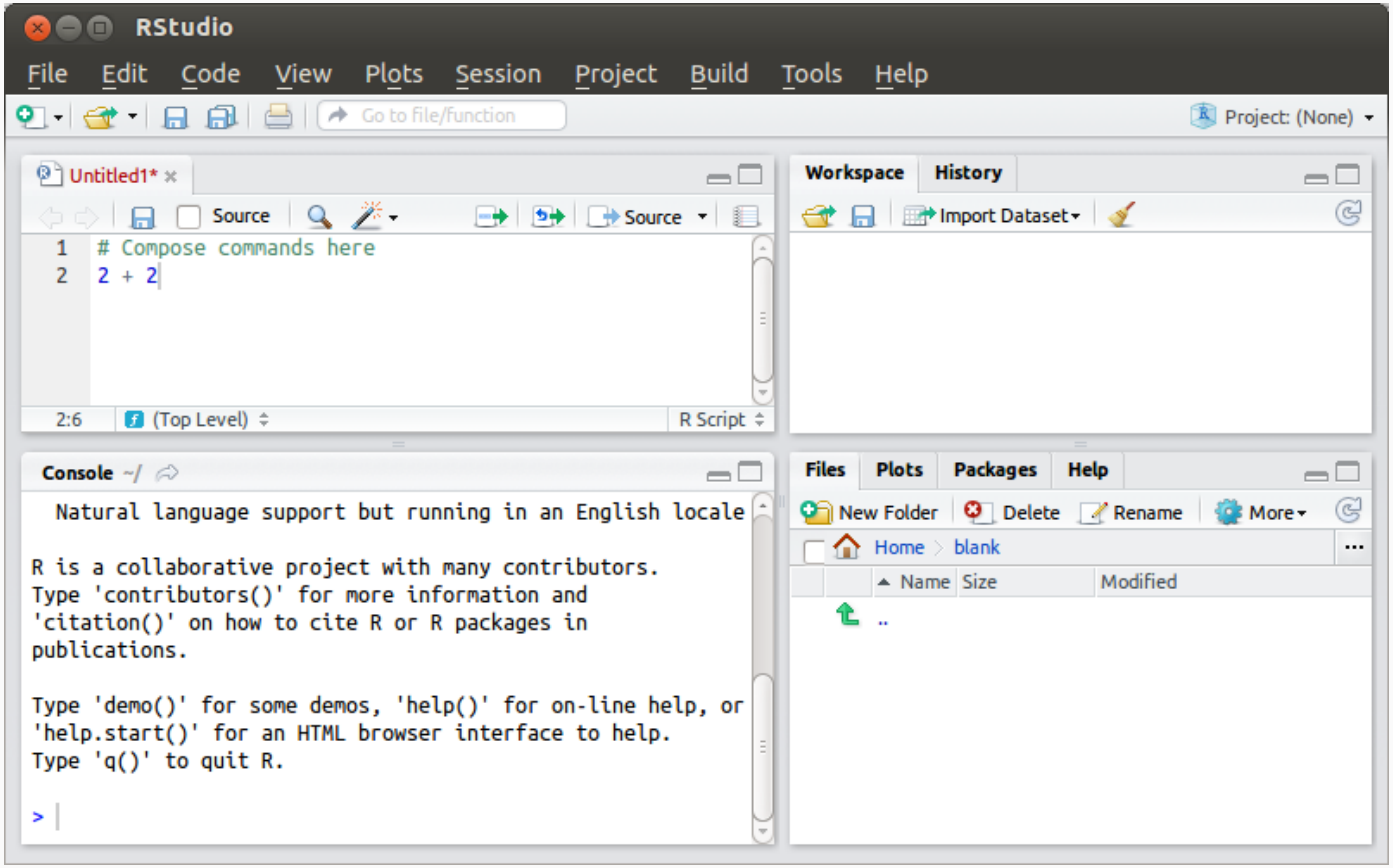
### R console occupies full left side



# RStudio with editor window open (the usual way)

## Four windows

### Left side split between editor (top) and R console (bottom)



# Outline

# Outline

# Data structures: vectors

The most basic data structure in R is the vector – which is just a fancy word for "a list of things in a particular order."

- Even a single number is a vector to R – it is a vector that happens to contain only one thing.
- When a vector holds data about units, like a column in a spreadsheet, a vector is synonymous with what is often called a "variable."
- Each vector has two intrinsic structural attributes:

  Length

  How many things (elements) does it contain?

  Mode

  What kinds of things does it contain – e.g., numeric values, typographic characters?

# Data structures: data frames

A data frame is a rectangular, spreadsheet-like data structure – typically organized with "observations" in rows and "variables" in columns.

Data frames

- May contain column vectors of any class; but
- Must contain column vectors of the same length.

The collection of packages known as the "Tidyverse" often use a special type of data frame called the tibble, which

- Has the same basic structure as the "traditional" data frame, with a few distinct features; and
- Can easily be converted to the "traditional" data frame.

# Assigning names to data

Any non-trivial “data” is assigned a name for further use, using the “backward-arrow” operator.

For example, we can “stick together” some numbers as a vector using c (for combine) and assign it a name, like `some_numbers`:

```
some_numbers <- c(1, 2, 3, 4, 5)
```

And we can do the same with some letters (in quotation marks):

```
some_letters <- c("e", "d", "c", "b", "a")
```

Assignment is “silent” – but we can check the objects’ contents by typing its name and pressing return.

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

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

# Combining vectors in a data frame

Because the two vectors assigned in the previous slide are the same length, we can stick them together side-by-side in a data frame using `data.frame`.

```
boring_df <- data.frame(some_numbers, some_letters)
```

And to view the data frame, enter its name.

```
boring_df
#   some_numbers some_letters
# 1            1            e
# 2            2            d
# 3            3            c
# 4            4            b
# 5            5            a
```

# Notes on naming

## R's rules about names

- May contain lower-case and upper-case letters, numbers, dots (`.`), and underscores (`_`).
- May not start with numbers – and they should almost always start with letters.
- Are case-sensitive – lower-case and upper-case versions of the same letter are treated as entirely different characters.
- Overwrite any existing object with the same name.

## Common sense about names

- Should be concise (to avoid too much typing).
- Should be Informative (to clarify content).

# Numeric indexing

Elements of data structures can be accessed by position using numeric square-bracket indexes.

## Vectors

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

some_letters[4]  # get the fourth element
# [1] "b"
```

## Data frames

```
boring_df
#   some_numbers some_letters
# 1            1            e
# 2            2            d
# 3            3            c
# 4            4            b
# 5            5            a

boring_df[3, 2]  # row-by-col (third row, second col)
# [1] "c"
```

# Indexing columns (variables) in data frames

Three common ways to select a (column) variable in a data frame:

1. By numeric position

```
boring_df[ , 2]  # get the second col (all rows)
# [1] "e" "d" "c" "b" "a"
```

2. By column name

```
boring_df[ , "some_letters"]  # get the col called "some_letters"
# [1] "e" "d" "c" "b" "a"
```

3. Dollar-sign (list) notation

```
boring_df$some_letters
# [1] "e" "d" "c" "b" "a"
```

# Indexing rows (observations) in data frames

Two common ways to select rows in a data frame:

1. By numeric position

```
boring_df[c(1, 3), ]  # get the first and third rows (all cols)
#   some_numbers some_letters
# 1            1            e
# 3            3            c
```

2. By logical expression

```
## Get rows in which the logical expression holds
boring_df[boring_df$some_numbers > 3, ]
#   some_numbers some_letters
# 4            4            b
# 5            5            a
```

# Outline

# Functions in R

Functions are what “do things” in R – if data objects are like nouns, functions are the verbs.

## Function syntax

To use a function:

1. Type its name (exactly, remember case-sensitivity),
2. Followed immediately by parentheses (curved brackets),
3. Insert any inputs (“arguments”) inside the parentheses, separated by commas.

Often the reason for using a function is to generate output which is immediately assigned to an object.

# An example using functions

Which two functions are used here?

```
marks <- c(78, 56, 91, 88, NA, 62, 67)  # one student was absent
class_ave <- mean(marks, na.rm=TRUE)
class_ave
# [1] 73.66667
```

Each function has a help page, which explains what the function does and what inputs it takes.

Typing a question mark followed by a function name calls up the help page. To find out what the `na.rm=TRUE` is about, try entering `?mean` in the R console.

# Outline

# Reading data into R

R has functions for reading in data in various formats, for example:

- Comma- or tab-delimited text: `read.csv` and `read.delim` in Base R, or `read_csv` and `read_tsv` in the readr package
- Spreadsheets (.xls, .xlsx): `read_excel` in the readxl package;
- Stata (.dta): `read.dta` (Stata 5-12) in the foreign package, `read.dta13` (Stata 13 onwards) in the readstata13 package, or `read_dta` (all versions) in the haven package;
- SPSS (.sav): `read.spss` in the foreign package, or `read_spss` in the haven package.

# Outline

# Setting up

## Install two packages

The installation only needs to be run once – I use the console.

```
install.packages(c("readxl", "tidyverse"))
```

## Download the data spreadsheet

The download only needs to be run once (if the data set is static).

```
## Break up the url for convenience, because it is long
site_url <- "http://hdr.undp.org/"
path_url <- "sites/default/files/"
fn_url   <- "2020_statistical_annex_table_1.xlsx"
## Paste the parts together
link_url <- paste0(site_url, path_url, fn_url)

## Download using the full url
download.file(url=link_url,
              destfile="hdi2020.xlsx")
```

# Outline

# Read in the spreadsheet (and have a quick look)

```
library(readxl)
HDI <- read_excel("hdi2020.xlsx",
                  range = "B8:K200",  # cells to read
                  col_names = FALSE,  # column names not read
                  na = c("", ".."))   # missing value strings
dim(HDI)
# [1] 193  10

head(HDI)
# # A tibble: 6 x 10
#   ...1         ...2  ...3   ...4  ...5   ...6  ...7   ...8  ...9
#   <chr>       <dbl> <lgl> <dbl> <chr> <dbl> <chr> <dbl> <chr>
# 1 VERY HIG~ NA      NA     NA   <NA>   NA   <NA>   NA   <NA>
# 2 Norway     0.957 NA     82.4 <NA>   18.1 b      12.9 <NA>
# 3 Ireland    0.955 NA     82.3 <NA>   18.7 b      12.7 <NA>
# 4 Switzerl~  0.955 NA     83.8 <NA>   16.3 <NA>   13.4 <NA>
# 5 Hong Kon~  0.949 NA     84.9 <NA>   16.9 <NA>   12.3 <NA>
# 6 Iceland    0.949 NA     83.0 <NA>   19.1 b      12.8 c
# # ... with 1 more variable: ...10 <dbl>
```

# The structure of the data frame

The data frame is still a bit “messy.”

```
str(HDI)
# tibble[,10] [193 x 10] (S3: tbl_df/tbl/data.frame)
#  $ ...1 : chr [1:193] "VERY HIGH HUMAN DEVELOPMENT" "Norway" "Ireland
#  $ ...2 : num [1:193] NA 0.957 0.955 0.955 0.949 0.949 0.947 0.945 0.
#  $ ...3 : logi [1:193] NA NA NA NA NA NA ...
#  $ ...4 : num [1:193] NA 82.4 82.3 83.8 84.9 ...
#  $ ...5 : chr [1:193] NA NA NA NA ...
#  $ ...6 : num [1:193] NA 18.1 18.7 16.3 16.9 ...
#  $ ...7 : chr [1:193] NA "b" "b" NA ...
#  $ ...8 : num [1:193] NA 12.9 12.7 13.4 12.3 ...
#  $ ...9 : chr [1:193] NA NA NA NA ...
#  $ ...10: num [1:193] NA 66494 68371 69394 62985 ...
```

# Outline

# Remove unneeded columns

## Which columns are not needed?

```
head(HDI)
# # A tibble: 6 x 10
#    ...1          ...2  ...3    ...4  ...5    ...6  ...7    ...8  ...9
#    <chr>        <dbl> <lgl> <dbl> <chr> <dbl> <chr> <dbl> <chr>
# 1 VERY HIG~ NA      NA      NA    <NA>    NA    <NA>    NA    <NA>
# 2 Norway      0.957 NA      82.4 <NA>    18.1 b       12.9 <NA>
# 3 Ireland     0.955 NA      82.3 <NA>    18.7 b       12.7 <NA>
# 4 Switzerl~   0.955 NA      83.8 <NA>    16.3 <NA>    13.4 <NA>
# 5 Hong Kon~   0.949 NA      84.9 <NA>    16.9 <NA>    12.3 <NA>
# 6 Iceland     0.949 NA      83.0 <NA>    19.1 b       12.8 c
# #  ... with 1 more variable: ...10 <dbl>
```

## Remove the “skinny” footnote columns.

```
## Use negative column indexes to remove columns
HDI <- HDI[ , -c(3, 5, 7, 9)]  # negative column index to remove

## Tidyverse alternative (dplyr package) (NOT RUN)
## HDI <- dplyr::select(HDI, -c(3, 5, 7, 9))
```

# Add meaningful column names

Add meaningful (informative and concise) names by "assigning into" the data frame's `colnames`:

```
## Old column names
colnames(HDI)
# [1] "...1"  "...2"  "...4"  "...6"  "...8"  "...10"

## Assign new column names
colnames(HDI) <- c("country", "hdi", "life_exp",
                   "school_exp", "school_mean", "gni_pc")
head(HDI)
# # A tibble: 6 x 6
#   country          hdi life_exp school_exp school_mean gni_pc
#   <chr>          <dbl>    <dbl>      <dbl>       <dbl>  <dbl>
# 1 VERY HIGH H~ NA          NA         NA           NA      NA
# 2 Norway         0.957     82.4       18.1         12.9 66494.
# 3 Ireland        0.955     82.3       18.7         12.7 68371.
# 4 Switzerland    0.955     83.8       16.3         13.4 69394.
# 5 Hong Kong, ~   0.949     84.9       16.9         12.3 62985.
# 6 Iceland        0.949     83.0       19.1         12.8 54682.
```

# Remove unneeded rows

## Which rows are not needed?

```
head(HDI, n=2)
# # A tibble: 2 x 6
#   country          hdi life_exp school_exp school_mean gni_pc
#   <chr>          <dbl>    <dbl>      <dbl>       <dbl>  <dbl>
# 1 VERY HIGH H~ NA          NA          NA          NA      NA
# 2 Norway         0.957     82.4        18.1        12.9 66494.

HDI[HDI$country == "MEDIUM HUMAN DEVELOPMENT", ]
# # A tibble: 1 x 6
#   country          hdi life_exp school_exp school_mean gni_pc
#   <chr>          <dbl>    <dbl>      <dbl>       <dbl>  <dbl>
# 1 MEDIUM HUMAN~    NA       NA          NA          NA     NA
```

## Remove rows with no numeric data (e.g., in the `hdi` column).

```
HDI <- HDI[! is.na(HDI$hdi), ]

## Tidyverse alternative (NOT RUN)
## HDI <- dplyr::filter(HDI, ! is.na(HDI$hdi))
```

# Check the data structure

Things to check:

- Dimensions (rows by columns);
- Column names;
- Object "classes" (e.g., character vs. numeric).

```
str(HDI)
# tibble[,6] [189 x 6] (S3: tbl_df/tbl/data.frame)
#  $ country    : chr [1:189] "Norway" "Ireland" "Switzerland" "Hong Ko
#  $ hdi        : num [1:189] 0.957 0.955 0.955 0.949 0.949 0.947 0.945
#  $ life_exp   : num [1:189] 82.4 82.3 83.8 84.9 83 ...
#  $ school_exp : num [1:189] 18.1 18.7 16.3 16.9 19.1 ...
#  $ school_mean: num [1:189] 12.9 12.7 13.4 12.3 12.8 ...
#  $ gni_pc     : num [1:189] 66494 68371 69394 62985 54682 ...
```

# Check the data summary

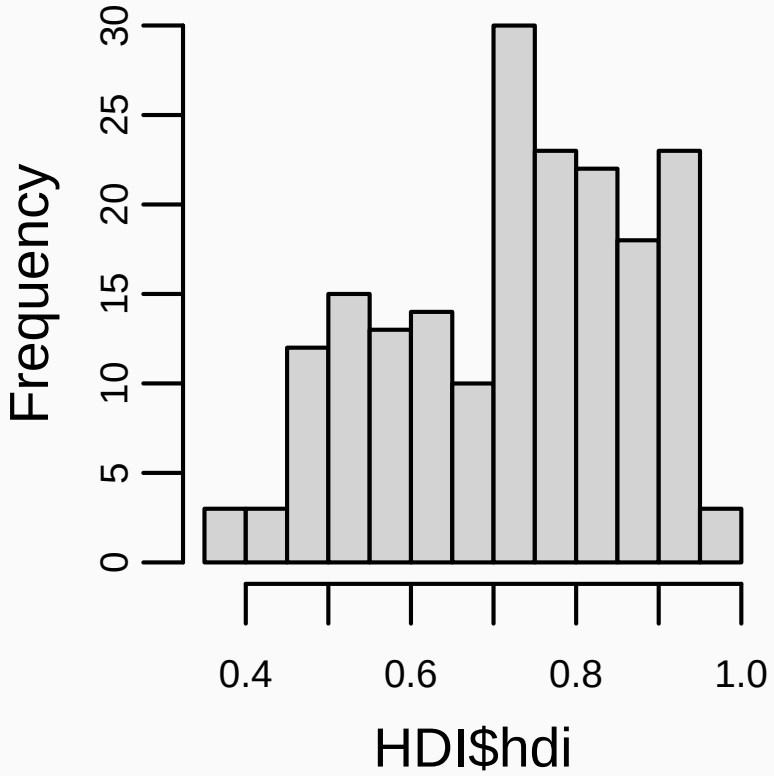
Things to check:

- Descriptive statistics;
- Missing values (NA frequencies are reported for each variable).

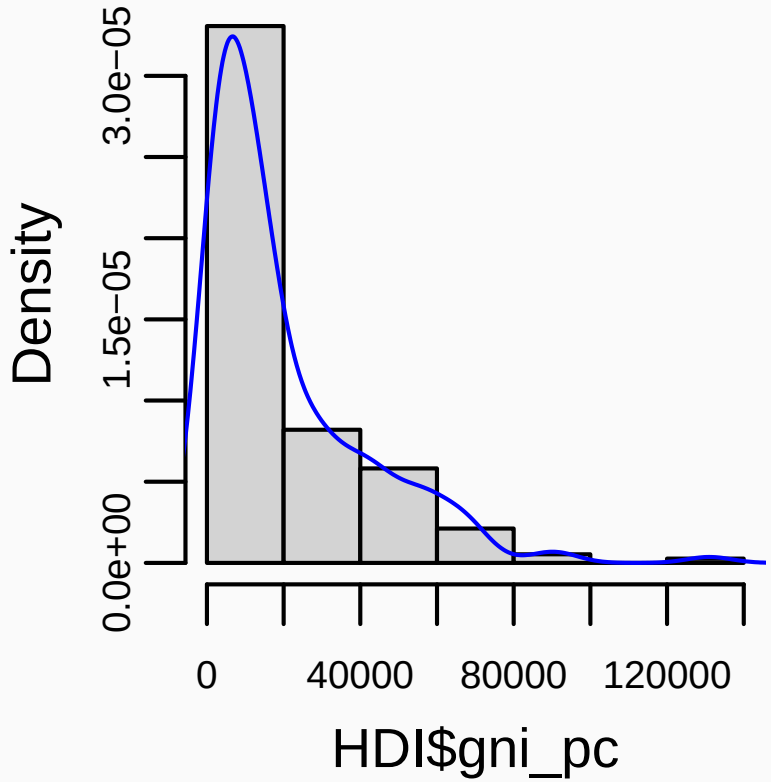
```
summary(HDI)
#    country                hdi            life_exp
#  Length:189          Min.   :0.3940   Min.   :53.28
#  Class :character    1st Qu.:0.6020   1st Qu.:67.44
#  Mode  :character    Median :0.7400   Median :74.05
#                      Mean   :0.7224   Mean   :72.71
#                      3rd Qu.:0.8290   3rd Qu.:77.91
#                      Max.   :0.9570   Max.   :84.86
#    school_exp      school_mean          gni_pc
#  Min.   : 5.005   Min.   : 1.644   Min.   :   753.9
#  1st Qu.:11.431   1st Qu.: 6.437   1st Qu.:  4910.2
#  Median :13.188   Median : 9.032   Median : 12707.4
#  Mean   :13.325   Mean   : 8.728   Mean   : 20219.7
#  3rd Qu.:15.227   3rd Qu.:11.326   3rd Qu.: 29497.2
#  Max.   :21.954   Max.   :14.152   Max.   :131031.6
```

# Run a few histograms?

```
hist(HDI$hdi,
     main="")
```




```
hist(HDI$gni_pc,
     freq=FALSE,
     main="")
lines(density(HDI$gni_pc),
      col="blue")
```



# Outline

# What is `swirl`

`swirl`

An R package that provides the infrastructure to run interactive self-study lessons, right in the R console.

(For more information: https://swirlstats.com/.)

"Introduction to R Programming"

A foundational `swirl` course consisting of 15 short lessons (work out your own pace, but most take about 15–20 minutes each).

# Install and run `swirl` courses

## Install (once-off)

```
## Install the swirl package -- the "infrastructure"
install.packages("swirl")

## Install the R programming course -- the content
swirl::install_course("R Programming")
```

## Run the course

```
## "Load" (attach) the swirl package
library(swirl)

## Run swirl
swirl()  # follow the prompts to choose a course, lessons
```

(Mostly do the courses in order, except you may want to skip the second one on “Workspace and Files” and come back to it later.)

# Outline

# Wrapping up

## Learning R

- Push ahead with the `swirl` lessons on “R Programming”;
- For further self-study, with a Tidyverse focus, try:

  Hadley Wickham and Garrett Grolemund, *R for Data Science* (O’Reilly Media, 2017) – available for free online at https://r4ds.had.co.nz/.

## For tomorrow

- Data *analysis* in R.