Introduction to R for data analysis

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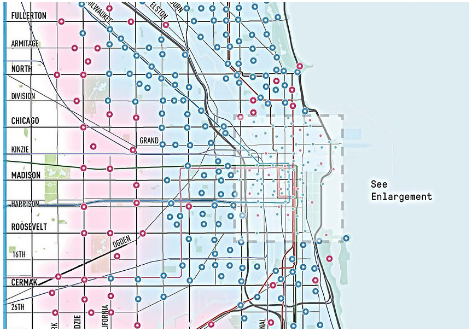


2. Aims of workshop

1. Get hands-on experience with the basic elements of data analysis in R.
2. Understand how to import data from a CSV file into an R data frame.
3. Use standard tools to summarize & manipulate data frames.
4. Learn how to install & use R packages.
5. Use ggplot2 to plot data.
6. Learn through “live coding”—this includes learning from our mistakes!

3. Our goal: Analyze Divvy data from 2016 & 2017

- Investigate bike sharing trends in Chicago.
- We will use data made available by Divvy:
  - ▷ www.divvybikes.com/system-data
- Much of the effort will be spent importing the data, inspecting the data, and preparing the data for analysis.
- Once we have carefully prepared the data, creating visualizations is (relatively) easy.

4. The programmatic approach

- Data analyses are usually *iterative* and *repetitive*. Therefore, you need to develop skills to *efficiently* create & refine your analyses.
- The *programmatic approach* to data analysis will allow us to…
  - ▷ Reuse our code to quickly create sophisticated analyses—*automation is your friend*!
  - ▷ Expand capabilities by installing new R packages.

5. It's your choice

Your may choose to…

- Use R on your laptop.
- Use RStudio on your laptop.
- Use R or RStudio on the RCC cluster.
- Pair up with your neighbour.
- Follow what I do on the projector.

6. Software we will use today

1. **R** and/or **RStudio**.
2. R packages **readr**, **ggplot2** & **cowplot**.

7. Outline of workshop

1. Initial setup.
2. Load & prepare the Divvy station data.
3. Load & prepare the Divvy trip data.
4. Create a map of the Divvy stations.
5. Create plots comparing bike sharing in 2016 & 2017.

8. Initial setup

- WiFi.
- Power outlets.
- Computer clutter.
- Workshop packet.
- Reading what I type.
- Pace, questions (e.g., keyboard shortcuts).
- Help.

9. Download or “clone” git repository

Download the workshop packet to your computer.

- Go to: **http://github.com/rcc-uchicago/R-intro-divvy**
- To download, click the green **“Clone or download”** button.

Or, if you have **git**, run this command:

```
git clone https://github.com/rcc-uchicago/
  R-intro-divvy.git
```

(Note the URL in the git command should not contain any spaces.)

- If necessary, uncompress the ZIP file.
- If necessary, rename folder to **R-intro-divvy**.

10. What's included in the workshop packet

- **slides.pdf**: These slides.
- **slides.Rmd**: R Markdown source used to generate these slides. *Copy & paste code from this file.*
- **readdivvydata.R**: Some R code used in the hands-on examples.

11. Set up your R environment

- Launch R or RStudio.

12. Run `sessionInfo()`

Check the version of R that you are using:

```
sessionInfo()
```

13. Clear your R environment

The R environment is where all variables (and functions) are stored and accessed. You should start with an empty environment. Run this:

```r
ls()
```

If this outputs names of objects, it means your environment is not empty and you should restart R with a clean environment. Do either:

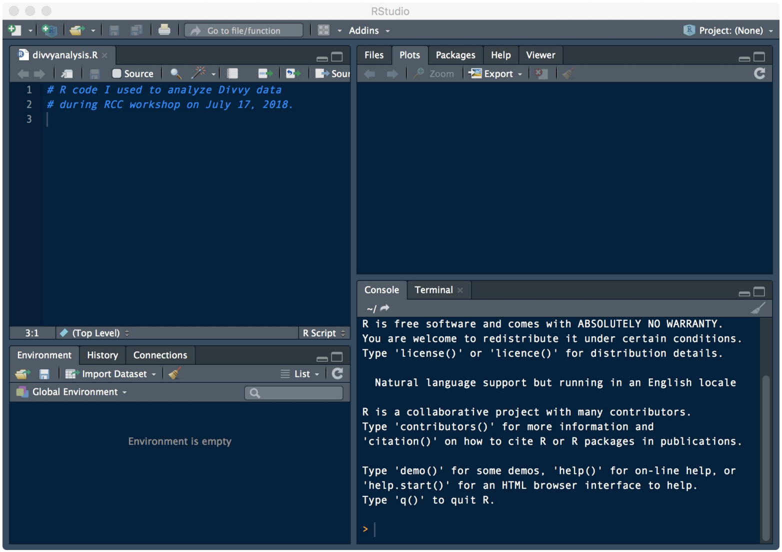
- `rm(list = ls())`.
- Or, in RStudio, **Session > Clear Workspace**.

14. Load code for the hands-on exercises

Open R Markdown source file, **slides.Rmd**.

- In RStudio, select **File > Open File**.
- Alternatively, use your favourite text editor.

15. The Console is the “brains” of RStudio



```
# R code I used to analyze Divvy data
# during RCC workshop on July 17, 2018.
```

```
~/
R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

  Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

>
```

16. Download the Divvy data

- Disk space required: at least **2 GB**.
- Download the 2016 & 2017 data files from here:
  - **www.divvybikes.com/system-data**
- Download them to the **R-intro-divvy** folder.
- You should have 4 ZIP files:

```
Divvy_Trips_2016_Q1Q2.zip
Divvy_Trips_2016_Q3Q4.zip
Divvy_Trips_2017_Q1Q2.zip
Divvy_Trips_2017_Q3Q4.zip
```

- Decompress (“unzip”) all of these files.

17. Check that you have all the files

After unzipping, you should have **15** CSV files. Check this:

```
list.files(pattern = "*.csv")
```

18. Set your working directory to “R-intro-divvy”

Check that you have the right working directory:

```
getwd() # Should end with "R-intro-divvy".
```

If you don’t, change your working directory:

- In R, use `setwd()` function.
- In RStudio, select **Session > Set Working Directory > Choose Directory...**‘

Before continuing, double-check that you have the right working directory.

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20. Take a quick look at CSV file

Open the CSV file **Divvy_Stations_2017_Q1Q2.csv** in RStudio, or in your favourite text editor (e.g., Notepad in Windows, TextEdit on Mac).

21. Import the station data into R

Load 2017 third & fourth quarter station data into an R “data frame”:

```
stations<-read.csv("Divvy_Stations_2017_Q3Q4.csv",
                   stringsAsFactors = FALSE)
```

This will define a new object, “stations”, in your environment:

```
ls()
```

It is a “data frame” object:

```
class(stations)
```

22. Inspect the station data

Check that the data were read correctly, and inspect the table:

```
nrow(stations)
ncol(stations)
head(stations)
tail(stations)
summary(stations)
```

Inspect the data in more detail:

```
sapply(stations,class)
object.size(stations)
```

23. Take a closer look at the “dpcapacity” column

Select only the “dpcapacity” column, and assign it to a new variable:

```
x <- stations$dpcapacity
```

Run these commands to take a closer look at the “dpcapacity” column:

```
class(x)
length(x)
summary(x)
table(x)
```

24. More on selecting rows & columns

Select first 4 rows of “name” column:

```
stations$name[1:4]
stations[1:4,2]
stations[1:4,"name"]
```

Select first 4 rows and multiple columns:

```
stations[1:4,c(2,3,6)]
stations[1:4,c("name","city","dpcapacity")]
```

Getting the row and column names:

```
colnames(stations)
rownames(stations)
```

25. Take an even closer look at “dpcapacity”

It is interesting that a few of the Divvy bike stations are much larger than the others, whereas others have no docks. Where are these stations?

```
subset(stations,dpcapacity == 0)
subset(stations,dpcapacity >= 40)
```

Alternatively, we can sort the table rows, then inspect the top and bottom rows:

```
rows <- order(stations$dpcapacity,decreasing=TRUE)
stations2 <- stations[rows,]
head(stations2)
tail(stations2)
```

26. Take a closer look at the “city” column

Previously, we inspected *numeric* data. Next’s, let’s look at an example of non-numeric data.

```
x <- stations$city
class(x)
summary(x)
```

The summary is not very useful here! The key is to convert to a “factor” (*i.e.,* categorical variable):

```
x <- factor(stations$city)
class(x)
summary(x)
```

27. Fixing the “city” column

Let’s fix the problem we found earlier. First, select the offending rows of the table:

```
rows <- which(stations$city == "Chicago ")
```

Fix the “city” column by *overwriting* the “city” entries in the selected rows:

```
stations[rows,"city"] <- "Chicago"
summary(stations$city)
```

The “city” column is more useful if it is a factor. Let’s modify this column inside the data frame:

```
stations$city <- factor(stations$city)
summary(stations$city)
```

28. What is a “factor”? (optional)

Factors are often very useful in data analyses. Let’s take a deeper look at what a factor *is*.

```
x <- stations$city
attributes(x)
unclass(x)
```

From the `unclass(x)` call, we see that a factor is really just an integer with values 1, 2, 3, *etc.*, with which each integer value is associated with a *label* (e.g., “Chicago”, “Evanston”).

29. Save your code & session state

It is important to periodically save:

1. your code,
2. the state of your R environment.

To save your environment, go to **Session > Save Workspace As...** in RStudio, or run this code:

```
save.image("divvyanalysis.RData")
```

Later, to restore your environment in a new session, select **Session > Load Workspace...** in RStudio, or run this code:

```
load("divvyanalysis.RData")
```

30. Main concepts covered so far

- The R environment & working directory.
- Read a data frame from a text (CSV) file.
- Tools to inspect a data frame.
- Tools to manipulate a data frame.
- Selecting rows & columns.
- Ordering rows of a data frame.
- Factors = categorical variables.
- Save state of R environment.

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3. **Load and prepare the Divvy trip data.**
4. Create a map of the Divvy stations.
5. Create a scatterplot comparing bike sharing activity in 2016 and 2017.

32. Import the Divvy trip data into R

Previously, we used `read.csv` to import station data into R. Let's now use `read.csv` to load the trip data from the 4th quarter of 2017:

```
trips <-
  read.csv("Divvy_Trips_2017_Q4.csv",
           stringsAsFactors = FALSE)
```

You may find that this command look longer to run than before. The trips data frame is much larger:

```
nrow(trips)
ncol(trips)
object.size(trips)
```

33. Import Divvy trip data using `readr`

Install the **readr** package from CRAN:

```r
install.packages("readr")
```

Load the package functions into your R environment:

```r
library(readr)
```

Let's use the `read_csv` function from this package:

```r
trips <- read_csv("Divvy_Trips_2017_Q4.csv")
```

34. Import Divvy trip data using `readr`

The `read_csv` output is *not* a data frame—it is a “tibble”.

```
class(trips)
```

Typically, I convert it to a data frame:

```
class(trips) <- "data.frame"
```

35. A first glance at the trips data

Let's use some of the same commands we used earlier to quickly get an overview of the trip data:

```
nrow(trips)
ncol(trips)
head(trips)
summary(trips)
```

36. Convert “gender” to a factor

Let’s start by converting the “gender” column to a factor:

```
trips$gender <- factor(trips$gender)
summary(trips$gender)
levels(trips$gender)
```

37. “Missing data”

- In R, “missing data” should be assigned the special value `NA` (“not available”).
- Many functions in R will correctly handle missing data as long as they are encoded as `NA`.
- The `read_csv` function from the `readr` package was “smart” enough to figure out that blank entries in the CSV file should be converted to `NA`.

38. Convert “station” columns to factors

The “from station” column is also more useful as a factor:

```
summary(trips$from_station_name)
trips$from_station_name <-
  factor(trips$from_station_name)
summary(trips$from_station_name)
```

39. A note about dates & times

- `summary(trips$start_time)` and `summary(trips$end_time)` are also not informative.
- Processing dates & times is more complicated.
- See `help(strptime)` and the **lubridate** package.

40. Combining trip data from two quarters

Up to this point, we have only examined at the trip data from one quarter of one year. Suppose we wanted to analyze the trip data from the 3rd and 4th quarters of 2017. How would we do that?

```
tripsQ4 <- trips
tripsQ3 <- read_csv("Divvy_Trips_2017_Q3.csv")
class(tripsQ3) <- "data.frame"
```

We can *merge* the two tables *by rows*—that is, we put one table on top of the other.

```
trips <- rbind(tripsQ3,tripsQ4)
```

41. Combining trip data from two quarters

Let’s double-check the result:

```
dim(tripsQ3)
dim(tripsQ4)
dim(trips)
head(trips)
```

When merging data sets by rows, we have beware of inconsistencies in the columns, e.g.,

```
class(tripsQ3$gender)
class(tripsQ4$gender)
class(trips$gender)
```

42. Preparing data is tedious

Data preparation is sometimes >90% of the effort!

- *Many analysis mistakes are due to poor data preparation.*

Common issues include:

- Formatting mistakes in CSV file.
- Converting table columns to the appropriate data type.
- Entry inconsistencies (e.g., additional spaces).
- Missing data.

43. Moving beyond data preparation

- So far, we have illustrated a few of the challenges of working with large tabular data sets (“data frames”).
- In order to proceed to fun stuff, I’ve automated the data preparation steps by writing an R *function* to do this.

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45. Refresh your environment

We will begin a new analysis, so let's refresh our environment:

```
rm(list = ls())
```

Or, in RStudio, go to **Session > Restart R.**

46. Import the 2016 & 2017 Divvy data

Load function `read.divvy.data` that automates the reading and processing of all the downloaded Divvy data:

```r
source("readdivvydata.R")
```

47. Import the 2016 & 2017 Divvy data

The `read.divvy.data` takes the name of the station file to import, and the names of trip data files to import & merge.

```
stationfile <- "Divvy_Stations_2017_Q3Q4.csv"
tripfiles <- list.files(pattern="Divvy_Trips_*")
```

48. Import the 2016 & 2017 Divvy data

Load and process the trip and station data:

```
divvy <- read.divvy.data(stationfile,tripfiles)
```

This may take a minute to run, or longer if you have not installed the readr package.

49. Inspect the 2016 & 2017 Divvy data

The output is a “list” object, in which each list element is a data frame. Let’s extract the data frames from the list:

```
names(divvy)
stations <- divvy$stations
trips    <- divvy$trips
rm(divvy)
head(stations)
head(trips)
nrow(trips)
```

50. Our first plot: a map of the Divvy stations

We will use the **ggplot2** package. It is a powerful (though not immediately intuitive) set of plotting functions that extend the base plotting functions in R.

```
install.packages("ggplot2")
```

I also recommend the **cowplot** package, an extension to ggplot2 developed by Claus Wilke at UT Austin.

```
install.packages("cowplot")
```

Load the ggplot2 and cowplot functions:

```
library(ggplot2)
library(cowplot)
```

51. Plot station longitude vs. latitude

The “stations” data frame gives the geographic co-ordinates (latitude & longitude) for each station. With ggplot, we can create a station map from the “stations” data frame in only a few lines of code:

```
aes1 <- aes(x = longitude,y = latitude)
p    <- ggplot(stations,aes1)
print(p)
out <- geom_point()
p2  <- ggplot_add(out,p)
print(p2)
```

52. Adjusting the plot

Let’s make a few adjustments to the plot:

```
out <- geom_point(shape = 21,fill = "darkblue",
                  color = "white",size = 3)
p3  <- ggplot_add(out,p)
print(p3)
```

53. Use colors to highlight the largest stations

To do this, map the “dpcapacity” column to colour in the plot:

```
aes1 <- aes(x    = longitude,
            y    = latitude,
            fill = dpcapacity)
p   <- ggplot(stations,aes1)
out <- geom_point(shape = 21,color = "white",
                  size = 3)
p <- ggplot_add(out,p)
print(p)
```

54. Use colors to highlight the largest stations

The colour scale is not great, so let’s improve it:

```
out <- scale_fill_gradient2(low = "skyblue",
  mid = "darkblue",high = "red",midpoint = 25)
p <- ggplot_add(out,p)
print(p)
```

55. Scale stations by the number of departures

To do this, we need to add a new column to the “stations” data frame containing the total number departures. It can be calculated from the “trips” data frame:

```
counts <- table(trips$from_station_name)
```

Because we carefully prepared the data frame in `read.divvy.data`, station counts should be the same order as the stations. We can check this:

```
all(names(counts) == stations$name)
```

56. Scale stations by the number of departures

Add the trip counts to the “stations” data frame:

```
counts <- as.vector(counts)
stations$departures <- counts
head(stations)
```

Let’s use this column in our new plot:

```
aes1 <- aes(x    = longitude,
            y    = latitude,
            size = sqrt(departures))
p    <- ggplot(stations,aes1)
out  <- geom_point(shape = 21,fill = "darkblue",
                   color = "white")
p    <- ggplot_add(out,p)
print(p)
```

57. Save & share your plot

For exploratory analyses, GIF and PNG are great formats because the files are easy to attach to emails or webpages:

```r
ggsave("station_map.png",p,dpi = 100)
```

For print or publication, save in a vector graphics format:

```r
ggsave("station_map.pdf",p)
```

58. Save your code & session state

This is a good time to save your session.

```
save.image("divvyanalysis.RData")
```

59. Compare 2016 & 2017 biking activity (optional)

Earlier, we noticed that that were more trips in 2017 than 2016. Which stations experienced the largest increase? To examine this question, we take the following steps:

1. Count trips from each station separately for 2016 and 2017.
2. Add these counts to the “stations” data frame.

60. Count trips separately for 2016 & 2017

We will use `subset` followed by `table` to do this:

```
d1 <- subset(trips,start.year == 2016)
d2 <- subset(trips,start.year == 2017)
x1 <- table(d1$from_station_name)
x2 <- table(d2$from_station_name)
```

61. Add counts to the stations data frame

Remember we need to convert the “table” output to a vector:

```
x1 <- as.vector(x1)
x2 <- as.vector(x2)
stations$dep.2016 <- x1
stations$dep.2017 <- x2
head(stations)
```

62. Scatterplot of trips by station (2016 vs. 2017)

As before, now that we have prepared a data frame, plotting with ggplot is relatively easy:

```r
aes1 <- aes(x = dep.2016,y = dep.2017)
p    <- ggplot(stations,aes1)
out  <- geom_point(shape = 20,size = 3,
                   color = "darkblue")
p    <- ggplot_add(out,p)
print(p)
```

63. Scatterplot of trips by station

It is difficult to tell which stations had more trips in 2017—we need to compare against the x = y line.

```
out2 <- geom_abline(slope = 1,color = "orange",
                    linetype = "dashed")
p    <- ggplot_add(out2,p)
print(p)
```

64. Save your code & session state

Save your final results for safekeeping.

```r
save.image("divvyanalysis.RData")
```

65. ggplot: Take home points

- Creating sophisticated plots requires relatively little effort *provided the data are in the right form.*
- All plots in ggplot2 require these three elements:
    1. A data frame.
    2. An “aesthetic mapping” that declares how columns are mapped to plot features (axes, shapes, colors, *etc.*).
    3. A “geom”, short for “geometric object,” that specifies the type of plot.
- All plots are created by *adding layers.*

66. Why data analysis in R?

- In R, a spreadsheet (“data frame”) is an *object* that can be inspected, manipulated and summarized with code.
- Therefore, we can write scripts to *automate* our data analyses.

67. Parting thoughts

1. Always record your analysis steps in a file so you can reproduce them later.
2. Keep track of which packages (and the versions) you used with `sessionInfo()`.
3. Use “R Markdown” to document your analyses.
4. Use packages—don’t reinvent the wheel.
5. Email `help@rcc.uchicago.edu` for advice on using R on the RCC cluster.
6. See the **workflowr** package for simplifying organizing & sharing of data analyses; e.g., **stephenslab.github.io/wflow-divvy**.
7. Thank you!