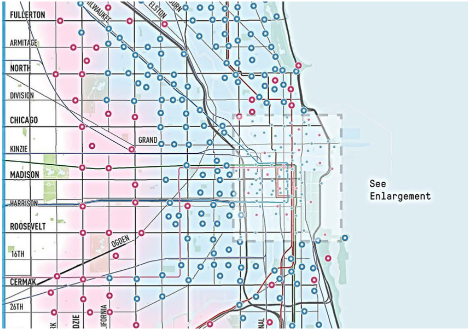
Introduction to R for data analysis

Peter Carbonetto

Research Computing Center and the Dept. of Human Genetics
University of Chicago



Aims of workshop

1. Work through a basic 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 create plots from data frames.
6. Learn through “live coding”—this includes learning from our mistakes!

Our goal: Analyze Divvy data from 2016 & 2017

- Investigate bike sharing trends in Chicago.
- We will use data made available from 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.

It’s your choice

Your may choose to…

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

Note: If you use the RCC cluster I’m assuming you know how to set up an interactive computing session with appropriate amount of time and memory, load R or RStudio, and display graphics (e.g., using ThinLinc).

Software we will use today

1. **R**
2. R packages **ggplot2** & **cowplot**.
3. **RStudio** (optional).

Note: I'm assuming you have already installed R and/or RStudio on your laptop, or you are using the RCC cluster.

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.

Initial setup

- WiFi
- Power outlets
- YubiKeys
- Pace, questions (e.g., keyboard shortcuts).
- Help.

Download or “clone” git repository

Download the workshop packet to your computer.

- Go to: **github.com/rcc-uchicago/R-intro-divvy-2**
- 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-2.git
```

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

- *Note:* If you are using the RCC cluster, also download workshop packet on the cluster.

What's in the workshop packet

```
R-intro-divvy-2
  /analysis # Scripts implementing data analyses.
  /code     # Additional code used in analyses.
  /data     # Original ("raw") data.
  /docs     # Additional workshop materials.
  /output   # Processed data & results files.
```

- This setup mimics how I typically organize the code, data and results for my projects.

Open the slides on your computer

- This PDF is useful for copying & pasting code from the slides.
- The PDF is in the **“docs”** folder of the workshop packet.
- You can also view the PDF by clicking the **“docs”** item in the file listing on the GitHub webpage.

Set up your R environment

- Launch R or RStudio.
- *We will run all the code from the "**analysis**" folder*.
- To change your working directory:
  - ▷ In R, use `setwd()` function.
  - ▷ In RStudio, select **Session > Set Working Directory > Choose Directory. . .** ‘

Before continuing, check that you have the right working directory:

```r
getwd()   # Should end with "analysis".
```

Run `sessionInfo()`

Check the version of R that you are using:

```
sessionInfo()
```

If you are using an older version of R (version 3.3 or earlier), I strongly recommend upgrading to the latest version. *Some of the examples may not work in older versions of R.*

Check your R environment

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

```
ls()
```

If you see names of objects listed, it means your environment is not empty, and you should restart R with a clean environment.

- Do `rm(list = ls())`.
- Or, in RStudio, go to **Session > Restart R**.

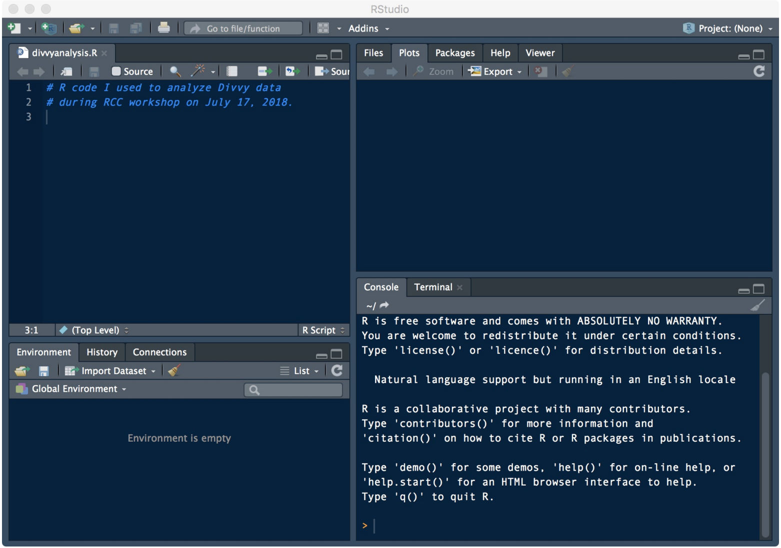
Create a file to keep track of your analysis code

- In RStudio, select **File > R Script**.
- Alternatively, use your favourite editor (nano, emacs, vim, Atom, *etc*).
- Add some comments to the title to remind yourself what this file is for, e.g.,

```
# Some of the R code I wrote during the RCC
# workshop on July 17, 2018.
```

- Save the file in the **"analysis"** folder. Name the file whatever you'd like (e.g., `divvyanalysis.R`).

The console is the “brains” of RStudio



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 **“data”** 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.

Check that you have all the files

After unzipping, you should have **15** CSV files.

```
Sys.glob("../data/*.csv")
```

If you don't see all 15 CSV files, you have not successfully downloaded and/or unzipped all the files in the "data" directory.

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Import the station data into R

Load the most recent station data into an R “data frame”:

```
stations <-
  read.csv("../data/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)
```

What does “read.csv” do, and what is a “data frame”? R has detailed documentation:

```
help(read.csv)
help(data.frame)
```

Inspect the station data

Run these commands to start inspecting the station data:

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

Inspect the data in more detail:

```
sapply(stations,class)
print(object.size(stations),units = "Kb")
```

What do we learn about the station data from running these commands? Does this reveal any issues with the data?

Take a closer look at the “dpcapacity” column

Create a new object containing only the “dpcapacity” column:

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

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

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

Did we gain any additional insight from running these commands?

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)
stations <- stations[rows,]
head(stations)
tail(stations)
```

What was risky about line 2?

Take a closer look at the “city” column

Above 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” (factor = categorical variable):

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

Did you discover an issue with the data from running these commands?

What is a “factor”?

Factors are very useful. Let’s take a deeper look.

```r
attributes(x)
unclass(x)
```

Improving 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” entry for the selected rows:

```
stations[rows,"city"] <- "Chicago"
```

The “city” column is more useful if it is a factor, so let’s convert it:

```
summary(stations)
stations <- transform(stations,
                      city = factor(city))
summary(stations)
```

There are many ways to select rows & columns

Select first 4 rows of “name” column:

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

- *Do you prefer one approach?*

Select first 4 rows and multiple columns:

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

Can rows be selected by name?

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

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, do something like this:

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

Later, to restore your environment in a new session, run `load("../output/divvyanalysis.RData")`.

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.
- Manipulate a data frame.
- Factors = categorical variables.
- Selecting & and columns.
- Order rows of a data frame.
- Save state of R environment.

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5. Create a scatterplot comparing bike sharing activity in 2016 and 2017.

Import the Divvy trip data into R

Previously, we used `read.csv` to import station data into R. Let's now use the same function to load the most recent trip data:

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

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

```
nrow(trips)
ncol(trips)
```

This gives an opportunity to demonstrate faster methods for importing large data sets.

Import Divvy trip data using `readr` (optional)

Install the **readr** package from CRAN:

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

Load the functions from the package into your R environment:

```
library(readr)
```

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

```
trips <-
  read_csv("../data/Divvy_Trips_2017_Q4.csv",
           na = "NA")
```

How much faster is `read_csv`?

- **Note:** The `na = "NA"` argument was added to reproduce behaviour of `read.csv`.

Import Divvy trip data using `readr` (optional)

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"
```

- For more on tibbles, see:
  - ▷ `http://r4ds.had.co.nz`
- The **readr** package has many other features not covered here.
- Another fast method is `fread` from the **data.table** package.

More on packages in R

"Vignettes" are a great way to learn about a package:

```
vignette(package = "readr")
vignette("readr")
```

- CRAN is the official package source:
  - ▷ `https://cran.r-project.org`.
- Other good places to find packages:
  - ▷ Bioconductor
  - ▷ GitHub.
- *What packages are already installed?* `rownames(installed.packages())`
- *Where do the packages live?* `.libPaths()`
- *How to learn more about a package?* `help(package=readr)`

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)
```

Unfortunately, the summary command isn't particularly informative for many of the columns.

- *What columns should we convert to factors?*

Convert “gender” to a factor

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

```
trips <- transform(trips,gender = factor(gender))
summary(trips$gender)
levels(trips$gender)
```

What problem have we stumbled upon?

Handling “missing” data

In R, “missing data” should always be assigned the special value `NA` (“not available” or “not assigned”):

```
rows <- which(trips$gender == "")
trips[rows,"gender"] <- NA
trips <- transform(trips,
                   gender = factor(gender))
summary(trips$gender)
```

Many functions in R will correctly handle missing data as long as they are encoded as `NA`.

- **Note:** `read_csv` automatically converts empty character strings to `NA`, but `read.csv` does not.

Convert “station” columns to factors

Next, let’s convert the “from station” and “to station” columns to factors:

```
trips <- transform(trips,
  from_station_name = factor(from_station_name),
  to_station_name = factor(to_station_name))
summary(trips)
```

The summary is now more informative. However, here it is better to specify the “levels” when converting to factors:

```
x <- stations$name
trips <- transform(trips,
  from_station_name = factor(from_station_name,x),
  to_station_name = factor(to_station_name,x))
```

Why is this important?

Example: summarizing trips by station (optional)

Create a new data frame containing the “from” and “to” trip totals:

```
from <- table(trips$from_station_name)
to   <- table(trips$to_station_name)
tripcounts <- data.frame(from = c(from),
                         to   = c(to))
```

With this new data frame, we can easily create a scatterplot comparing the rate of departures to arrivals at each station:

```
plot(tripcounts$from,tripcounts$to,pch = 20,
     panel.first = abline(a = 0,b = 1))
```

Exercise: Use `subset` to find the one station that has many more departures than arrivals.

A note about dates & times

- `summary(trips)` is also not useful for the dates & times.
- Processing dates & times is more complicated.
- See `help(strptime)` and the **lubridate** package.

Main concepts covered in second part

- Install & use a package.
- Handle missing data (NA’s).
- Create a data frame.
- Create a plot from a data frame.

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.
- Many other examples of Poor Practices in recording data.

(And we haven't yet dealt with merging data from multiple files—this usually creates more headaches!)

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 "hidden" some of the additional complications—I wrote a function in R to import and merge all the Divvy data into a single data frame.

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Import the 2016 & 2017 Divvy data

I wrote a function `read.divvy.data` to automate the reading and processing of the Divvy data: it reads all the CSV files, then merge them into two data frames: one for the stations, and one for the trips.

```
source("../code/functions.R")
ls()
```

Choose which station and trip files to import.

```
tripfiles <- Sys.glob("../data/Divvy_Trips*.csv")
stnfile <- "../data/Divvy_Stations_2017_Q3Q4.csv"
```

Import the 2016 & 2017 Divvy data

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

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

The output is a “list” containing two data frames:

```
names(divvy)
stations <- divvy$stations
trips    <- divvy$trips
rm(divvy)
head(stations)
head(trips)
nrow(trips)
print(object.size(trips),units = "Gb")
```

- *Were more trips taken in 2016 or 2017?*
- *Which columns were converted to factors?*

Out first ggplot: a map of the Divvy stations

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

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

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

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

Load the ggplot2 and cowplot functions:

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

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:

```
p <- ggplot(data    = stations,
            mapping = aes(x = longitude,
                          y = latitude))
print(p)
p2 <- p + geom_point()
print(p2)
```

Adjusting the plot

Let's make a few small adjustments to improve the plot:

```
p3 <- p + geom_point(shape = 21,fill = "darkblue",
                     color = "white",size = 2)
p3 <- p3 + theme_cowplot()
print(p3)
```

What geographic features of Chicago are recognizable from this plot?

Scale stations by the number of departures

Next, let's add an additional piece of information to this visualization:

- Number of departures at each station, should (?) roughly correspond to population density.

To do this, we need to add a new column to the "stations" data frame containing the total number departures, which is calculated from the "trips" data frame:

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

The counts should be the same order as the stations—*why is this?*

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

Scale stations by the number of departures

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

```
stations$departures <- c(counts)
head(stations)
```

Let’s use this column in our new plot:

```
p <- ggplot(data = stations,
  mapping = aes(x    = longitude,
                y    = latitude,
                size = sqrt(departures)))
p <- p + geom_point(shape = 21,fill = "red",
                    color = "white")
p <- p + theme_cowplot(font_size = 11)
print(p)
```

How to save and share your plot

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

```
ggsave("../output/station_map.png",
       plot = p,dpi = 150)
```

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

```
ggsave("../output/station_map.pdf",plot = p)
```

Save your code & session state

This is a good time to save your session.

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

Compare 2017 biking activity against 2016

Earlier, we observed an increase in trips from 2016 to 2017. Which stations experienced the largest increase?

- To examine this, we need to count trips separately for 2016 and 2017.
- Then we add these counts to the "stations" data frame.

We will use the `subset` and `table` to do this:

```
d1 <- subset(trips,start.year == 2016)
d2 <- subset(trips,start.year == 2017)
x1 <- table(d1$from_station_id)
x2 <- table(d2$from_station_id)
stations$dep.2016 <- c(x1)
stations$dep.2017 <- c(x2)
head(stations)
```

Scatterplot of trips by station (2016 vs. 2017)

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

```
p <- ggplot(data = stations,
            mapping = aes(x = dep.2016,
                          y = dep.2017))
p <- p + geom_point(shape = 20,size = 2)
print(p)
```

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

```
p <- p + geom_abline(slope = 1,color = "skyblue",
           linetype = "dashed")
p <- p + theme_cowplot()
print(p)
```

One station stands out because it has had a much larger increase in trips than other stations. Where is this station?

Save your code & session state

Save your final results for safekeeping.

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

ggplot: Take home points

- Creating sophisticated plots requires relatively little effort *provided the data are in the right form.*
- All plots in ggplot have these three elements:
  1. A data frame.
  2. An “aesthetic mapping” that declares how columns are plotted.
  3. A “geom”, short for “geometric object,” that specifies the type of plot.
- Plots are created by combining “layers” using the + operator.

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.

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 packages—don't reinvent the wheel.
4. Email `help@rcc.uchicago.edu` for advice on using R on the RCC cluster.
5. Use "R Markdown" to document your analyses.
6. See the **workflowr** package for simplifying organizing & sharing of data analyses; e.g., **stephenslab.github.io/wflow-divvy**.
7. Thank you!