Introduction to R - Young Researchers Fellowship Program

Lecture 2 - Introduction to the tidyverse and data importing

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The tidyverse or how modern R code is being written

Tidy data

Tidying your data means storing it in a consistent form that matches the semantics of the dataset with how it is stored (Wickham et al, 2023)

- Tidy data is a standard way of mapping the meaning of a dataset to its structure.
- A dataset is messy or tidy depending on how rows, columns, and tables are matched up with observations, variables, and types.
- In tidy data:
  - Each variable forms a column.
  - Each observation forms a row.
  - Each type of observational unit forms a table.

Who came up with this?

- Hadley Wickham introduced the concept of tidy data in his paper "Tidy Data" published in the Journal of Statistical Software in 2014.
- In the R for Data Science book (R4DS), the tidyverse is introduced as a collection of R packages designed to tidy data and work with it in a data science context.
- The tidyverse philosophy revolutionized the way R code is written and data is handled, making it more efficient and easier to understand.

The data science vs. the research perspective

- According to Hadley Wickham, *data science is an exciting discipline that allows you to transform raw data into understanding, insight, and knowledge*.
- This means we need not be afraid that the tidyverse will make us lose the ability to do research.
    - In this view, data science is not only predictive modeling.

The tidyverse steps in a data science project

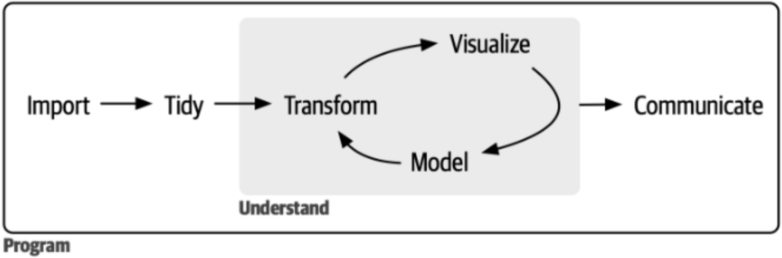


Figure 1: Tidy steps in Data

Source: R for Data Science by Wickham, Cetinkanya-Rundel & Grolemund (2023)

The tidyverse steps in a research project

1. **Import**: read data from a file or database.
2. **Tidy**: transform the data into a format that makes it easy to work with.
3. **Transform**: perform operations on the data to create new variables or summaries.

(together, transform and tidy are often referred to as wrangling - it feels like a wrestling match sometimes!)

4. **Visualize**: generate static graphics for exploratory data analysis.
5. **Model**: fit quantitative models to understand relationships between variables, complementary to visualization.
6. **Communicate**: generate reports or dashboards, or create a Shiny app. The most important step!

Where does programming fit in?

- Programming is an outer step in the process as it will be used all along the way.
- We use programming to automate the steps in the process and solve problems effectively.

The tidyverse packages

- The tidyverse is a collection of R packages that share an underlying design philosophy, grammar, and data structures.
- The packages in the tidyverse are designed to work together, and it is easier to learn them together.

The core tidyverse packages

- **ggplot2**: for data visualization.
- **dplyr**: for data manipulation.
- **tidyr**: for data tidying.
- **readr**: for data import.
- **purrr**: for functional programming.
- **tibble**: for tibbles, a modern reimagining of data frames.
- **stringr**: for strings.
- **forcats**: for factors.

Installing the tidyverse

- We install them all at once through the `tidyverse` package, which is a meta-package that installs the core tidyverse packages.

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

Importing data

Importing data with the tidyverse

- The `readr` package is part of the tidyverse and provides a fast and friendly way to read rectangular data.
    - "Rectangular data" is data that is organized into rows and columns.
    - This is data that appears in a `data.frame` in R, and stored in `.csv`, `.tsv`, or `.txt` files.
    - Other types of data, like spatial data, are not rectangular and are not handled by `readr`.
- The base R `read.csv()` function is also used to read data, but `readr` is faster, more user-friendly, and offers a greater range of possibilities for data loading.

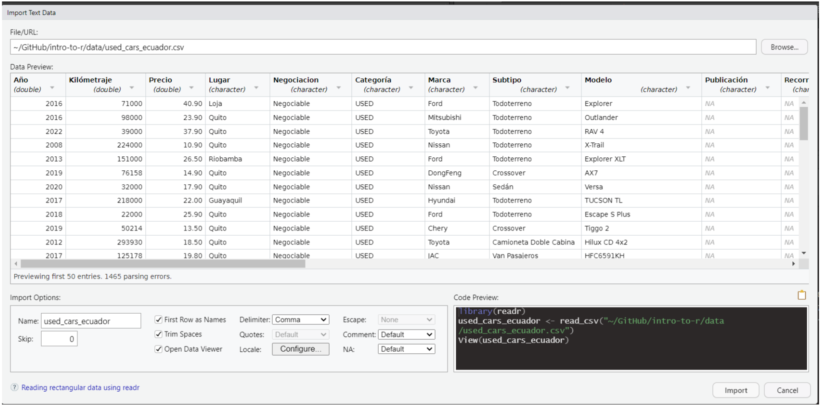
The Ecuadorian used cars dataset

- Kaggle is a platform for data science competitions and datasets.
- The dataset we will use for loading is the Ecuadorian used cars dataset.
- The dataset contains information about used cars in Ecuador, such as the brand, model, year, price, and more
  - It was obtained by scraping the patiotuerca.com website.

Importing data with the Import button in RStudio

- RStudio has a built-in feature to import data from a file.
- You can click on the "Import Dataset" button in the Environment pane and select the file you want to import.
    - Loads different types of files, such as `.csv`, `.tsv`, `.txt`, `.xlsx`, and more, based on different packages
    - Loads the data into your environment as a `data.frame`, and generates the code to do so.
- Recommended for beginners as they learn the syntax for the `readr` package.

Importing data with the Import button in RStudio



Import Text Data

File/URL: ~/GitHub/intro-to-r/data/used_cars_ecuador.csv

Data Preview:

Año (double)	Kilómetraje (double)	Precio (double)	Lugar (character)	Negociacion (character)	Categoría (character)	Marca (character)	Subtipo (character)	Modelo (character)	Publicación (character)	Recorr (char
2016	71000	40.90	Loja	Negociable	USED	Ford	Todoterreno	Explorer	NA	NA
2016	98000	23.90	Quito	Negociable	USED	Mitsubishi	Todoterreno	Outlander	NA	NA
2022	39000	37.90	Quito	Negociable	USED	Toyota	Todoterreno	RAV 4	NA	NA
2008	224000	10.90	Quito	Negociable	USED	Nissan	Todoterreno	X-Trail	NA	NA
2013	151000	26.50	Riobamba	Negociable	USED	Ford	Todoterreno	Explorer XLT	NA	NA
2019	76158	14.90	Quito	Negociable	USED	DongFeng	Crossover	AX7	NA	NA
2020	32000	17.90	Quito	Negociable	USED	Nissan	Sedán	Versa	NA	NA
2017	218000	22.00	Guayaquil	Negociable	USED	Hyundai	Todoterreno	TUCSON TL	NA	NA
2018	22000	25.90	Quito	Negociable	USED	Ford	Todoterreno	Escape S Plus	NA	NA
2019	50214	13.50	Quito	Negociable	USED	Chery	Crossover	Tiggo 2	NA	NA
2012	293930	18.50	Quito	Negociable	USED	Toyota	Camioneta Doble Cabina	Hilux CD 4x2	NA	NA
2017	125178	19.80	Quito	Negociable	USED	JAC	Van Pasajeros	HFC6591KH	NA	NA

Previewing first 50 entries. 1465 parsing errors.

Import Options:

Name: used_cars_ecuador
Skip: 0

☑ First Row as Names
☑ Trim Spaces
☑ Open Data Viewer

Delimiter: Comma
Quotes: Default
Locale: Configure...
Escape: None
Comment: Default
NA: Default

Code Preview:

```
library(readr)
used_cars_ecuador <- read_csv("~/GitHub/intro-to-r/data
/used_cars_ecuador.csv")
View(used_cars_ecuador)
```

Figure 2: Import data in RStudio

Steps after importing data

- After importing the data, you should:
  - Check the structure of the data with `str()`.
  - Check the first few rows of the data with `head()`.
  - Check the last few rows of the data with `tail()`.
  - Check the summary of the data with `summary()`.
- A tidyverse function, loaded from the `dplyr` package, is `glimpse()`, which provides a more detailed view of the data.
- Further, using `janitor::clean_names()` will clean the column names.
  - This is a function from the `janitor` package, which is not part of the tidyverse but is useful for cleaning data.
  - Spanish names often have accents, which can be problematic for programming and technically invalid.
- Not using `clean_names()` would require the use of the apostrophe to refer to the columns.

Reading Microsoft Excel files

- Plenty of packages deal with Excel files in R, but the `readxl` package is part of the tidyverse and is the recommended package for reading Excel files.
    - Alternatives are the `openxlsx` and `writexl` packages.
- The `readxl` package is fast and user-friendly, and it can read `.xls` and `.xlsx` files.
- The `readxl` package has two main functions: `read_excel()` and `excel_sheets()`.

Reading Microsoft Excel files

- The `read_excel()` function reads an Excel file and returns a `tibble` or a `data.frame`.
- Will also work with the import button in RStudio.
- Might need to pre-clean the loaded data by skipping columns, rows, or specifying the range of cells to read.

Reading Microsoft Excel files - SUPERCIAS Companies' Directory

- The SUPERCIAS Companies Directory is a dataset that contains information about companies registered in Ecuador.
- Requires skipping the first 4 rows.

```r
library(readxl)
library(dplyr)

# Read the Excel file

supercias <-
    read_excel("data/directorio_companias_supercias.xlsx",
               skip = 4)
```

Reading other types of files

- The `readr` package has a set of functions that are used to read different types of files:
  - `read_csv()`: reads comma-separated files.
  - `read_tsv()`: reads tab-separated files.
  - `read_delim()`: reads in files with a custom delimiter (common for `.csv` files with ; delimiters)
  - `read_fwf()`: reads in fixed-width files.
  - `read_table()`: reads in files with a custom column separator.
- For data coming from statistical software, the `haven` package is a tidyverse package that reads in `.dta`, `.sav`, and `.sas` files.
  - SPSS files might come in `.sav` or `.por` formats.
  - SAS files might come in `.sas7bdat` or `.xpt` formats.
  - Stata files might come in `.dta` format.
- More complex files, like JSON, XML, and HTML, can be read in with the `jsonlite`, `xml2`, and `rvest` packages, respectively.

Tidyverse fundamentals: tibbles and `dplyr`

The tibble: a modern data frame

- The `tibble` is a modern reimagining of the `data.frame` in R.
- It is part of the tidyverse and is used to store rectangular data.
- It is more user friendly, as when you print a `tibble`, it only shows the first 10 rows and the columns that fit on the screen.
- Other differences are that `tibble` does not convert strings to factors by default, and it does not use row names.

The tibble: a modern data frame

- We can transform a data frame into a tibble with the `as_tibble()` function.
- The `tibble` package is part of the tidyverse, so you do not need to install it separately if you've installed it.

dplyr: plying data into shape with the tidyverse

- The dplyr could be considered as the most important package in the tidyverse, used for the transform part of the tidy process.
- Provides a set of functions that perform common data manipulation operations such as filtering, selecting, mutating, summarizing, and arranging.
- dplyr brings with itself a grammar of data manipulation and a modern, different coding style based on the pipe operator %>% and tidyverse verbs.

The dplyr verbs or functions

Among others:

- `filter()`: to filter rows based on a condition.
- `select()`: to select columns.
- `mutate()`: to create new columns.
- `arrange()`: to reorder rows.
- `summarize()`: to summarize data.
- `group_by()`: to group data.
- `distinct()`: to select distinct rows.
- `rename()`: to rename columns.

The dplyr verbs or functions

- These are called “verbs” because they are functions that perform actions on a dataset.
- All follow the same general syntax:

```
verb(data, arguments)
```

where data is a data frame or tibble, and arguments are the arguments that the function takes.

Selecting columns with `select()`

- The `select()` function is used to select columns from a data frame.
- In base R, you would use the `$` operator to select columns or indexing with the `[ ]` operator.
- The `select()` function is more flexible and allows you to select columns based on their names or positions.

The used cars example

```
library(dplyr)

# Select columns from the cars dataset
select(cars, Precio, Lugar, Negociacion)
```

```
# A tibble: 9,021 x 3
   Precio Lugar     Negociacion
    <dbl> <chr>     <chr>
 1   40.9 Loja      Negociable
 2   23.9 Quito     Negociable
 3   37.9 Quito     Negociable
 4   10.9 Quito     Negociable
 5   26.5 Riobamba  Negociable
 6   14.9 Quito     Negociable
 7   17.9 Quito     Negociable
 8   22   Guayaquil Negociable
 9   25.9 Quito     Negociable
```

Selecting columns with select()

- You may also use the – operator to exclude columns.
- The `tidyselect()` helper functions can be used to select columns based on patterns.
  - `starts_with()`
  - `ends_with()`
  - `contains()`

Filtering rows with `filter()`

- The `filter()` function is used to filter rows based on a logical condition.
- In base R, you would use the `[ ]` operator to filter rows, or `subset()`
- The `filter()` function is more flexible and allows you to filter rows based on multiple conditions.
  - Multiple conditions go within the same `filter()` function, separated by commas.
  - These would be combined as an `AND`‘&‘ (all conditions must be met) logical operator.

The used cars example

```
# Filter rows from the cars dataset

filter(cars, Marca == "Chevrolet", Precio < 10000)
```

```
# A tibble: 1,771 x 26
     Año Kilómetraje Precio Lugar Negociacion Categoría Marca
   <dbl>       <dbl>  <dbl> <chr> <chr>       <chr>     <chr>
 1  2014      118000   14.8 Quito Negociable  USED      Chevrole
 2  2020       98000   12.4 Quito Negociable  USED      Chevrole
 3  2019       27000    8.9 Quito Negociable  USED      Chevrole
 4  2019       27000    8.9 Quito Negociable  USED      Chevrole
 5  2022        9400   16.9 Quito Negociable  USED      Chevrole
 6  2016        9000  145   Quito Negociable  USED      Chevrole
 7  2009      296000   17.9 Quito Negociable  USED      Chevrole
 8  2013      173000   18.9 Quito Negociable  USED      Chevrole
 9  2015      235621   10.9 Quito Fijo        USED      Chevrole
10  2012      170000    9.9 Quito Fijo        USED      Chevrole
```

The pipe operator %>%

- The pipe operator %>% is used to chain operations together.
- The pipe operator takes the output of the operation on the left and passes it as the first argument to the operation on the right.
  - Allows for very readable and efficient workflows!
- Think of it as an operator which facilitates the flow of composite functions in algebra.

Figure 3: The Magrittr Hex Logo

The pipe operator %>%

- As an example, consider the following code:

```
filtered_data <- filter(cars, Marca == "Chevrolet", Precio < 100

selected_data <- select(filtered_data, Precio, Marca)

selected_data
```

```
# A tibble: 1,771 x 2
   Precio Marca
    <dbl> <chr>
 1   14.8 Chevrolet
 2   12.4 Chevrolet
 3    8.9 Chevrolet
 4    8.9 Chevrolet
 5   16.9 Chevrolet
 6  145   Chevrolet
 7   17.9 Chevrolet
```

The pipe operator %>%

- This can even be done with functions that are not part of the tidyverse.

```
cars %>%
    janitor::clean_names() %>%
    filter(marca == "Chevrolet", precio < 10000) %>%
    select(ano, precio, lugar)
```

```
# A tibble: 1,771 x 3
     ano precio lugar
   <dbl>  <dbl> <chr>
 1  2014   14.8 Quito
 2  2020   12.4 Quito
 3  2019    8.9 Quito
 4  2019    8.9 Quito
 5  2022   16.9 Quito
 6  2016  145   Quito
 7  2009   17.9 Quito
```

Renaming columns with rename()

- The rename() function is used to rename columns in a data frame.
- In base R, you would use the names() function to rename columns.
- The rename() function is more flexible and allows you to rename columns based on their names.

The used cars example

```
# Rename columns in the cars dataset
cars %>%
    janitor::clean_names() %>%
    rename(price = precio)
```

```
# A tibble: 9,021 x 26
     ano kilometraje price lugar     negociacion categoria marca
   <dbl>       <dbl> <dbl> <chr>     <chr>       <chr>     <chr>
 1  2016       71000  40.9 Loja      Negociable  USED      Ford
 2  2016       98000  23.9 Quito     Negociable  USED      Mitsu
 3  2022       39000  37.9 Quito     Negociable  USED      Toyot
 4  2008      224000  10.9 Quito     Negociable  USED      Nissa
 5  2013      151000  26.5 Riobamba  Negociable  USED      Ford
 6  2019       76158  14.9 Quito     Negociable  USED      DongF
 7  2020       32000  17.9 Quito     Negociable  USED      Nissa
 8  2017      218000  22   Guayaquil Negociable  USED      Hyund
 9  2018       22000  25.9 Quito     Negociable  USED      Ford
```

Mutating columns with mutate()

- The mutate() function is used to create new columns in a data frame.
- In base R, you would use the $ operator to create new columns, based on them being a new column or a transformation of an existing column.

The used cars example

```
# Mutate columns in the cars dataset

cars %>%
    janitor::clean_names() %>%
    mutate(precio_round = round(precio, 2))
```

```
# A tibble: 9,021 x 27
      ano kilometraje precio lugar     negociacion categoria marc
    <dbl>       <dbl>  <dbl> <chr>     <chr>       <chr>     <chr
 1   2016       71000   40.9 Loja      Negociable  USED      Ford
 2   2016       98000   23.9 Quito     Negociable  USED      Mits
 3   2022       39000   37.9 Quito     Negociable  USED      Toyo
 4   2008      224000   10.9 Quito     Negociable  USED      Niss
 5   2013      151000   26.5 Riobamba  Negociable  USED      Ford
 6   2019       76158   14.9 Quito     Negociable  USED      Dong
 7   2020       32000   17.9 Quito     Negociable  USED      Niss
 8   2017      218000   22   Guayaquil Negociable  USED      Hyun
```

Transmuting

- The `transmute()` function is used to create new columns and drop the old ones.
- It is a combination of `mutate()`, followed by `select()` and is useful when you want to create new columns and drop the old ones.

The used cars example

```
# Transmute columns in the cars dataset

cars %>%
    janitor::clean_names() %>%
    transmute(anio = ano,
              precio,
              precio_round = round(precio, 2))
```

```
# A tibble: 9,021 x 3
    anio precio precio_round
   <dbl>  <dbl>        <dbl>
 1  2016   40.9         40.9
 2  2016   23.9         23.9
 3  2022   37.9         37.9
 4  2008   10.9         10.9
 5  2013   26.5         26.5
 6  2019   14.9         14.9
```

Types of pipes

- The pipe operator %>% is often called the "magrittr" pipe, named after the magrittr package that introduced it.
  - Now, it comes with the dplyr package.
- There are other types of pipes in programming languages which are used for different purposes.
  - The "forward pipe" %>% is used to pass the output of one function as the first argument of the next function.
  - The "assignment pipe" %<>% is used to pass the output of one function as the first argument of the next function, but also modifies the original input object.
  - Other advanced pipes are the "tee pipe" %T>% and the "exposition pipe" %$%.
- We typically can remain with the forward pipe %>% for most of our work.

The brand new native pipe, |>

- The native pipe operator |> was introduced in R 4.1.0 (recent).
- It remains largely the same as the magrittr pipe %>%.
  - Differences emerge in the advanced use of the pipe, such as when using the `.` placeholder.
  - Hadley discusses differences and provides recommendations in this article
- The second edition of R4DS, which we are following, has now been updated to use the native pipe.
  - Hadley claims that as beginner users of the pipe, you will be unaffected by the “change”.
  - The native pipe won’t require you to load `dplyr` to use it.
  - You may turn on the native pipe in RStudio options.

Tidyverse vs. base R - some brief comments

- The tidyverse often follows a certain style of programming that is different from base R.
- The tidyverse is typically easier to learn, but it is not the only way to write R code.
- Further, tidyverse code is often more readable and easier to understand than base R code.
  - The use of the pipe operator %>% makes the code more readable and easier to follow (i.e. more *expressive*)

Tidyverse style

- The tidyverse style is based on the following principles:
  - Use the pipe operator %>% to chain operations together.
  - Use the tidyverse functions for data manipulation.
  - Use the `tibble` data structure instead of the `data.frame`.
- In terms of how to work with tidyverse functions, typically we'll find the following:
  - The first argument is a data frame or tibble (i.e. functions are "pipeable").
  - Functions will use underscores to separate words rather than points (which is the base R style).

Writing code tidyverse style

- The tidyverse style guide[1] introduces a set of conventions for writing R code in the tidyverse style.
  - "Code linters" like `lintr` can be used to check your code against the style guide.
  - Install the `styler` package to automatically format your code according to the style guide, with a built-in RStudio GUI.

1. Use only valid names: lowercase, underscore for spacing, no dots, no spaces, no special characters.

```
# Good

this_is_a_good_name <- 10

# Bad

this.is.a.bad.name <- 10
```

[1] A helpful summary can be found in R4DS

Writing code tidyverse style

2. Use spaces to make code more readable! Put spaces on either side of mathematical operators apart from ˆ (i.e. +, −, ==, <, etc.), and around the assignment operator (<−).
    - No spaces close to parentheses
    - Ok to add spaces to help with function alignment (generally we like to align the arguments of a function call).

```
# Good

x <- 10 + 5

# Bad

x<-10+5
```

Writing code tidyverse style

3. Pipes should always have a space before it and should typically be the last thing on a line.
    - If the function you're piping into has named arguments, each of these arguments should be on a new line.
    - Indentation is used to make the code more readable.
    - For short piping workflows, it is ok to put everything on one line (i.e. exceptions to rules apply if they make sense).

```
# Good

cars %>%
    filter(marca == "Chevrolet") %>%
    select(precio, lugar) %>%
    filter(precio < 10000,
           lugar == "Quito") %>%
    mutate(precio_round = round(precio, 2),
           precio_log = log(precio))
```

Writing code tidyverse style

Base R vs. tidyverse

Cool data importing: using packages to load data from the web

- The readr package can read data from the web using the read_csv() function.
- For instance, we may read the used cars dataset from our GitHub repository using the public csv raw link.

```
# Load the cars dataset from the web

cars_web <-
    read_csv("https://raw.githubusercontent.com/laboratoriolide/
```

- The same applies for other read_*() functions in the readr package.

Cool data importing: using packages to load data from the web

- We may use the `wbstats` package to load data from the World Bank API.
- The `wbstats` package provides a set of functions to search, download, and visualize data from the World Bank API.
  - Use `wb_search()` to search for indicators.
  - Will need the indicator_id to download the data.

```
library(wbstats)

# Vector of indicators

indicators <- c(
  'inv_gdp'= 'NE.GDI.FTOT.ZS', #  Gross fixed capital formation
  'gdp_pc' = 'NY.GDP.PCAP.KD', # GDP per capita (constant 2010 U
  'gdp_g'= 'NY.GDP.PCAP.KD.ZG', # GDP per capita growth (annual
```

Downloading files from the web

- The `download.file()` function can be used to download files from the web.
- The `download.file()` function takes two arguments: the URL of the file and the path where you want to save the file.
- The `unzip()` function can be used to unzip files.

```
# Download a file from the web

options(timeout = 900)

download.file("https://mercadodevalores.supercias.gob.ec/reporte
              destfile = "data/downloads/supercias_downloaded.xl
```

Packages to access data

- Many other packages allow you to access data from the web, such as:
    - `rvest`: for web scraping.
    - `statcanR` and `cansim`: for accessing Statistics Canada data.
    - `WDI`: for accessing World Bank data, exclusively World Development Indicators.
    - `rgovcan`: for accessing open data from the Government of Canada.
    - `tidycensus`: for accessing US Census data[2]
- Can directly access data in CRAN packages too.
    - Stored data in CRAN packages can be accessed with the `data()` function.
    - The `datasets` package contains many datasets that are useful for learning R.
    - The `nycflights13` package contains information about all flights departing from New York City in 2013.
    - The `wooldridge` package contains datasets from the Wooldridge Econometrics textbook.

[2] There is plenty on accessing US Census data. See this book and this webpage for more.

APIs

- Application Programming Interfaces (APIs) are a set of rules and protocols that allow one software application to interact with another.
- APIs are used to access data from the web, and many organizations provide APIs to access their data.
- While working with APIs is a programming skill in and of itself, there are many R packages that make it easier to work with APIs.
  - The `httr` package is a low-level package for working with web APIs.
  - The `jsonlite` package is used to work with JSON data, which is a common data format used by APIs.
  - `spotifyr` is a package that allows you to access data from the Spotify API for music charts.
  - `lastfmR` is a package that allows you to access data from the Last.fm API (though not available on CRAN).
  - `geniusR` is a package that allows you to access data from the Genius API for music lyrics.