SOC-GA 2332 Intro to Stats Lab 1

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9/5/2025

- My office hours: Wednesday 1:00 pm - 2:00 pm in Room 352. You can directly email me to schedule a time if the above time does not work (rg4895@nyu.edu).
- Alternatively, you can send me questions over email. I tend to keep normal business hours (M-F 9am-5pm) and typically respond within 24 hours during those times.
- Plan of assignments (tentative):

Assignment	Release	Due
1	09/12/2025	09/26/2025
2	10/03/2025	10/17/2025
3	10/24/2025	11/14/2025
4	11/21/2025	12/05/2025

- Assignments will be graded on effort. Please email me in advance if you need additional time.
- Assignments will be posted on GitHub and can be turned in over email (rg4895@nyu.edu).
- Assignments will help you
  - understand key concepts in statistics using simulations
  - familiarize yourself with codings in `R`
  - prepare for the final replication project
- Using the resources at your disposal (the internet, your classmates, LLMs) is allowed and encouraged. Try to understand all the code you write yourself even if you use other resources to assist you.
- The final replication project is based on this ASR paper:
  Going Back in Time? Gender Differences in Trends and Sources of the Racial Pay Gap, 1970 to 2010, by Hadas Mandel and Moshe Semyonov

Prerequisite

- Download & install `R`: https://cloud.r-project.org/
- Download & install `RStudio`: https://rstudio.com/products/rstudio/download/

Part 1: Basics of RStudio and R Markdown

What is R & RStudio

- **R** is a free programming language commonly used for statistical programming and graphics. Download & install: https://cloud.r-project.org/
- **RStudio** is an IDE (Integrated Development Environment) for `R`. It's an application that enables you to write, run, and save your `R` code and programming outputs. Download & install: https:

//rstudio.com/products/rstudio/download/

The layout of RStudio

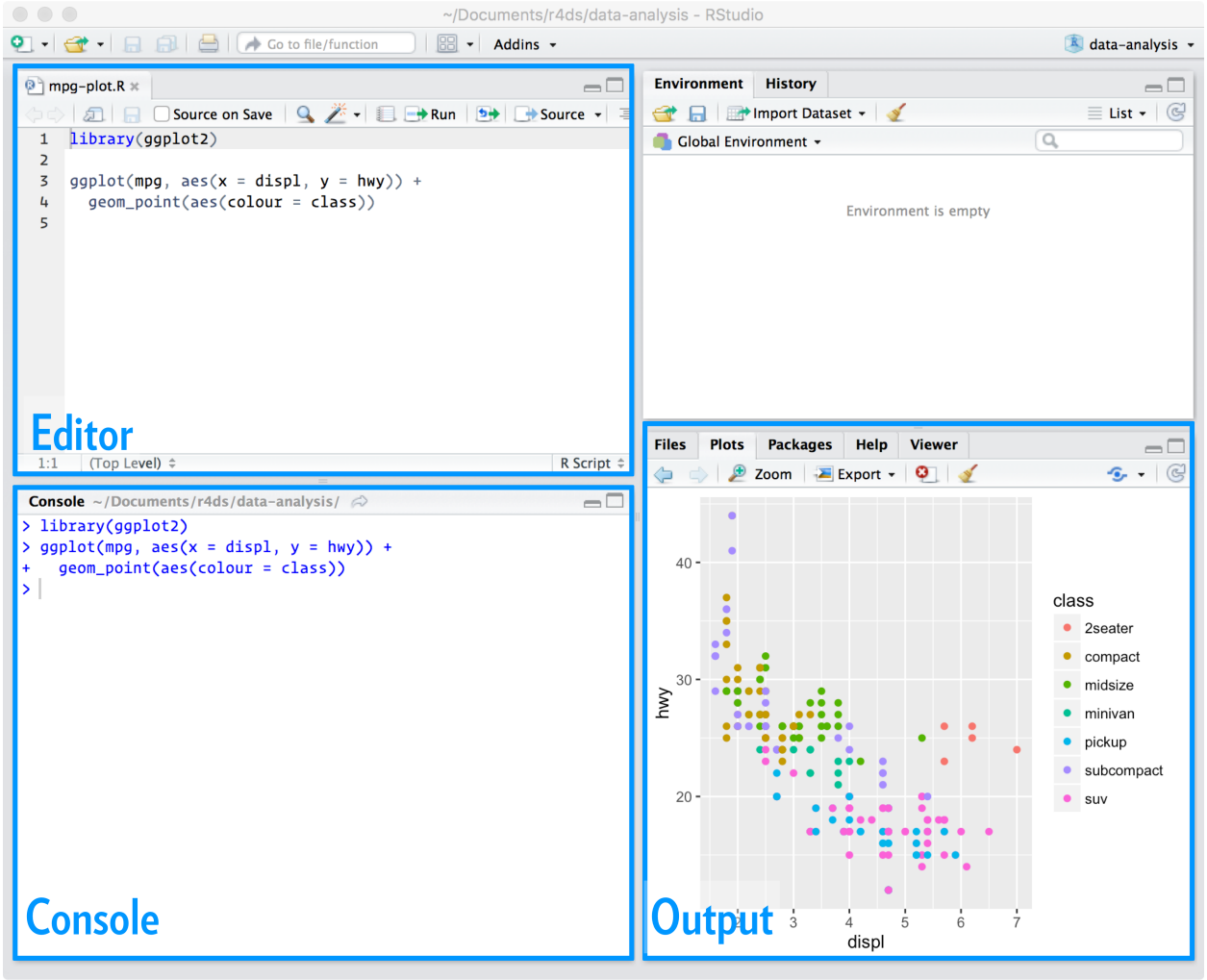


Figure 1: Layout of Rstudio (Wickham & Grolemund 2017)

Coding in R Script vs. R Markdown

- **R Script** is a simple code script document. The output of `R` script cannot be saved within the script.
- **R Markdown** is a simple formatting syntax for authoring HTML, PDF, and even Microsoft Word documents.
- Different from R Script, **R Markdown** allows users to **present both their code and the code's output (tables, plots, etc.) in a single document**, usually by "knitting" (rendering) an R Markdown to a HTML or PDF file.
- R Markdown allows you to divide your code into sections, which helps you **better organize** your code.
- R Markdown also allows you to type **mathematical equations** efficiently. Equation formats are identical to LaTeX.

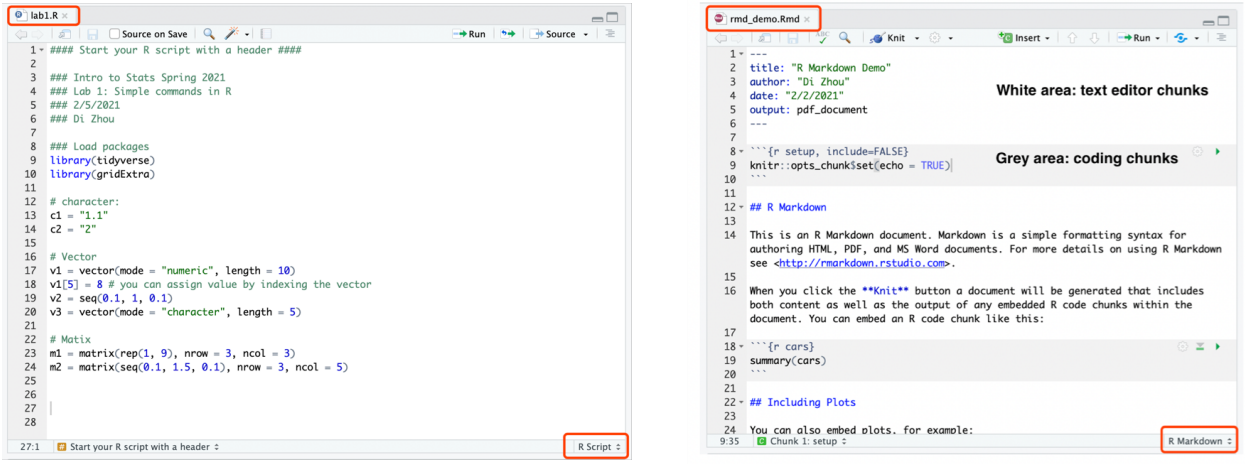


Figure 2: R Script (Left) and R Markdown (Right)

- If you are **coding for assignments, R Markdown is required**. If you are coding for simpler tasks, you can use R script.

R Markdown: Layout, the Markdown languages, and Knitting

- In a `R Markdown` file, chunks with a *white* background are *text editor* chunks. You can incorporate formatted text (including mathematical equations) using the Markdown language. Use this cheatsheet for Markdown guidance.
- Chunks with a *grey* background are *coding* chunks. You will code in these chunks. To create a chunk type "'`{r}` followed by another three tick marks.
- You can run your code by line, or by chunk. The output (if any) will be displayed after the current coding chunk.
- You can knit (export/convert) a `R Markdown` file to HTML, PDF, or Word using the `Knit` button.
- You can add a line break by hitting enter twice, or typing \, or adding `<br>`, at the end of the first line.

Setting up Folders and Projects

- Always start by creating a R project for each new coding project. This allows you to create a separate working directory, workspace settings, history, and source documents for each project you work on.
- Projects can be created by going to `File > New Project` and following the steps.
- Each time you come back to work on your code, begin by opening the project you created for it. You can tell what project you're in by looking at the R icon on your dock.
- It's helpful to create one umbrella folder for each project and (depending on the complexity of your project) subfolders for data, code, and output. Best practice is to name all your folders with no spaces or special characters (only letters, numbers, and underscores or dashes).

* Coding Practice *

Additional tips: Typing equations in R Markdown

- To type mathematical symbols and expressions, you need to follow a particular Markdown syntax. For example, to print the Greek letter α, you need to type `$\alpha$` in the text editor chunk of your `R Markdown` file.

- You don't need to memorize all of the expressions. Google or refer to this guide when you work on mathematical equations.
- To insert equations, you need to wrap your expression with the dollar sign. To type "inline equations" (equations that won't break your lines), use the dollar sign `$` to wrap your expression: `$\hat{\mu} = \frac{\sum_{i = 1}^{n}y_i}{n}$` gives: $\hat{\mu} = \bar{y} = \frac{\sum_{i=1}^{n} y_i}{n}$.

For "displayed equations" (equations that will break your lines), use the double dollar sign `$$` to wrap your expression: `$$\hat{\mu} = \bar{y} = \frac{y_1 + y_2 + y_3 + ... + y_n}{n} = \frac{\sum_{i = 1}^{n} y_i}{n}$$` gives:

$$\hat{\mu} = \bar{y} = \frac{y_1 + y_2 + y_3 + ... + y_n}{n} = \frac{\sum_{i=1}^{n} y_i}{n}$$

- In R Markdown, hovering over your equation expressions will give you a preview of the equation you write.

* Coding Practice *

Additional tips: Knitting R Markdown to HTML or PDF

- As mentioned earlier, you can knit R Markdown files to HTML, PDF, or Word.
- Before you knit, always make sure you can run your code from beginning to end. You won't be able to knit if some codes throw error messages. (We will talk about debugging later.) It's helpful to knit every so often as you're coding so that if it hits issues, it's easier to pinpoint where they're coming from.
- There are many options in R Markdown that helps you manipulate how you want to present your document. These can be manipulated for specific chunks or globally by changing the `knitr::opts_chunk$set()` command at the top of your Markdown document. For example, you can hide the code chunk and only show the output by adding `echo = FALSE` in your code chunk options. You can also use `include = FALSE` to prevent the code AND its output to appear in your knitted document. You can also use `eval = FALSE` to prevent your code from running (but it will be displayed) in your knitted document. For detailed documentation of knitting options, read here.

* Coding Practice *

Part 2: Coding in R

In this part, we will go through the basics of the `R` language, including installing packages, types of variable objects, types of data objects, and how to code a function in `R`.

1. Installing and using packages

- Assuming you are starting a new coding task, you should first open RStudio, create a project, and then create a coding file (either `R script` or `R Markdown`), and save the file to a path in your computer.
- After creating a `.Rmd` or `.R` file, you need to install and load necessary packages. A common way to do this is using `install.packages()` and `library()` so that you can use functions from other statistical packages. However, my preferred method is to use the `pacman` package's `p_load()` function.
- You only need to install packages **once**.
- For example, to use the packages `tidyverse`, `gridExtra`, and `kableExtra`, you can use one of the methods in the following code chunk:

```
# installing packages with install.packages() and library()

# after you install once, you can delete the line below and keep only the 'library' line
# install.packages(c("tidyverse", "gridExtra", "kableExtra"))
```

```r
# Load package to environment
library(tidyverse)
library(gridExtra)
library(kableExtra)

# installing packages with pacman & p_load()

# install.packages("pacman")
pacman::p_load(tidyverse,
               gridExtra,
               kableExtra)
```

2. Types of variables in R

We use R to perform data cleaning and statistical analysis. But before that, we need to have a basic understanding about how to create, save, and retrieve unit of information in R. First, we will talk about **types of variables**. This is similar but not entirely the same as the types of variables we discussed in class (categorical vs numeric). In R, types of variables is relevant because R processes different variable types differently.

- Most common data types in R:
  (i) **Logical** variable: `TRUE` (`T`) or `FALSE` (`F`)
  (ii) **Character** variable (think of the "nominal categorical variables" we covered in lecture): a string, e.g. "female", "married"
  (iii) **Numeric** variable:
    - **Integer** (think of the "discrete variables" we covered in lecture): e.g. 1L, 2L, ...
    - **Double** (think of the "continuous variables" we covered in lecture): e.g. 1.44, 3.14
    - R automatically converts between these two classes when needed for mathematical purposes.
- Variable types matter when you use different functions in R. For example, you cannot perform arithmetic (e.g. mean or median) with character variables even if they appear to be numbers.
- Check variable type using `typeof()` on the target variable or `str()` (structure) on the target dataset
- To create a variable, you give it a name first, then use either `<-` or `=` followed by the value you want to assign. E.g. `variable1 <- "female"`
- It's preferable to **leave spaces around your `<-` or `=`** so that your code is easy to read. If you want to automatically format your code you can highlight it and use `Cmd + Shift + A`.

```r
## run the following codes in your environment:

## logical
TRUE
FALSE
1 == 2 ## == tells if A equals to B; != tells if A does not equal to B

## character
c1 = "1.1"
c2 = "2"

## numeric
n1 = 1.1
```

```r
n2 = 2

## try run:
c1 + c2 ## this will throw an error message
n1 + n2

## check variable type
str(c1)
str(n1)

typeof(c1)
typeof(n1)

## you can also use is.xxx() to get a T/F for a particular data type:
is.numeric(c1)
is.numeric(n1)

is.character(c1)
is.character(n1)

is.integer(c1)
is.integer(n1)
```

3. Types of data in R

Here, data are defined as a collection of variables.

- Most common data types in R:
  - (i) ***Vectors***: A collection of elements of the same data type, e.g. logical vector, character vector, numeric vector. **In most cases, each column of a dataset (variable) is a vector**.
  - (ii) **Matrices**: A vector with two dimensions. Elements in a matrix must share the same variable type (numeric, character, etc.).
  - (iii) **Arrays**: Arrays are similar to matrices but can have more than two dimensions.
  - (iv) ***Data frames***: Similar to matrices but different columns can have different variables types (numeric, character, logical, etc.). **In most cases, this is the format of a dataset, or a collection of vectors**.
  - (v) **Lists**: An ordered collection of objects with no constraint on their variable or data types, e.g. a list of character, a list of numeric, a list of vector, a list of list, a list of a mix of logical variables, character variables, and dataframes.
  - (vi) **Factors**: A vector that is *ordered* (think of the "ordinal categorical variables" we covered in lecture). It can organize a categorical variable in a particular order for your desired ranking/ordering needs. For example, you can change a vector of educational levels `c("high school graduate", "4-year college", "some college", "below high school", "graduate or above")` to have an internal ranking `"below high school" < "high school graduate" < "some college" < "4-year college" < "graduate or above"` so that when you plot, these categories are ordered.
- Similar to variable, to create a data object, you give it a name first, then use either `<-` or `=` followed by the data object you want to assign, e.g. `vector1 <- c(1, 2, 5.3, 6, -2, 4)`.
- It's preferable to **leave space after each comma `", "`** in your code to make it easy to read.

```r
## run the following codes in your environment:

## --------- Vector --------- ##
v1 = c(1, 2, 5.3, 6, -2, 4) ## numeric vector
v2 = c("one", "two", "three") ## character vector
v3 = c(TRUE, TRUE, TRUE, FALSE, TRUE, FALSE) ## logical vector

v1[2] = 8 ## you can assign value by indexing the vector

v4 = seq(0.1, 1, 0.1) ## seq() creates a sequence (from, to, interval)
v5 <- rep(0.1, 10) ## rep() repeats an element for n times (element, n)

## check if vector
is.vector(v1)

## check length of vector
length(v1)

## vector operation
v6 = v4 + v5

## you can do basic calculations/have descriptions on vector (this is related to your assignment 1!)
sum(v1)
length(v1)


## --------- Data frames --------- ##
var1 <- c(1, 2, 3, 4)
var2 <- c("red", "white", "red", NA)
var3 <- c(TRUE, TRUE, TRUE, FALSE)
mydf <- data.frame(var1, var2, var3)
names(mydf) <- c("ID", "Color", "Passed") ## update variable names

## base R methods of data frame indexing
mydf[ , 1:2] ## columns 1, 2 of data frame
mydf[c(1,3), ] ## row 1, 3 of data frame
mydf[, c("ID", "Color")] ## columns ID and Color from data frame
mydf$Color ## variable `Color` in the data frame
mydf[, "Color"] ## variable `Color` in the data frame

## convert a vector or matrix to df
as.data.frame(v1)
```

4. What's a function

- Functions execute certain tasks. For example, the function `class(x)` is a function that tells you the type of your input variable or data object. Similarly, the function `library(lib_name)` is a function that loads a library you specified in the parenthesis to your environment.
- A function consists of a name, a set of arguments (input), and an output. The function `class(x)` has the function name `class`, and the input `x`, and will return an output -a character tells you the type of `x`. The function `library(lib_name)` has the function name `library`, the input `lib_name`, and will return an output in the form of loading the package to your environment.
- You can always learn about the structure of a function using the "Help" tab in RStudio. You can also

call the function documentation by typing `?` followed by the function name in the Console panel in RStudio. For example you can try type `?class` in the Console panel - what do you see? If you don't have the package loaded (or aren't sure) you can use `??` followed by the command.

- You can write your own functions in R using the function syntax below:

```
your_function_name <- function(input){

  # A series of actions or operations of your function
  code
  code
  code

  return(output)

}
```

- For example, write a function that add 1 to each value of an vector:

```
# function
add_one <- function(vector){
  out_vector = vector + 1
  return(out_vector)
}

# try:
add_one(v1)
```

* Coding Practice *

5. Additional Tips for Using R

- Managing your working environment:
  - (i) Keep an eye on objects in your environment. It's always easier to keep track of your work if you clear your environment every time you start a new task. In addition, by removing large data objects in your environment, R will run more smoothly.
  - (ii) To clean the working environment, I often change the environment display from `List` to `Grid`, and select the objects I want to remove, then use the little broom logo in the Environment tab. You can also use `rm(list=ls())` to clear everything in your work space, but use this with caution!
- In-line comments and other coding style suggestions:
  - (i) Make sure you comment your code (start comments with the `#` sign) **as detailed as you can**. It will help your grader, your reader, and your(future)self to understand what's going on in the code.
  - (ii) In general, it's better to be generous in spacing. Add spaces between numbers, =, commas, etc. You can start a new line after each comma (`,`) in your code, it's often possible to **break a very long line of code to multiple lines**.
  - (iii) R language is **case-sensitive**. Make sure you are using the correct function name, for example, `as.Dataframe()` instead of `as.date()`.
- Suggestions to speed up your coding process:
  - (i) Many cheat sheets can be accessed through `Help > Cheat Sheets` (or by searching on the internet).
  - (ii) Keyboard shortcuts can be very helpful to speed up your coding process. All shortcuts can be found and edited through `Tools > Global Options > Code > Modify Keyboard Shortcuts`.

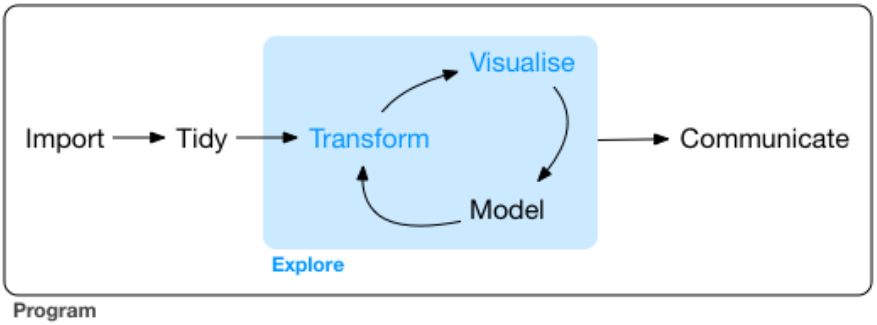
It's useful to have easy shortcuts for common actions, such as inserting a pipe, creating a new code chunk, formatting your code, arrows, etc.

(iii) Snippets are useful if there's a function you use a lot or one that has hard-to-remember formatting. These can be found and edited through `Tools > Global Options > Code > Edit Snippets`.

Part 3 Tidy Data and Tidyverse

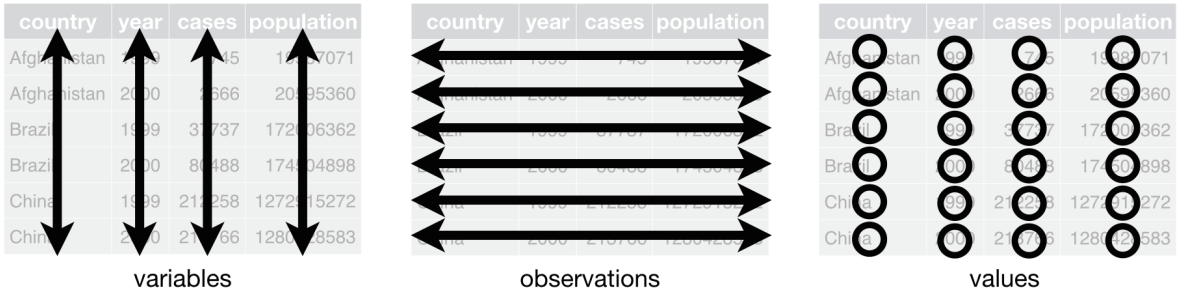
Working with Data: The Standard Workflow (Wickham & Grolemund 2017)

A typical data science project starts with data cleaning ("tidying"). In practice, we spend a lot of time just cleaning the data so that it is ready for descriptive analysis and modeling. For example, dealing with missing values, incoherent variable codings across survey years, outliers, inflations, etc.



Tidy Data

- Before doing analysis to your data, look carefully at your dataframe, and ask: **Is this a "tidy" data set?**
- In a tidy data set:
  - Each unit of observation is saved in its own row.
  - Each variable is saved in its own column.
  - Each value must have its own cell.



- Look at the following three dataframes. Which are tidy? Which are not? Why?
  - Dataframe A

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

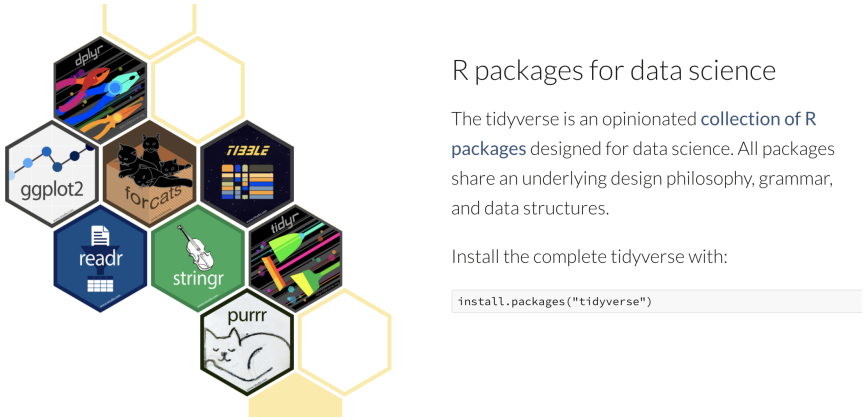
- Dataframe B

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

- Dataframe C

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

- Tidy data is a foundation for data transformation in `R` using the `tidyverse` package collection. For data cleaning, we use a lot of functions from the `dplyr` package. For plotting, we often use the `ggplot2` package. By loading `tidyverse` to your environment, you will have all these packages loaded.



Part 4 Using Tidyverse for Data Wrangling

1. Import Comma-separated files

- Comma-separated files (.csv) are the most common data files.
- Here I use the built-in function `read.csv()` to load .csv data files. Be sure to have the correct **working directory** (i.e., path of the folder where files are stored) before reading data. You can check your working directory by using the `getwd()` command and you can change it using `setwd()`.

```
## load csv files
gapminder <- read.csv("data/gapminder.csv")
tidy_df1 <- read.csv("data/tidy_example_1.csv")
tidy_df2 <- read.csv("data/tidy_example_2.csv")
```

- You can also use the `janitor::clean_names()` function to "clean" variable names, meaning take out any spaces and make everything lowercase separated by underscores. This is totally optional, but I find it helpful so you don't have to remember how specific variable names are formatted.

```
# load janitor package
pacman::p_load("janitor")

# creating a version of gapminder with clean variable names
```

```r
clean_gapminder <- clean_names(gapminder)

# looking at the new column names vs. the old ones
colnames(gapminder)
```

```
## [1] "country"   "continent" "year"      "lifeExp"   "pop"       "gdpPercap"
```

```r
colnames(clean_gapminder)
```

```
## [1] "country"    "continent"  "year"       "life_exp"   "pop"
## [6] "gdp_percap"
```

2. Browse data in R

- You can click the little table logo next to your data object in the `Enviornment` panel to view data, or type `View(data_object)` in the R Console. (Be careful about doing this with huge datasets!)
- Common things to check about your data:
  - Sample size, i.e. number of observations: `nrow(data_object)`
  - Number of varibles: `ncol(data_object)`, and names of variables: `colnames(data_object)`
  - Alternatively, `dim(data_object)` gives both the number of observations and the number of variables.
  - Summary statistics of each variable: `summary(data_object)`
  - Type of data of each variable: `str(data_object)`
- You can also view the first and last several rows of your data: `head(data_object)`, `tail(data_object)`

```r
## view data in a pop-up window
View(gapminder)

## summary statistics by variable
summary(gapminder)

## variable names
names(gapminder)

## number of rows and columnes
nrow(gapminder)
ncol(gapminder)
dim(gapminder)

## check first several observations
head(gapminder)
head(gapminder, n = 10)

## check last several observations
tail(gapminder, n = 5)

## check mean, variance, sd, sum, length of a variable (column)
## note that var and sd function in R uses n-1 as the denominator
mean(gapminder$lifeExp)
var(gapminder$lifeExp)
sd(gapminder$lifeExp)
sum(gapminder$lifeExp)
length(gapminder$lifeExp)
```

3. Basic `tidyverse` command

- We are going to use functions from the `dplyr` package under the `tidyverse` package collection.
- `dplyr` has a "pipeline" structure, where start from a dataframe and use the pipe `%>%` command to lay out the actions you want to take to that object.
- Using pipes and tidyverse commands is called "tidy R" (as opposed to "base R" coding). I would suggest using tidy R whenever possible: it's easier to read and more common among R coders.
- Let's start with the following basic commands for manipulating data frame:

(i) Pick observations by their values `filter()`
(ii) Reorder the rows `arrange()`
(iii) Select/index observations `slice()`
(iv) Pick variables by their names `select()`
(v) Rename variables by `rename()`
(vi) Create new variables with functions of existing variables `mutate()`

```
## ---------- filter ---------- ##

## filter only Asian countries:
gapminder %>% filter(continent == "Asia")

## "or": filter observations whose continent equals either Asia or Americas
gapminder %>% filter(continent == "Asia" | continent == "Americas")

## "or": Instead of using | , you can also use %in% followed by a value vector
gapminder %>% filter(continent %in% c("Asia", "Americas"))

## "and": filter observations that satisfy both conditions
gapminder %>% filter(continent == "Asia" & year == 2007)

## negation: not equal to
gapminder %>% filter(continent != "Asia")

## negation: filter values that's not equal to any value included in the vector
gapminder %>% filter(!(continent %in% c("Asia", "Americas")))

## combine "and" and Negation:
gapminder %>% filter(continent == "Asia" & year != 2007)

# Filter only 2007 data:
gapminder %>% filter(year == 2007)
```

```
## save data as a new data object
gapminder_2007 <- gapminder %>% filter(year == 2007)
```

- It's good practice to save your dataframe under a new name everytime you modify it. This is helpful so that you don't get confused about which dataframe is being referenced if you run your code out of order, and it allows you to use every version of your dataframe as needed.

```
## ---------- arrange ---------- ##

## arrange() helps you sort observations
## sort by GDP per capita, from lowest to highest
```

```r
gapminder_2007 %>% arrange(gdpPercap)

## sort by GDP per capita, from highest to lowest
## use the desc() function to your variable to sort in descending order
gapminder_2007 %>% arrange(desc(gdpPercap))
```

```r
## ---------- select ---------- ##

## select desired variables by name
gapminder %>% select(country, pop)

# You can deselect using - before column name
gapminder %>% select(-country, -pop)
```

```r
## ---------- rename ---------- ##
gapminder %>% rename(gapminder, population = pop) ## new name = old name
```

```r
## ---------- mutate ---------- ##

## create new variables using "mutate"
gapminder %>%
  mutate(gdpPercap_in_thousand = gdpPercap/1000,
       gdp = pop * gdpPercap,
       log_gdp = log(gdp), ## natural log
       log2_gdp = log2(gdp),
       id = row_number())  ## create id by row number
```

```r
## ---------- pipeline ---------- ##

gapminder %>%
  filter(year == 2007) %>%
  arrange(desc(gdpPercap)) %>%
  slice(1:5)
```

* Coding Practice *

5. Make untidy data tidy

- In many cases, data are untidy.
- One typical example is that the data is in a long format, with a single column containing multiple variable values.
- What if it's not tidy?
  - There are two `pivot` functions in `tidyverse` that help you make untidy data tidy.
  - `pivot_longer()` helps you to bring the information in the column names to being values in a single column.
  - `pivot_wider()` does the opposite
- Remember what count as tidy **depends on your questions**, specifically, what counts as **an observation** in your study.

```r
## observe the data structure of the two untidy examples
View(tidy_df1)
View(tidy_df2)

## for `tidy_df2`, we need "cases" and "population" to have their own columns
```

```r
tidy_df2 %>%
  pivot_wider(names_from = type,
              values_from = count)

## we can save clean df as a new object
tidy_clean <- tidy_df2 %>%
  pivot_wider(names_from = type,
              values_from = count)

## and export as .csv to your data folder
write.csv(tidy_clean, "tidy_clean.csv", row.names = F)

## for df1, we need to first bring years from column names to a variable
## then put values of "cases" and "population" in two columns

tidy_df1 %>%

  ## bring years from column names to a variable
  pivot_longer(cols = c(year_1999, year_2000),
               names_to = "year",
               values_to = "count") %>%

  ## remove "year_" prefix in the year variable
  mutate(year = str_remove(year, "year_")) %>%

  ## put values of "cases" and "population" in two columns
  pivot_wider(names_from = type,
              values_from = count)
```

6. Summarise and group data

- The `summarise()` function collapses many values down to a single summary, e.g. mean, median, standard deviation, max, min, etc.
- The `group_by()` function creates a grouped copy of a table, thus you can apply various functions to each group.
- Combining `group_by()` with `summarise()`, you can get various **descriptive statistics** for your data, either for the entire dataset, or by group (e.g. groups by gender, race, education level, etc.).

```r
## example for summarise()
gap_summary <- gapminder %>%
  filter(year == 2007) %>%
  summarise(avg_life = mean(lifeExp))

## example for combining group_by() and summarise()
gap_summary2 <- gapminder %>%
  filter(year == 2007) %>%
  group_by(continent) %>%
  summarise(avg_life = mean(lifeExp))


## you can get many different summary statistics for each group using summarise()
gap_summary3 <- gapminder %>%
  filter(year == 2007) %>%
```

```
  group_by(continent) %>%
  summarise(year = 2007,
            n_country = n(),
            max_gdpPercap = max(gdpPercap),
            min_gdpPercap = min(gdpPercap),
            mean_gdpPercap = mean(gdpPercap),
            sd_gdpPercap = sd(gdpPercap))

gap_summary3
```

- Whenever there are NA values (meaning some values are not available in a column), it is necessary to add `, na.rm = TRUE` in function. For example,

```
gapminder %>%
  filter(year == 2007) %>%
  group_by(continent) %>%
  summarise(avg_life = mean(lifeExp, na.rm = TRUE))
```

* Coding Practice *

Part 5 Preparations for Assignment 1

- In lecture, we talked about the difference between population and sample, and population parameter and sample statistic.
- We can simulate some of the concepts using `R`, as `R` can "randomly" sample from a hypothetical "population".

```
## set randomization "seed"
## this is to ensure you can replicate results,
## even if population creation and sampling is "randomized"
set.seed(3636)

## create a hypothetical population where samples can be drawn
pop <- runif(n = 100000, min = 0, max = 1) ## a uniform distribution (r unif)
## other options include normal distribution: rnorm(n, mean, sd)

## sample from the population
sample <- pop %>%
  sample(size = 100, replace = FALSE) ## sample without replacement

## calculate the sd of the sample (R uses n-1 as the denominator)
sd(sample)
```

- We know from lecture that the sample SD has a different form from the population SD.
- The reason why we have $n-1$ as the denominator is that it gives an **unbiased** estimation of the population SD.
- We can simulate this conclusion using R.

```
## create an empty vector to store sample SDs (200 simulations)
sd_vector_n_1 <- rep(NA,200)
sd_vector_n <- rep(NA,200)

## "loop" or repeat the sampling process for 200 times
set.seed(3636)
for (i in seq(1, 200, 1)) {
```

```r
  sample <- sample(pop, size = 100, replace = FALSE) ## sample without replacement
  sd_vector_n_1[i] <- sd(sample)
  sd_vector_n[i] <- sd(sample) * (100 - 1) / 100
}

## the population sd
pop_sd <- sd(pop) * (length(pop) - 1) / length(pop)

## which one is closer
mean(sd_vector_n) - pop_sd
mean(sd_vector_n_1) - pop_sd
```