Day 2, Lecture Two: Data Management and Visualization

Andie Creel

January, 2023

1 Goal

The goal of this lecture is:

1) Learn how to set up an R Project
2) Learn best practices for file structures
3) Importing data
4) Basic data visualization with ggplot
5) Exporting results

2 Creating an R Project

2.1 What's an R Project?

An R project contains multiple scripts, your data, results you export, and any other files you have associated with that project.

R projects are an extremely useful organizational tool, and you should use them for every research project.

They act as an address for your computer to recognize that everything in that project stays together.

2.2 New R Project

1) Open R Studio
2) File/New Project… (alternatively, little clear box with R button)
3) Navigate to the file you want the r project to exist in. **Make sure you can find this again so that we can drag folders into it.**
4) Give it a short, informative name
5) Done! Notice you're top right hand corner.. you're R Studio session has loaded your R Project

Do this as a group together.

3 File Structure

- File structure can make or break a research project
  - Acts as an outline that gives you forward momentum
  - Allows your collaborators to clearly follow what you did

    - Allows you to return to a project after and quickly remember what step you were on and what remains to be done

- There are best practices for file structure that are worth following now

3.1 Best practices

Matt Wibbenmeyer (fellow at RFF) wrote a Notes on Project Management and Collaboration for RFF RAs and interns that I still use. It is worth reading and you can find it here. I share it with all my RAs and collaborators.

There will be your **project** `project/`. This is the file your R Project files lives. Everything else will be in this folder or sub folders. I typically have the following sub folders.

- `data/`
    - `raw_data/`: The original data. Do not edit this! You never know when what you originally thought was a good idea was actually bad. Always keep a copy of your original data here.
    - `clean_data/`: Where you store the clean data sets that you'll use for your models
- `scripts/`: all of the r scripts you write
    - `1_data_cleaning.R`
    - `2_descriptives.R`
    - `3_analysis.R`
    - `4_figures.R`
- `results/`: where you store final graphs and tables
- `manuscript/`: where you store your writing that (figures crossed) becomes your paper
- `presentations/`: Any presentations you prepare for the research project

In our new r project, let's create a clean and raw data, scrip, and result sub folder. You can do this with the file-green-plus button in the files tap of our bottom right corner.

4 Importing Data

You can import a lot of different data sets in a lot of different ways. The most common data sets I import are CSVs.

4.1 Note on Excel Files

I try to avoid going back and forth. Excel is useful for data entry (especially when you're collecting your data in the field). But once you're done with data collection, I would avoid going between R and Excel.

My advice would be to export your excel sheet to a csv. CSVs are more memory efficient and easier to read into R. However, if you edit the Excel file remember you'll need to re-export your csv.

Code for if you do need to read in an excel file instead of a csv.

```r
# ------------------------------------------------------------------------
# Install (only once) and load the readxl package
# ------------------------------------------------------------------------
# install.packages("readxl")
library(readxl)
```

```r
# ---------------------------------------------------------------------------
# read in an excel sheet
# ---------------------------------------------------------------------------
myData <- read_excel("raw_data/an_excel_file.xls",
                      sheet = "the_name_of_the_sheet_I_am_importing")
```

4.2 Code for reading in a CSV so you have it

There are a million ways to read in CSVs. Let's write out the code so you have it all.

```r
# ---------------------------------------------------------------------------
# Base r
#   Pro: no need to load package
#   Con: less efficient, slower, and worse at getting variable types right
#   Use case: when you have a small and simple data set
# ---------------------------------------------------------------------------
myData <- read.csv("/raw_data/an_imaginary_csv.csv")

# ---------------------------------------------------------------------------
# Tidyverse package: readr
#   Pro: faster, intuitive at predicting variables types
#   Con: Requires a package
#   Use case: almost all the time
# ---------------------------------------------------------------------------
# install.packages("readr")
library(readr)

myData <- read_csv("/raw_data/an_imaginary_csv.csv")

# ---------------------------------------------------------------------------
# Another package: vroom
#   Pro: excellent for big data
#   Con: a bit clunkier than readr
#   Use case:  big data
# ---------------------------------------------------------------------------
# install.packages("vroom")
library(vroom)

myData <- vroom("/raw_data/an_imaginary_csv.csv")
```

5 Today's example

5.1 Data Download and Clean

First step: download csv and drag it into raw_data folder.

- Here is the link: https://github.com/a5creel/intro_to_programming/blob/main/lecture_material/4_data_manage_vis/raw_data/mpg.csv
- Click the download button
- *Pull it into the `raw_data` file we created while going through file structure*

Create a script called `0_data_clean.R` in the `scripts` folder

```
# Andie Creel / Goal: data cleaning / Started: January 11 2023

# -------------------------------------------------------------------------
# load libraries
# -------------------------------------------------------------------------
library(readr) # reading in csv
library(dplyr) # data cleaning
# library(ggplot2) # if we're fighting with get data loaded

# -------------------------------------------------------------------------
# read in: reading in data is slow, so i always call it _og in case
#     I regret something later and want to return to this step
# -------------------------------------------------------------------------
myData_og <- read_csv("data/raw_data/mpg.csv")

# alternatives in case this isn't working
# myData_og <- read_csv("https://raw.githubusercontent.com/a5creel/intro_to_programming/main/lecture_ma

# data(mpg)
# myData_og <- mpg
# rm(mpg)

# -------------------------------------------------------------------------
# clean data: what we learned this morning
# -------------------------------------------------------------------------

# our research Q is:
#   - only interested in Ford, dodge and toyota
#   - not about the type of fuel "fl"
myData <- myData_og %>%
  filter(manufacturer == "ford" | manufacturer == "dodge" | manufacturer == "toyota") %>%
  select(-fl)


# write clean data
write_csv(myData, "data/clean_data/my_clean_data.csv")
```

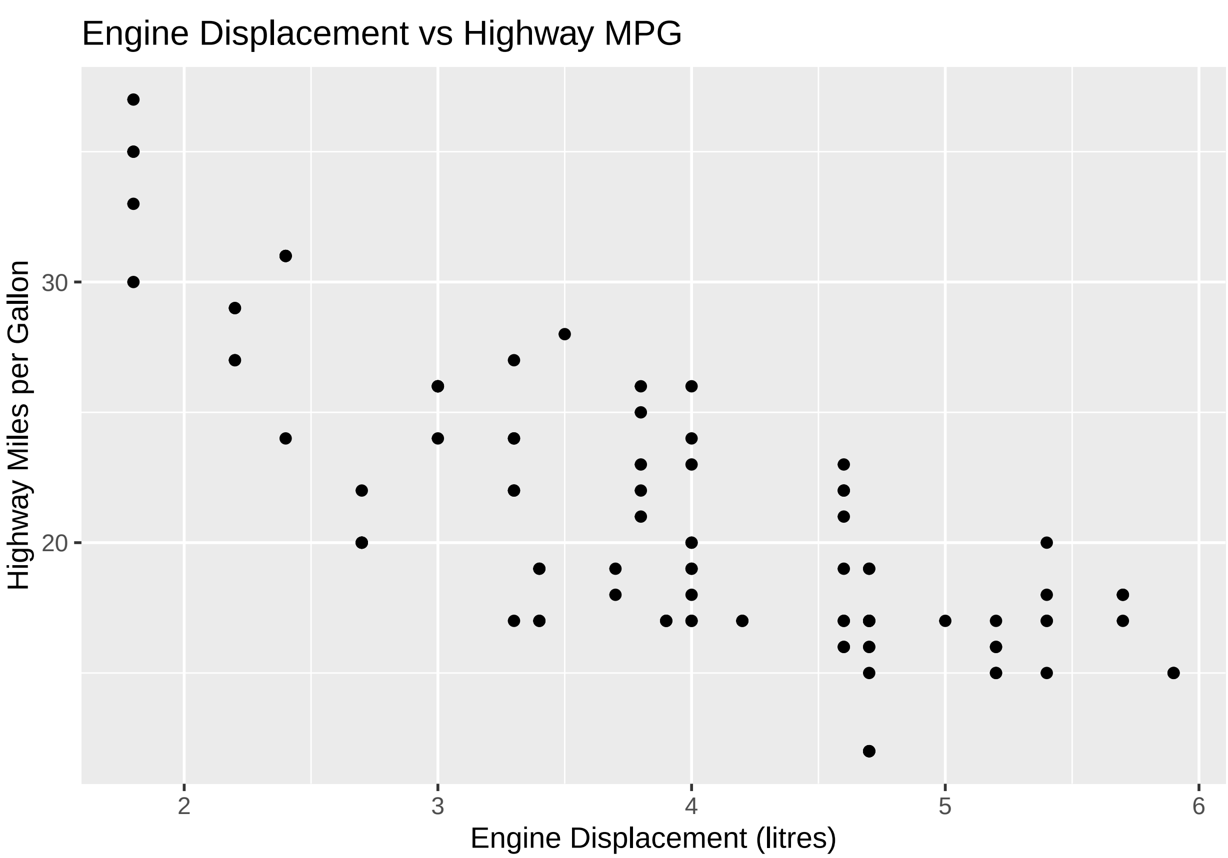
5.2 Data Vis

- Normally, you'd do some more exploratory analysis in another file
- You'd also do more data cleaning than this
- But we're going to move onto data visualization for times sake
- We'll do 4 chats together to get a feel for it
- Then we'll polish one to see the times of things we can change.

Create a `2_figures.R` script in the `scripts` folder

```
# Andie Creel / Goal: create figures / Started: January 11 2023

# -------------------------------------------------------------------------
```

```r
# load libraries
# -------------------------------------------------------------------------
rm(list = ls()) # clear work space at beginning of script
library(dplyr)
library(readr)
library(ggplot2)

# -------------------------------------------------------------------------
# read in clean data
# -------------------------------------------------------------------------
myData <- read_csv("data/clean_data/my_clean_data.csv")

# -------------------------------------------------------------------------
# Scatter plot: geom_point()
#   hwy: highway miles per gallon
#   displ: engine displacement which is approx. engine size
# -------------------------------------------------------------------------

ggplot(myData, aes(x = displ, y = hwy)) +
  geom_point() +
  labs(title = "Engine Displacement vs Highway MPG",
       x = "Engine Displacement (litres)",
       y = "Highway Miles per Gallon")
```




```r
# USE THE CHAT GPT THING TO GET THE REST TOGETHER.
```

```r
ggplot(mpg, aes(x = factor(cyl), y = hwy)) +
  geom_boxplot() +
  labs(title = "Highway MPG Distribution by Cylinder Count",
       x = "Number of Cylinders",
       y = "Highway Miles per Gallon")
```