

PLSC 31101: Computational Tools for Social Science

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Fall 2019

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Part I

Before Class

Chapter 1

Syllabus

- Instructor: Rochelle Terman, rterman@uchicago.edu
- TA: Pete Cuppernall, pcuppernall@uchicago.edu
- Time: Tuesdays and Thursdays, 12:30 pm – 1:50 pm
- Place: Cobb Hall 303
- Office hours:
 - Rochelle Terman: Tuesdays, 2:30-4:30, Pick 411. Sign up here
 - Pete Cuppernall: Mondays, 2:00-4:00, Gates-Blake 211

1.1 Course Description

The purpose of this course is to provide graduate students with the critical computing skills necessary to conduct research in quantitative / computational social science. This course is not an introduction to statistics, computer science, or specialized social science methods. Rather, the focus will be on practical skills necessary to be successful in further methods work. The first portion of the class introduces students to basic computer literacy, terminologies, and the R programming language. The second part of the course provides students the opportunity to use the skills they learned in part 1 towards practical applications such as webscraping, data collection through APIs, automated text analysis, etc. We will assume no prior experience with programming or computer science.

Objectives

By the end of the course, students should be able to:

- Understand basic programming terminologies, structures, and conventions.
- Write, execute, and debug R code.
- Produce reproducible analyses using R Markdown.
- Clean, transform, and wrangle data using the `tidyverse` packages.
- Scrape data from websites and APIs.
- Parse and analyze text documents.
- Be familiar with the concepts and tools of a variety of computational social science applications.
- Master basic Git and GitHub workflows
- Learn independently and train themselves in a variety of computational applications and tasks through online documentation.

1.2 Who should take this course

This course is designed for Political Science Graduate students, but any graduate student is welcome. We will not presume any prior programming or computer science experience.

1.3 Requirements and Evaluation

Final Grades

This is a graded class based on the following:

- Completion of assigned homework (50%)
- Participation (25%)
- Final project (25%)

Assignments

Assignments will be assigned at the end of every Thursday session. They will be due one week later, unless otherwise noted. The assignments are intended to expand upon the lecture material and to help students develop the actual skills that will be useful for applied work. The assignments will be frequent but each of them should be fairly short.

You are encouraged to work in groups, but the work you turn in must be your own. Group submission of homework, or turning in copies of the same code or output, is not acceptable. While you are encouraged to use the internet to help you debug, but do not copy and paste large chunks of code that you do not understand. Remember, the only way you actually learn how to write code is to write code!

Portions of the homework in R should be completed using R markdown, a markup language for producing well-formatted documents with embedded R code and outputs. To submit your homework, knit the R Markdown file to PDF, and then submit the PDF file through Canvas (unless otherwise noted).

Class Participation

The class participation portion of the grade can be satisfied in one or more of the following ways:

- attending the lectures
- asking and answering questions in class
- attending office hours
- contributing to class discussion through the Canvas site, and/or
- collaborating with the computing community, either by attending a workshop or meetup, submitting a pull request to a github repository (including the class repository), answering a question on StackExchange, or other involvement in the social computing / digital humanities community.

Final Project

Students have two options for class projects:

1. **Data project:** Use the tools we learned in class on your own data of interest. Collect and/or clean the data, perform some analysis, and visualize the results. Post your reproducible code on Github.
2. **Tool project:** Create a tutorial on a tool we didn't cover in class. Ideas include: bash, LaTex, pandoc, quanteda, tidytext, etc. Post it on github.

Students are required to write a short proposal by **November 7** (no more than 2 paragraphs) in order to get approval / feedback from the instructors.

Project materials (i.e. a github repo) will be due by end of day on **December 9**. We will specify submission details in class.

On **December 10** we will have a **lightning talk session** where students can present their projects in a maximum 5 minute talk.

Late Policy and Incompletes

All deadlines are strict. Late assignments will be dropped a full letter grade for each 24 hours past the deadline. Exceptions will be made for students with a documented emergency or illness.

I will only consider granting incompletes to students under extreme personal/family duress.

Academic Integrity

I follow a zero-tolerance policy on all forms of academic dishonesty. All students are responsible for familiarizing themselves with, and following, university policies regarding proper student conduct. Being found guilty of academic dishonesty is a serious offense and may result in a failing grade for the assignment in question, and possibly course.

1.4 Activities and Materials

Course Structure

Classes will follow a “workshop” style, combining lecture, demonstration, and coding exercises. We envision the class to be as interactive / hands on as possible, with students programming every session. **You must bring a laptop to class.**

It is important that students **complete the requisite reading** before class. I anticipate spending 1/2 the class lecturing, and 1/2 practicing with code challenges.

Course Website

All course notes will be posted on <https://plsc-31101.github.io/course/>, including class notes, code demonstrations, sample data, and assignments. Students will be assigned reading from these notes before every class.

Students are encouraged to submit pull requests to the website repository, for example if they find a typo, or if they found a particularly helpful resource that would aid other students.

Students projects will also be shared on the course website.

Canvas

We will use Canvas for communication (announcements and questions) and turning in assignments.

You should ask questions about class material and assignments through the Canvas website so that everyone can benefit from the discussion. We encourage you to respond to each other’s questions as well. Questions of a personal nature can be emailed to us directly.

Computer Requirements and Software

By the end of the first week, you should install the following software on your computer:

- Access to the UNIX command line (e.g., a Mac laptop, a Bash wrapper on Windows)
- Git
- R and RStudio (latest versions)

This requires a computer that can handle all this software. Almost any Mac will do the job. Most Windows machines are fine too if they have enough space and memory.

See Install Page for more information. We will be having an **InstallFest on Wednesday, Oct 2 from 9:30 to 11:30 in Pick 504.** for those students experiencing difficulties downloading and installing the requisite software.

1.5 Curriculum Outline / Schedule

1. Oct 1 - Introduction

- course objectives, logistics, overview of programming and reproducible research.

2. Oct 3 - R Tools

- R Studio, R Markdown, packages, help.

3. Oct 8 - R Syntax

- basic syntax, variables, functions, data types.

4. Oct 10 - Data Structures

- vectors, lists, factors, matrices, data frames.

5. Oct 15 - Indexing and Subsetting

- subsetting formats, operators, boolean conditionals, sub-assignment, applications.

6. Oct 17 - Introduction to Data

- common terms, formats, tidy data, storage, import/export, exploratory data analysis.

7. Oct 22 - Manipulating data with `dplyr`

- importing data, subsetting, summarizing, and conducting calculations across groups, piping.

8. **Oct 24** - Tidying data with `tidyverse`
 - tidy data principles, gather, spread, separate, unite
9. **Oct 29** - Merging and Linking Data
 - relational data, keys, joins, missing values.
10. **Oct 31** - Visualization
 - base plotting, ggplot, grammar of graphics, writing images.
11. **Nov 5** - Hypothesis testing and regressions
 - models, model objects, stargazer.
12. **Nov 7** - Strings and Regex
13. **Nov 12** - R programming 1
 - conditional flow, functions.
14. **Nov 14** - R Programming 2
 - iterations, map.
15. **Nov 19** - Collecting data with APIs
 - requests, RESTful APIs, queries, API libraries.
16. **Nov 21** - Webscraping
 - HTML, CSS, In-Browser tools, scraping tools.
17. **Nov 26** - Text analysis 1
 - preprocessing, DTM, dictionary methods, distinctive words.
18. **Nov 28** - Text analysis 2
 - supervised vs. unsupervised learning, Vector-space models, topic models.
19. **Dec 3** - Git / Github
20. **Dec 5** - TBD
21. **Dec 10, 1:30-3:30pm** - Final project lightning talks

Chapter 2

Installation

To participate in PLSC 31101, you will need access to the software described below.

Once you've installed all of the software below, test your installation by following the instructions at the bottom on this page.

2.1 R

R is a programming language that is especially powerful for data exploration, visualization, and statistical analysis.

To download R, go to CRAN (the **C**omprehensive **R** Archive **N**etwork).

A new major version of R comes out once a year, and there are 2-3 minor releases each year. It's a good idea to update regularly. Upgrading can be a bit of a hassle, especially for major versions, which require you to reinstall all your packages, but putting it off only makes it worse.

2.2 R Studio

To interact with R, we use RStudio. Please install the latest desktop version of RStudio IDE. We will not support RStudio cloud.

2.3 R Packages

You'll also need to install some R packages. An R package is a collection of functions, data, and documentation that extends the capabilities of base R. Using packages is key to the successful use of R.

Many of the packages that you will learn in this class are part of the so-called **tidyverse**. The packages in the **tidyverse** share a common philosophy of data and R programming, and are designed to work together naturally.

You can install the complete tidyverse with a single line of code in R Studio:

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

On your own computer, type that line of code in the RStudio console, and then press enter to run it. R will download the packages from CRAN and install them on to your computer. If you have problems installing, make sure that you are connected to the internet, and that <https://cloud.r-project.org/> isn't blocked by your firewall or proxy.

We will also be requiring a few other important packages. Run the following line of code to download all of them at once:

```
install.packages("rmarkdown", "knitr", "gapminder",
                 "stargazer", "rtweet", "kableExtra",
                 "nycflights13", "devtools")
```

2.4 LaTex

In order to knit rmarkdown files to pdf files, you need to install some version of Latex. For students who have not installed LaTeX before, we recommend that you install TinyTeX (<https://yihui.name/tinytex/>).

Open RStudio and type these lines into the command-line console:

```
install.packages("tinytex")
tinytex::install_tinytex()
```

2.5 The Bash Shell

Bash is a commonly-used shell that gives you the power to do simple tasks more quickly.

Windows

Install Git for Windows by downloading and running the installer. This will provide you with both Git and Bash in the Git Bash program. **NOTE:** on the ~6th step of installation, you will need to select the option “Use Windows’ default console window” rather than the default of “Use MinTTY” in order for nano to work correctly.

After the installer does its thing, it leaves the window open, so that you can play with the “Git Bash”.

Chances are that you want to have an easy way to restart that Git Bash. You can install shortcuts in the start menu, on the desktop or in the QuickStart bar by calling the script /share/msysGit/add-shortcut.tcl (call it without parameters to see a short help text).

Mac OS X

The default shell in all versions of Mac OS X is bash, so no need to install anything. You access bash from the Terminal (found in /Applications/Utilities). You may want to keep Terminal in your dock for this class.

Linux

The default shell is usually Bash, but if your machine is set up differently you can run it by opening a terminal and typing bash. There is no need to install anything.

2.6 Git

Git is a version control system that lets you track who made changes to what when and has options for easily updating a shared or public version of your code on github.com. You will need a supported web browser (current versions of Chrome, Firefox or Safari, or Internet Explorer version 9 or above).

Windows

Git should be installed on your computer as part of your Bash install (described above).

Mac OS X

For OS X 10.9 and higher, install Git for Mac by downloading and running the most recent “mavericks” installer from this list. After installing Git, there will not be anything in your `/Applications` folder, as Git is a command line program. **For older versions of OS X (10.5-10.8)** use the most recent available installer labelled “snow-leopard” available here.

Linux

If Git is not already available on your machine you can try to install it via your distro’s package manager. For Debian/Ubuntu run `sudo apt-get install git` and for Fedora run `sudo yum install git`.

2.7 Other helpful tools

While not required, I recommend you install the following tools:

1. Google Chrome is an up-to-date web browser.
2. Sublime Text is a free, advanced text editor.

2.8 Testing your installation

If you have trouble with installation, please come to the Installfest on **Wed Oct 2, 10-12 in Pick 411**.

Open a command line window (‘terminal’ or, on windows, ‘git bash’), and enter the following commands (without the \$ sign):

```
$ R --version  
$ git --version
```

If everything has been installed correctly, those commands *should* print output version information.

NB: If you’re using git bash, the `R --version` command may not work. In this case, just make sure you can open up RStudio.

Software Carpentry maintains a list of common issues that occur during installation may be useful for our class here: Configuration Problems and Solutions wiki page.

Credit: Thanks to Software Carpentry for providing installation guidelines.

Chapter 3

Homework Rubric

Each question will be graded along the following criteria:

Check Minus: The code doesn't run, or does not do what the question is asking.

Check: The code works, but exhibits one of the following problems:

- 1) poor documentation / disorganized;
- 2) repetitive / redundant / overly complex;
- 3) graphs and tables lack labels or are otherwise difficult to understand.

Check Plus: The code works, and is:

- 1) well-documented and organized;
- 2) clean and efficient;
- 3) graphs and tables have proper labels and are easily readable.

Part II

Course Notes

Chapter 4

Introduction

4.1 The Motivation

Here's the dream:

....

Computers have revolutionized research, and that revolution is only beginning. Every day, social scientists and humanists all over the world use them to study things that are too big, too small, too fast, too slow, too expensive, too dangerous, or just too hard to study any other way.

Now here's the reality

....

Every day, scholars all over the world waste time wrestling with computers. Tasks that should take a few moments take hours or days, and many things never work at all. When scholars try to get help, they are inundated with unhelpful information, and give up.

This sorry state of affairs persists for three reasons:

1. **No room, no time.** Everybody's schedule is full — there's simply not space to add more about computing without dropping something else.
2. **The blind leading the blind.** The infrastructure doesn't exist to help scholars develop the skills they need. Senior researchers can't teach the next generation how to do things that they don't know how to do themselves.
3. **Autodidact Chauvinism.** Since there are no classrooms, scholars are pressured to teach themselves. But self-learning is time consuming and

nearly impossible without a base level of knowledge.

Despite these challenges, there are great reasons to learn how to program:

1. Practical Efficiency

Even though it takes some time at first, learning how to program can save you an enormous amount of time doing basic tasks that you would otherwise do by hand, once you get the hang of it.

2. New Tools

Some things are impossible, or nearly impossible to do by hand. Computers open the door for new tools and methods, but many require programming skills.

3. New Data

The Internet is a wealth of data, waiting to be analyzed! Whether its collecting Twitter data, working with the Congress API, or scraping websites, programming knowledge is a must.

4. Better Scholarship

(Quality) programming can open the door to better transparency, reproducibility, and collaboration in the Social Sciences and the Humanities.

Goal of the Class: Learn to Learn

The basic learning objective of this course is to leave here with the knowledge and skills required to learn on your own, whether that's through programming documentation, StackExchange and other online fora, courses or D-Lab workshops.

By the end of the course, students should be able to:

- Understand basic programming terminologies, structures, and conventions.
- Write, execute, and debug R code.
- Produce reproducible analyses using R Markdown.
- Clean, transform, and wrangle data using the `tidyverse` packages.
- Scrape data from websites and APIs.
- Parse and analyze text documents.
- Be familiar with the concepts and tools of a variety of computational social science applications.
- Master basic Git and GitHub workflows
- **Learn independently and train themselves in a variety of computational applications and tasks through online documentation.**

This Course will not...

- teach you to be a professional programmer or software developer

- teach you statistics, computer science, or specialized social science / digital humanities methods

Why not just take a Computer Science course?

Computer science courses don't anticipate the types of questions social scientists might ask, and therefore they - introduce many unnecessary concepts - do a poor job of explaining how computer programming tools might be used by social scientists - are too resource intensive for the average social scientist

Programming is not just use useful for computer scientists, methodologists, or people who work with “big data.”

A Practical example

To illustrate, here's a practical example that comes out of my own research:

Task 1 (by hand)

Topic: International Human Rights “Naming and Shaming”

Question: Who Shames Whom on What?

Data: UN Human Rights Committee’s Universal Periodic Review

From Antigua & Barbuda 2011 review:

1. Continue with the efforts to prevent, punish and eradicate all forms of violence against women (Argentina);
2. Accede to the Second Optional Protocol to the International Covenant on Civil and Political Rights, aimed at abolishing the death penalty, and take all necessary steps to remove the death penalty from Antigua and Barbuda law (Australia);
3. Improve conditions in Antigua and Barbuda’s prisons and detention facilities (Australia);

The Task: Parse a bunch of reports (PDFs) into a dataset (CSV). Add metadata for issue, action, sentiment.

From	To	Text	Action	Sentiment	Issue	Institution	Response
Argentina	Antigua & Barbuda	Continue with the efforts to prevent, punish and eradicate all forms of violence against women	continue	2	Women's rights		support
Australia	Antigua & Barbuda	Accede to the Second Optional Protocol to the International Covenant on Civil and Political Rights, aimed at abolishing the death penalty, and take all necessary steps to remove the death penalty from Antigua and Barbuda law	accede	5	Death penalty,International instruments	ICCPR, OP	reject
Australia	Antigua & Barbuda	Improve conditions in Antigua and Barbuda's prisons and detention facilities	improve	4	Detention		support

How much time will it take?

By hand: 40,000 recommendations x 3 min per recommendation x 8-hour days x 5-day weeks = **12 months**

Task 2 (by hand)

What if we wanted to extend this research?

Question: How does UPR shaming compare to actual human rights abuses?

Data: Amnesty International's Urgent Actions

Task: Collect all of Amnesty International's Urgent Actions, add metadata for issue, country.

The image shows two separate news cards from Amnesty International's Urgent Actions section, presented side-by-side. Both cards have a black header bar with the word 'RESEARCH' and a small icon. Below the header, the card on the left is titled 'SUDAN' and dated '20 AUGUST 2015'. The text reads: 'Sudan: Further Information: Eight girls free, one other risks flogging'. The card on the right is titled 'IRAN' and dated '20 AUGUST 2015'. The text reads: 'Iran: Retired professor jailed for writing: Hossein Rafiee'.

How much time will it take?

By hand: 25,000 recommendations x 3 min per recommendation x 8-hour days x 5-day weeks = **7.5 months**

Tasks 1 & 2 (with a computer)

With a computer, we can write a program that:

1. Parses recommendations into a CSV.
2. Codes recommendations by issue, action, sentiment using computational text analysis tools.
3. Uses webscraping to collect all of Amnesty International's urgent actions.
4. Run simple regression models with R to correlate Amnesty reports with UPR shaming.

Total time: 2 months

Time Saved: 1.5 years

4.2 About This Class

About Me

My name is Rochelle Terman and I'm a faculty member in Political Science.

- A few years ago, I didn't know how to program. Now I program almost every day.
- I program mostly in Python and R. I have a special interest in text analysis and webscraping.
- My substantive research is on international norms and human rights.
- I won't be able to answer all your questions.
- No one will.
- But especially me.

Course Structure

The course is divided into two main sections:

1. Skills

Basic computer literacy, terminologies, and programming languages:

- Base R: objects and data structures.
- `tidyverse` for data analysis.
- Modeling and visualization.
- Key programming concepts (iteration, functions, conditional flow, etc).

We're using R because it's the common programming language among Political Scientists. But if you understand the *concepts*, you should be able to pick up Python and other languages pretty easily.

2. Applications

Use the skills they learned in part 1 towards practical applications:

- Webscraping.
- APIs.
- Computational Text Analysis.
- Version control and communication.

The goal is to **introduce** the students to a medley of common applications so that they can discover which avenue to pursue in their own research, and what such training would entail.

Class Activities

Classes will follow a “workshop” style, combining lecture, demonstration, and coding exercises. We envision the class to be as interactive / hands on as possible, with students programming every session. **You must bring a laptop to class.**

It is important that students **complete the requisite reading** before class. I anticipate spending 1/2 the class lecturing, and 1/2 practicing with code challenges.

Course Websites

Class notes and other materials are available here: <https://github.com/plsc-31101/course/>

We will also be using Canvas to distribute/accept assignments, and for discussion. Please use the discussion forums liberally.

Evaluation

This is a graded class based on the following: - Completion of assigned homework (50%) - Participation (25%) - Final project (25%)

If you want to audit, please let me know ASAP.

Assignments

- In general, assignments are assigned at the end of lecture, and due the following week.
- Exceptions will be noted.
- The first assignment is due next week, before class on Thursday Oct 10. It is on Canvas.
- Turn in assignments on Canvas.
- Work in groups, but submit your own.

Participation

The class participation portion of the grade can be satisfied in one or more of the following ways:

- attending the lectures,
- asking and answering questions in class,
- attending office hours,
- contributing to class discussion through the Canvas/Piazza site,
- collaborating with the computing community.

Final Project

Students have two options for class projects:

1. *Data project*: Using the tools we learned in class on your own data of interest.
2. *Tutorial project*: Create a tutorial on a tool we didn't cover in class.

Both options require an R markdown file narrating the project.

Students are required to write a short proposal by **November 7** (no more than 2 paragraphs) in order to get approval / feedback from the instructors.

Project materials (i.e. a github repo) will be due by end of day on **December 9**. We will specify submission details in class.

On **December 10** we will have a **lightning talk session** where students can present their projects in a maximum 5 minute talk.

Software

- Installation instructions are on the website.
- Get started **EARLY**.
- Then go to the Installfest (Wednesday, Oct 2, 9:30-11:30 in Pick 504) to double check your installation.
- If you have computer troubles, post the problem on the discussion forums, with as much detail as possible.

4.3 Learning How to Program

Before we talk about what it takes to learn how to program, let's first review what programming is.

What is Programming?

A *program* is a sequence of instructions that specifies how to perform a computation. Most programs are written in a human-readable *programming language* (or “source code”) and then executed with the help of a *compiler* or *interpreter*.

A few basic instructions appear in just about every language:

1. **input:** Get data from the keyboard, a file, the network, or some other device.
2. **output:** Display data on the screen, save it in a file, send it over the network, etc.
3. **math:** Perform basic mathematical operations like addition and multiplication.
4. **conditional execution:** Only perform tasks if certain conditions are met.
5. **iteration:** Do the same task over and over again on different inputs.

That being said, programming languages differ from one another in the following ways:

1. **Syntax:** whether to add a semicolon at the end of each line, etc.
2. **Usage:** JavaScript is for building websites, R is for statistics, Python is general purpose, etc.
3. **Level:** how close you are to the hardware. ‘C’ is often considered to be the lowest (or one of the lowest) level languages.
4. **Object-oriented:** “objects” are data + functions. Some programming languages are object-oriented (e.g. Python) and some aren’t (e.g. C).
5. **Many more:** Here’s a list of all the types of programming languages out there.

What Language Should You Learn?

Most programmers can program in more than one language. That’s because they know *how to program* generally, as opposed to “knowing” Python, R, Ruby, or whatever.

So what should your first programming language be? That is, what programming language should you use to learn *how to program*? At the end of the day, the answer depends on what you want to get out of programming. Many people recommend Python because it’s fun, easy, and multi-purpose. Here’s an article that can offer more advice.

In this class, we’ll be using R because it’s the most popular language in our disciplinary community (of Political Scientists.)

Regardless of what you choose, you will probably grow comfortable in one language while learning the basic concepts and skills that allow you to ‘hack’ your

way into other languages. That's because **programming is an extendible skill.**

Thus “knowing how to program” means learning how to *think* like a programmer, not necessarily knowing all the language-specific commands off the top of your head. **Don’t learn specific programming languages; learn how to program.**

What Programming is Really Like



Here’s the sad reality: When you’re programming, 80% or more of your time will be spent debugging, looking stuff up (like program-specific syntax, documentation for packages, useful functions, etc.), or testing. This does not just apply to beginner or intermediate programmers, although you will grow more “fluent” over time.

Google software engineers write an average of 10-20 lines of code per day. **The Lesson:** Programming is a slow activity, especially in the beginning.

If you’re a good programmer, you’re a good detective!

How to Learn

Here are some tips on how to learn computer programming:

1. Learning to program is 5% intelligence, 95% endurance.
2. Like learning to play an instrument or speak a foreign language, it takes practice, practice, practice.
3. Program a little bit every day.
4. Program with others. Do the problem sets in pairs or groups.
5. It’s better to type than to copy and paste.

6. Most “programming” is actually researching, experimenting, thinking.
7. Stay organized.

The 15 minute rule

15 min rule: when stuck, you HAVE to try on your own for 15 min; after 15 min, you HAVE to ask for help.- Brain AMA pic.twitter.com/MS7FnjXoGH

— Rachel Thomas (?) August 14, 2016

We will follow the **15 minute rule** in this class. If you encounter a problem in your assignments, spend 15 minutes troubleshooting the problem on your own. After 15 minutes, if you still cannot solve the problem, **ask for help**.

(Hat tip to Computing for Social Sciences)

Debugging

Those first 15 minutes should be spent trying to debug your code. Here are some tips:

- Read the errors!
- Read the documentation
- Make it smaller
- Figure out what changed
- Check your syntax
- Print statements are your friend

Using the Internet

You should also make use of Google and StackOverflow to resolve the error. Here's some tips for how to google errors:

- google: name-of-program + text in error message.
- Remove user- and data-specific information first!
- See if you can find examples that do and don't produce the error. Try other people's code, but don't fall into the copy-paste trap.

Asking for Help

We will use Canvas/Piazza for class-related questions and discussion. You are highly encouraged to ask questions, and answer one another's questions.

1. Include a brief, informative title.
2. Explain what you're trying to do, and how it failed.

3. Include a reproducible example.

Here are some helpful guidelines on how to properly ask programming questions:

1. “How to Ask Programming Questions,” ProPublica
2. “How do I ask a good question?” StackOverflow
3. “How to properly ask for help” Computing for Social Science

Chapter 5

R Basics

This unit introduces you to the R programming language, and the tools we use to program in R. We will explore:

1. **What is R?**, a brief introduction to the R language;
2. **R Studio**, a tour of the Interactive Development Environment RStudio;
3. **R Packages**, extra tools and functionalities;
4. **R Markdown**, a type of R script file we'll be working with in this class.

5.1 What is R?

R is a versatile, open source programming and scripting language that's useful both for statistics and data science. It's inspired by the programming language S. Some of its **best features** are:

- It's free, open source, and available on every major platform. As a result, if you do your analysis in R, most people can easily replicate it.
- It contains massive set of packages for statistical modelling, machine learning, visualisation, and importing and manipulating data. Over 14,000 packages are available as of August 2019. Whatever model or graphic you're trying to do, chances are that someone has already tried to do it (and a package for it exists).
- It's designed for statistics and data analysis, but also general-purpose programming.
- It's an Interactive Development Environment tailored to the needs of interactive data analysis and statistical programming.
- It has powerful tools for communicating your results. R packages make it easy to produce html or pdf reports, or create interactive websites.

- A large and growing community of peers.

R also has a number of **shortcomings**:

- It has a steeper learning curve than SPSS or Stata.
- R is not a particularly fast programming language, and poorly written R code can be terribly slow. R is also a profligate user of memory.
- Much of the R code you'll see in the wild is written in haste to solve a pressing problem. As a result, code is not very elegant, fast, or easy to understand. Most users do not revise their code to address these shortcomings.
- Inconsistency is rife across contributed packages, even within base R. You are confronted with over 20 years of evolution every time you use R. Learning R can be tough because there are many special cases to remember.

5.2 R Studio

Throughout this class, we will assume that you are using R via RStudio. First time users often confuse the two. At its simplest R is like a car's engine while RStudio is like a car's dashboard.

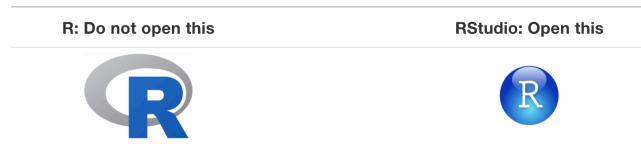


More precisely, R is a programming language that runs computations, while RStudio is an *integrated development environment (IDE)* that provides an interface with many convenient features and tools. So just as the way of having access to a speedometer, rear-view mirrors, and a navigation system makes driving much easier, using RStudio's interface makes using R much easier as well.

RStudio includes a console, syntax-highlighting code editor, as well as tools for plotting, history, debugging and workspace management. It's also free and open-source. Yay!

NB: We don't have to use RStudio to use R. For example, we write R code in a plain text editor (like `textedit` or `notepad`), and then execute the script using the shell (e.g. `terminal` in Mac). But this is not ideal.

After you install R and RStudio on your computer, you'll have two new applications you can open. We'll always work in RStudio—not in the R application.



After you open RStudio, you should see something similar to this:



5.2.1 Console

There are two main ways of interacting with R: using the **console** or by using the **script editor**.

The console window (in RStudio, the bottom left panel) is the place where R is waiting for you to tell it what to do, and where it will show the results of a command.

You can type commands directly into the console, but they will be forgotten when you close the session. Try it out now.

```
> 2 + 2
```

If R is ready to accept commands, the R console shows a `>` prompt. If it receives a command (by typing, copy-pasting or sent from the script editor using **Ctrl-Enter**), R will try to execute it, and when ready, show the results and come back with a new `>-prompt` to wait for new commands.

If R is still waiting for you to enter more data because it isn't complete yet, the console will show a `+` prompt. It means that you haven't finished entering a complete command. This happens when you have not 'closed' a parenthesis

or quotation. If you're in RStudio and this happens, click inside the console window and press **Esc**; this should help get you out of trouble.

```
> "This is an incomplete quote
+
```

More Console Features

1. Retrieving previous commands: As you work with R you'll often want to re-execute a command which you previously entered. Recall previous commands using the up and down arrow keys.
2. Console title bar: This screenshot illustrates a few additional capabilities provided by the Console title bar:
 - Display of the current working directory.
 - The ability to interrupt R during a long computation.
 - Minimizing and maximizing the Console in relation to the Source pane (using the buttons at the top-right or by double-clicking the title bar).



5.2.2 Scripts

It's better practice to enter commands in the script editor, and save the script. This way, you have a complete record of what you did, you can easily show others how you did it and you can do it again later on if needed. Open it up either by clicking the *File* menu, and selecting *New File*, then R script, or using the keyboard shortcut Cmd/Ctrl + Shift + N. Now you'll see four panes.



The script editor is a great place to put code you care about. Keep experimenting in the console, but once you have written code that works and does what

you want, put it in the script editor.

RStudio will automatically save the contents of the editor when you quit RStudio, and will automatically load it when you re-open. Nevertheless, it's a good idea to save your scripts regularly and to back them up.

5.2.3 Running code

While you certainly can copy-paste code you'd like to run from the editor into the console, this workflow is pretty inefficient. The key to using the script editor effectively is to memorize one of the most important keyboard shortcuts in RStudio: **Cmd/Ctrl + Enter**. This executes the current R expression from the script editor in the console.

For example, take the code below. If your cursor is somewhere on the first line, pressing **Cmd/Ctrl + Enter** will run the complete command that generates `dems`. It will also move the cursor to the next statement (beginning with `reps`). That makes it easy to run your complete script by repeatedly pressing **Cmd/Ctrl + Enter**.

```
dems <- (55 + 70) * 1.3
reps <- (20 - 1) / 2
```

Instead of running expression-by-expression, you can also execute the complete script in one step: **Cmd/Ctrl + Shift + S**. Doing this regularly is a great way to check that you've captured all the important parts of your code in the script.

5.2.4 Comments

Use `#` signs to add comments within your code chunks, and you are encouraged to regularly comment within your code. Anything to the right of a `#` is ignored by R. Each line of a comment needs to begin with a `#`.

```
# This is a comment.
# This is another line of comments.
```

5.2.5 Diagnostics and errors

The script editor will also highlight syntax errors with a red squiggly line and a cross in the sidebar:



You can hover over the cross to see what the problem is:



If you try to execute the code, you'll see an error in the console.

```
> x y <- 10
Error: unexpected symbol in "x y"
>
```

When errors happen, your code is halted – meaning it's never executed. Errors can be frustrating in R, but with practice you'll be able to debug your code quickly.

5.2.6 Errors, Messages, and Warnings

One thing that intimidates new R and RStudio users is how it reports errors, warnings, and messages. R reports errors, warnings, and messages in a glaring font, which makes it seem like it is scolding you. However, seeing red text in the console is not always bad.

1. **Errors:** When the text is a legitimate error, it will be prefaced with “Error:” and try to explain what went wrong. Generally when there’s an error, the code will not run. *Think of errors as a red traffic light: something is wrong!*
2. **Warnings:** When the text is a warning, it will be prefaced with “Warning:” and R will try to explain why there’s a warning. Generally your code will still work, but perhaps not in the way you would expect. *Think of warnings as a yellow traffic light: everything is working fine, but watch out/pay attention.*
3. **Messages:** When the text doesn’t start with either “Error” or “Warning”, it’s just a friendly message. These are helpful diagnostic messages and they don’t stop your code from working. *Think of messages as a green traffic light: everything is working fine and keep on going!*

5.2.7 R Environment

Turn your attention to the upper right pane. This pane displays your “global environment”, and it contains the data objects you have saved in your current session. Notice that we have the two objects created earlier, `dems`, and `reps`, along with their values.

You can list all objects in your current environment by running:

```
ls()  
#> [1] "dems" "reps"
```

Sometimes we want to remove objects that we no longer need.

```
x <- 5  
rm(x)
```

If you want to remove all objects from your current environment, you can run:

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

Acknowledgments

This page is in part derived from the following sources:

1. R Studio Support.
2. Advanced R, licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International Public License
3. R for Data Science licensed under Creative Commons Attribution-NonCommercial-NoDerivs 3.0
4. A ModernDive into R and the tidyverse

5.3 R Packages

The best part about R are its user-contributed packages (also called “libraries”). A *package* is a collection of functions (and sometimes data) that can be used by other programmers.

A good analogy for R packages is they are like apps you can download onto a mobile phone:



So R is like a new mobile phone: while it has a certain amount of features when you use it for the first time, it doesn't have everything. R packages are like the apps you can download onto your phone from Apple's App Store or Android's Google Play.

Let's continue this analogy by considering the Instagram app for editing and sharing pictures. Say you have purchased a new phone and you would like to share a photo you have just taken with friends and family on Instagram. You need to:

1. **Install the app:** Since your phone is new and does not include the Instagram app, you need to download the app from either the App Store or Google Play. You do this once and you're set for the time being. You might need to do this again in the future when there is an update to the app.
2. **Open the app:** After you've installed Instagram, you need to open the app.

The process is very similar for using an R package. You need to:

1. **Install the package:** This is like installing an app on your phone. Most packages are not installed by default when you install R and RStudio. Thus if you want to use a package for the first time, you need to install it first. Once you've installed a package, you likely won't install it again unless you want to update it to a newer version.
2. **“Load” the package:** Loading a package is like opening an app on your phone. Packages are not loaded by default when you start RStudio on your computer; you need to load each package you want to use every time you start RStudio.

5.3.1 Installing Packages

First, we download the package from one of the CRAN mirrors onto our computer. For this we use `install.packages("package-name")`. If you have not set a preferred CRAN mirror in your `options()`, a menu will pop up asking you to choose a location.

Let's download the package `dplyr`.

```
install.packages("dplyr")
```

If you run into errors later in the course about a function or package not being found, run the `install.packages` function to make sure the package is actually installed.

Important: Once we download the package, we never need to run `install.packages` again (unless we get a new computer.)

5.3.2 Loading Packages

Once we download the package, we need to load it into our session to use it. This is required at the beginning of each R session. This step is necessary because if we automatically loaded every package we have ever downloaded, our computer would fry.

```
library(dplyr)
```

The message tells you which functions from `dplyr` conflict with functions in base R (or from other packages you might have loaded).

5.3.3 Challenges

Let's go ahead and download some core, important packages we'll use for the rest of the course. Download (if you haven't done so already) and load the following packages:

- `tidyverse`
- `rmarkdown`
- `knitr`
- `gapminder`
- `devtools`
- `stargazer`
- `rtweet`
- `kableExtra`

Acknowledgments

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4. A ModernDive into R and the tidyverse

5.4 R Markdown

Throughout this course, we'll be using R Markdown for lecture notes and homework assignments. R Markdown documents combine executable code, results, and prose commentary into one document. Think of an R Markdown files as a modern day lab notebook, where you can capture not only what you did, but also what you were thinking.

The filename of an R Markdown document should end in `.Rmd` or `.rmd`. They can also be converted to an output format, like PDF, HTML, slideshows, Word files, and more.

R Markdown documents contain three important types of content:

1. An (optional) YAML header surrounded by ---s.
2. Chunks of R code surrounded by ` ` `.
3. Text mixed with simple text formatting like `# heading` and `_italics_`.

5.4.1 YAML header

YAML stands for “yet another markup language”. R Markdown uses it to control many details of the output.

```
---
title: "Homework 1"
author: "Rochelle Terman"
date: "Fall 2019"
output: html_document
---
```

In this example, we specified the document's title, author, and date; we also specified that we want it to eventually convert it into an HTML document.

5.4.2 Markdown

Prose in `.Rmd` files is written in Markdown, a lightweight set of conventions for formatting plain text files. Markdown is designed to be easy to read and easy to write. It is also very easy to learn. The guide below shows how to use Pandoc's Markdown, a slightly extended version of Markdown that R Markdown understands.

Text formatting

```
*italic* or _italic_
**bold** __bold__
`code`
superscript^2^ and subscript~2~
```

Headings

```
# 1st Level Header
## 2nd Level Header
### 3rd Level Header
```

Lists

```
* Bulleted list item 1
* Item 2
  * Item 2a
  * Item 2b
1. Numbered list item 1
1. Item 2. The numbers are incremented automatically in the output.
```

Links and images

```
<http://example.com>
[linked phrase](http://example.com)
! [optional caption text](path/to/img.png)
```

Tables

```
First Header | Second Header
```

-----	-----
Content Cell	Content Cell
Content Cell	Content Cell

The best way to learn these is simply to try them out. It will take a few days, but soon they will become second nature, and you won't need to think about them. If you forget, you can get to a handy reference sheet with Help > Markdown Quick Reference.

5.4.3 Code Chunks

To run code inside an R Markdown document, you do it inside a “chunk”. Think of a chunk like a step in a larger process. A chunk should be relatively self-contained, and focused around a single task.

Chunks begin with a header which consists of ` ``{r, followed by an optional chunk name, followed by comma separated options, followed by }`. Next comes your R code and the chunk end is indicated by a final ` ```.

You can continue to run the code using the keyboard shortcut that we learned earlier: **Cmd/Ctrl + Enter**. You can also run the entire chunk by clicking the Run icon (it looks like a play button at the top of the chunk), or by pressing **Cmd/Ctrl + Shift + Enter**.

RStudio executes the code and displays the results inline with the code:

5.4.4 Knitting

To produce a complete report containing all text, code, and results, click the “Knit” button at the top of the script editor (looks like a ball of yarn) or press **Cmd/Ctrl + Shift + K**. This will display the report in the viewer pane, and create a self-contained HTML file that you can share with others. The **.html** file is written in the same directory as your **.Rmd** file.

5.4.5 Cheatsheets and Other Resources

When working in RStudio, you can find an R Markdown cheatsheet by going to Help > Cheatsheets > R Markdown Cheat Sheet.

A helpful overview of R Markdown can also be found in R for Data Science

A deep dive into R Markdown can be found here



Figure 5.1:

5.4.6 Challenges

Challenge 1.

Create a new R Markdown document with *File > New File > R Markdown...*. Read the instructions. Practice running the chunks.

Now add some new markdown. Try adding some first-, second-, and third-level headers. Insert a link to a website.

Challenge 2.

In the first code chunk, modify `cars` to `mtcars`. Re-run the chunk, and see modified output.

Challenge 3.

Knit the document into an PDF file. Verify that you can modify the input and see the output update.

Acknowledgments

This page is in part derived from the following sources:

1. R for Data Science licensed under Creative Commons Attribution-NonCommercial-NoDerivs 3.0

Chapter 6

R Syntax

Frustration is natural when you start programming in R. R is a stickler for punctuation, and even one character out of place will cause it to complain. But while you should expect to be a little frustrated, take comfort in that it's both typical and temporary: it happens to everyone, and the only way to get over it is to keep trying.

To understand computations in R, two slogans are helpful:

- Everything that exists is an object.
- Everything that happens is a function call.

John Chambers

6.1 Variables

6.1.1 Arithmetic

In its most basic form, R can be used as a simple calculator. Consider the following arithmetic operators:

- Addition: `+`
- Subtraction: `-`
- Multiplication: `*`
- Division: `/`
- Exponentiation: `^`
- Modulo (remainder): `%%`

```
1 / 200 * 30
#> [1] 0.15
(59 + 73 + 2) / 3
```

```
#> [1] 44.7
5 % 2
#> [1] 1
```

But when we do this, none of our results are saved for later use.

6.1.2 Assigning Variables

An essential part of programming is creating objects (or variables)¹ Variables are names for values.

A variable is created when a value is assigned to it. We do that with `<-`.

```
x <- 3
```

`<-` is called the *assignment operator*. It assigns values on the right to objects on the left, like this:

```
object_name <- value
```

So, after executing `x <- 3`, the value of `x` is 3. The arrow can be read as 3 goes into `x`.

Note: Don't use `=` for assignments. It will work in some contexts, but will cause confusion later.

We can use variables in calculations just as if they were values.

```
x <- 3
x + 5
#> [1] 8
```

Inspect objects to display values.

In R, the contents of an object can be printed by simply executing the object name.

```
x <- 3
x
#> [1] 3
```

Whitespace makes code easier to read.

Notice that we surrounded `<-` with spaces. In R, white space is ignored (unlike Python). It is good practice to use spaces, because it makes code easier to read.

¹Technically, objects and variables are different things, but we'll use the two interchangeably for now.

```
experiment<-"current vs. voltage" # this is bad
experiment <- "current vs. voltage" # this is better
```

6.1.3 Variable Names

Object names can only contain letters, numbers, `_` and `..`

You want your object names to be descriptive. `x` is not a good variable name (sorry!). You'll also need a convention for multiple words. I recommend `snake_case` where you separate lowercase words with `_`.

```
i_use_snake_case
otherPeopleUseCamelCase
some.people.use.periods
And_aFew.People_RENOUNCEconvention
```

Let's make an assignment using `snake_case`:

```
r_rocks <- 2 ^ 3
```

And let's try to inspect it:

```
r_rock
#> Error in eval(expr, envir, enclos): object 'r_rock' not found
R_rocks
#> Error in eval(expr, envir, enclos): object 'R_rocks' not found
```

R is case-sensitive!

Use the TAB key to autocomplete.

Because typos are the absolute worst, we can use R Studio to help us type. Let's inspect `r_rocks` using RStudio's tab completion facility. Type “`r_`”, press TAB, add characters until you have a unique prefix, then press return.

```
r_rocks
#> [1] 8
```

6.1.4 Challenges

Challenge 1: Making and Printing Variables.

Make 3 variables: name (with your full name), city (where you were born) and year (when you were born.)

Challenge 2: Swapping Values

Draw a table showing the values of the variables in this program after each statement is executed.

In simple terms, what do the last three lines of this program do?

```
lowest <- 1.0
highest <- 3.0
temp <- lowest
lowest <- highest
highest <- temp
```

Challenge 3: Predicting Values

What is the final value of `position` in the program below? Try to predict the value without running the program, then check your prediction.

```
initial <- "left"
position <- initial
initial <- "right"
```

Challenge 4: Syntax

Why does the following code fail?

```
age == 31
```

and the following?

```
31 <- age
```

6.2 Functions

R has a large collection of built-in functions that helps us do things. When we use a function, we say we're *calling* a function.

```
function_name(arg1 = val1, arg2 = val2, ...)
```

Here are some helpful built-in functions:

```
my_var <- c(1, 5, 2, 4, 5)

sum(my_var)
#> [1] 17
length(my_var)
```

```
#> [1] 5
min(my_var)
#> [1] 1
max(my_var)
#> [1] 5
unique(my_var)
#> [1] 1 5 2 4
```

6.2.1 Arguments

An *argument* is a value that is *passed* into a function. Every function returns a **result**.

Let's try using `seq()`, which makes regular sequences of numbers. While we're at it, we'll learn more helpful features of RStudio.

Type `se` and hit TAB. A popup shows you possible completions. Specify `seq()` by typing more (a “q”) to disambiguate, or by using ↑/↓ arrows to select. Notice the floating tooltip that pops up, reminding you of the function's arguments and purpose.

Press TAB once more when you've selected the function you want. RStudio will add matching opening () and closing () parentheses for you. Type the arguments `1, 10` and hit return.

```
seq(1, 10)
#> [1] 1 2 3 4 5 6 7 8 9 10
```

How many arguments did we pass into the `seq` function?

6.2.2 Store Function Output

Notice, when we called the `seq` function, nothing changed in our environment. That's because we didn't save our results to an object. Let's try it again by assigning a variable.

```
y <- seq(1, 10)
y
#> [1] 1 2 3 4 5 6 7 8 9 10
```

6.2.3 Argument Restrictions and Defaults

Let's use another function, called `round`:

```
round(60.123)
#> [1] 60
```

`round` must be given at least one argument. And it must be given things that can be meaningful rounded.

```
round()
round('a')
```

Functions may have **default** values for some arguments.

By default, `round` will round off any number to zero decimal places. But we can specify the number of decimal places we want.

```
round(60.123)
#> [1] 60
round(60.123, digits = 2)
#> [1] 60.1
round(60.123, 2)
#> [1] 60.1
```

6.2.4 Documentation and Help Files

How do we know what kinds of arguments to pass into a function? Every built-in function comes with documentation.

- `? + object` opens a help page for that specific object
- `?? + object` searches help pages containing the name of the object

```
?mean
??mean
```

All help files are structured the same way. The section **Arguments** tells us exactly what kind of information we can pass into a function. The **Value** section explains what the output of the function is. The **Examples** contain real examples of the function in use.

6.2.5 Challenges

Challenge 1: What Happens When

Explain, in simple terms, the order of operations in the following program: when does the addition happen, when does the subtraction happen, when is each function called, etc.

What is the final value of `radianc`?

```
radiance <- 1.0
radiance <- max(2.1, 2.0 + min(radiance, 1.1 * radiance - 0.5))
```

Challenge 2: Why?

Run the following code.

```
rich <- "gold"
poor <- "tin"
max(rich, poor)
```

Using the help files for `max`, explain why it returns the result it does.

6.3 Data Types

Every value in a program has a specific **type**. In R, those types are called “classes”, and there are 4 of them:

- character (text or “string”)
- numeric (integer or decimal)
- integer (just integer)
- logical (TRUE or FALSE booleans)

Example	Type
“a”, “swc”	character
2, 15.5	numeric
2 (Must add a L at end to denote integer)	integer
TRUE, FALSE	logical

6.3.1 What’s that Type?

R is dynamically typed, meaning that it “guesses” what class a value is.

Use the built-in function `class()` to find out what type a value has.

```
class(3)
#> [1] "numeric"
class(3L)
#> [1] "integer"
class("Three")
#> [1] "character"
class(T)
#> [1] "logical"
```

This works on variables as well. But remember: the *value* has the type — the *variable* is just a label.

```
three <- 3
class(three)
#> [1] "numeric"

three <- "three"
class(three)
#> [1] "character"
```

A value's class determines what the program can do to it.

```
3 - 1
#> [1] 2
3 - "1"
#> Error in 3 - "1": non-numeric argument to binary operator
```

6.3.2 Coercion

We just learned we cannot subtract numbers and strings. Instead, use `as.. + name of class` as functions to convert a value to that type.

```
3 - as.numeric("1")
```

This is called **coercion**. Here's another example:

```
my_var <- "FALSE"
my_var
#> [1] "FALSE"
as.logical(my_var)
#> [1] FALSE
```

What difference did you notice?

6.3.3 Other Objects

There are a few other “odd ball” types in R:

NA are missing values

Missing values are specified with `NA`. `NA` will always be coerced to the correct type if used inside `c()`

```
x <- c(NA, 1)
x
#> [1] NA  1
```

```
typeof(NA)
#> [1] "logical"
typeof(x)
#> [1] "double"
```

Inf is infinity.

You can have either positive or negative infinity.

```
1/0
#> [1] Inf
1/Inf
#> [1] 0
```

NaN means “Not a number”. It’s an undefined value.

```
0/0
#> [1] NaN
```

6.3.4 Challenges

Challenge 1: Making and Coercing Variables

1. Make a variable `year` and assign it as the year you were born.
2. Coerce that variable to a string, and assign it to a new variable `year_string`.
3. Someone in your class says they were born in 2001. Really? Really. Find out what your age difference is, using only `year_string`.

Challenge 2: Fix the Code

Change the following code to make the output TRUE.

```
val_1 <- F
val_2 <- "F"

class(val_1) == class(val_2)
#> [1] FALSE
```


Chapter 7

Data Classes and Structures

To make the best use of the R language, you'll need a strong understanding of basic data structures, and how to operate on them.

This is **critical** to understand because these are the objects you will manipulate on a day-to-day basis in R. But they are not always as easy to work with as they seem at the outset. Dealing with object types and conversions is one of the most common sources of frustration for beginners.

R's base data structures can be organised by their dimensionality (1d, 2d, or nd) and whether they're homogeneous (all contents must be of the same type) or heterogeneous (the contents can be of different types). This gives rise to the five data types most often used in data analysis:

	Homogeneous	Heterogeneous
1d	Atomic vector	List
2d	Matrix	Dataframe
nd	Array	

Each data structure has its own specifications and behavior. In the rest of this chapter, we will cover the types of data objects that exist in R and their attributes.

1. Vectors
2. Lists
3. Factors
4. Matrices
5. Dataframes

7.1 Vectors

Let's start with one-dimensional (1d) objects. There are two kinds:

1. **Atomic vectors** - also called, simply, **vectors**.
2. **Lists**: Lists are distinct from atomic vectors because lists can contain other lists.

We'll discuss **atomic vectors** first.

7.1.1 Creating Vectors

Vectors are 1-dimensional chains of values. We call each value an *element* of a vector.

Atomic vectors are usually created with `c()`, which is short for ‘combine’:

```
x <- c(1, 2, 3)
x
#> [1] 1 2 3
length(x)
#> [1] 3
```

We can also add elements to the end of a vector by passing the original vector into the `c` function, like so:

```
z <- c("Beyonce", "Kelly", "Michelle", "LeToya")
z <- c(z, "Farrah")
z
#> [1] "Beyonce"   "Kelly"      "Michelle"   "LeToya"     "Farrah"
```

Notice that vectors are always flat, even if you nest `c()`'s:

```
# these are equivalent
c(1, c(2, c(3, 4)))
#> [1] 1 2 3 4
c(1, 2, 3, 4)
#> [1] 1 2 3 4
```

7.1.2 Naming a Vector

We can also attach names to our vector. This helps us understand what each element refers to.

You can give a name to the elements of a vector with the `names()` function. Have a look at this example:

```
days_month <- c(31, 28, 31, 30, 31, 30, 31, 31, 30, 31, 30, 31)
names(days_month) <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")
days_month
#> Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
#> 31 28 31 30 31 30 31 31 30 31 30 31
```

You can name a vector when you create it:

```
some_vector <- c(name = "Rochelle Terman", profession = "Professor Extraordinaire")
some_vector
#> name profession
#> "Rochelle Terman" "Professor Extraordinaire"
```

Notice that in the first case, we surrounded each name with quotation marks. But we don't have to do this when creating a named vector.

Names don't have to be unique, and not all values need to have a name associated. However, names are most useful for subsetting, described in the next chapter. When subsetting, it is most useful when the names are unique.

7.1.3 Calculations on Vectors

One of the most powerful things about vectors is that we can perform arithmetic calculations on them.

For example, we can sum up all the values in a numerical vector using **sum**:

```
a <- c(1, -2, 3)
sum(a)
#> [1] 2
```

We can also sum two vectors. It is important to know that if you **sum** two vectors in R, it takes the element-wise sum. For example, the following three statements are completely equivalent:

```
c(1, 2, 3) + c(4, 5, 6)
c(1 + 4, 2 + 5, 3 + 6)
c(5, 7, 9)
```

7.1.4 Types of Vectors

So there are four common types of vectors, depending on the class: *
logical * **integer** * **numeric** (same as **double**) * **character**.

Logical Vectors

Logical vectors take on one of three possible values:

1. TRUE
2. FALSE
3. NA (missing value)

```
c(TRUE, TRUE, FALSE, NA)
#> [1] TRUE TRUE FALSE NA
```

Numeric Vectors

Numeric vectors contain numbers. They can be stored as *integers* (whole numbers) or *doubles* (numbers with decimal points). In practice, you rarely need to concern yourself with this difference, but just know that they are different but related things.

```
c(1, 2, 335)
#> [1] 1 2 335
c(4.2, 4, 6, 53.2)
#> [1] 4.2 4.0 6.0 53.2
```

Character Vectors

Character vectors contain character (or ‘string’) values. Note that each value has to be surrounded by quotation marks *before* the comma.

```
c("Beyonce", "Kelly", "Michelle", "LeToya")
#> [1] "Beyonce" "Kelly" "Michelle" "LeToya"
```

7.1.5 Coercion

We can change or convert a vector’s type using `as.....`

```
num_var <- c(1, 2.5, 4.5)
class(num_var)
#> [1] "numeric"
as.character(num_var)
#> [1] "1"   "2.5" "4.5"
```

Remember that all elements of a vector must be the same type. So when you attempt to combine different types, they will be **coerced** to the most “flexible” type.

For example, combining a character and an integer yields a character:

```
c("a", 1)
#> [1] "a" "1"
```

Guess what the following do without running them first:

```
c(1.7, "a")
c(TRUE, 2)
c("a", TRUE)
```

TRUE == 1 and FALSE == 0.

Notice that when a logical vector is coerced to an integer or double, TRUE becomes 1 and FALSE becomes 0. This is very useful in conjunction with `sum()` and `mean()`

```
x <- c(FALSE, FALSE, TRUE)
as.numeric(x)
#> [1] 0 0 1

# Total number of TRUES
sum(x)
#> [1] 1

# Proportion that are TRUE
mean(x)
#> [1] 0.333
```

Coercion often happens automatically.

This is called *implicit coercion*. Most mathematical functions (+, log, abs, etc.) will coerce to a double or integer, and most logical operations (&, |, any, etc) will coerce to a logical. You will usually get a warning message if the coercion might lose information.

```
1 < "2"
#> [1] TRUE
"1" > 2
#> [1] FALSE
```

Sometimes coercions, especially nonsensical ones, won't work.

```
x <- c("a", "b", "c")
as.numeric(x)
#> Warning: NAs introduced by coercion
#> [1] NA NA NA
```

```
as.logical(x)
#> [1] NA NA NA
```

7.1.6 Challenges

Challenge 1: Create and examine your vector

Create a character vector called `fruit` that contain 4 of your favorite fruits. Then evaluate its structure using the commands below.

```
# First create your fruit vector
# YOUR CODE HERE

# Examine your vector
length(fruit)
class(fruit)
str(fruit)
```

Challenge 2: Coercion

```
# 1. Create a vector of a sequence of numbers between 1 to 10.

# 2. Coerce that vector into a character vector

# 3. Add the element "11" to the end of the vector

# 4. Coerce it back to a numeric vector.
```

Challenge 3: Calculations on Vectors

Create a vector of the numbers 11-20, and multiply it by the original vector from Challenge 2.

7.2 Lists

Lists are different from vectors because their elements can be of **any type**. Lists are sometimes called recursive vectors, because a list can contain other lists. This makes them fundamentally different from vectors.

7.2.1 Creating Lists

You construct lists by using `list()` instead of `c()`:

```
x <- list(1, "a", TRUE, c(4, 5, 6))
x
#> [[1]]
#> [1] 1
#>
#> [[2]]
#> [1] "a"
#>
#> [[3]]
#> [1] TRUE
#>
#> [[4]]
#> [1] 4 5 6
```

7.2.2 Naming Lists

As with vectors, we can attach names to each element on our list:

```
my_list <- list(name1 = elem1,
                 name2 = elem2)
```

This creates a list with components that are named `name1`, `name2`, and so on. If you want to name your lists after you've created them, you can use the `names()` function as you did with vectors. The following commands are fully equivalent to the assignment above:

```
my_list <- list(elem1, elem2)
names(my_list) <- c("name1", "name2")
```

7.2.3 List Structure

A very useful tool for working with lists is `str()` because it focuses on reviewing the structure of a list, not the contents.

```
x <- list(a = c(1, 2, 3),
          b = c("Hello", "there"),
          c = 1:10)
str(x)
#> List of 3
#> $ a: num [1:3] 1 2 3
#> $ b: chr [1:2] "Hello" "there"
#> $ c: int [1:10] 1 2 3 4 5 6 7 8 9 10
```

A list does not print to the console like a vector. Instead, each element of the list starts on a new line.

```
x.vec <- c(1,2,3)
x.list <- list(1,2,3)
x.vec
#> [1] 1 2 3
x.list
#> [[1]]
#> [1] 1
#>
#> [[2]]
#> [1] 2
#>
#> [[3]]
#> [1] 3
```

Lists are used to build up many of the more complicated data structures in R. For example, both data frames and linear models objects (as produced by `lm()`) are lists:

```
head(mtcars)
#>          mpg cyl disp hp drat    wt  qsec vs am gear carb
#> Mazda RX4     21.0   6 160 110 3.90 2.62 16.5  0  1    4    4
#> Mazda RX4 Wag 21.0   6 160 110 3.90 2.88 17.0  0  1    4    4
#> Datsun 710    22.8   4 108  93 3.85 2.32 18.6  1  1    4    1
#> Hornet 4 Drive 21.4   6 258 110 3.08 3.21 19.4  1  0    3    1
#> Hornet Sportabout 18.7   8 360 175 3.15 3.44 17.0  0  0    3    2
#> Valiant       18.1   6 225 105 2.76 3.46 20.2  1  0    3    1
is.list(mtcars)
#> [1] TRUE
mod <- lm(mpg ~ wt, data = mtcars)
is.list(mod)
#> [1] TRUE
```

You could say that a list is some kind super data type: you can store practically any piece of information in it!

For this reason, lists are extremely useful inside functions. You can “staple” together lots of different kinds of results into a single object that a function can return.

```
mod <- lm(mpg ~ wt, data = mtcars)
str(mod)
#> List of 12
#> $ coefficients : Named num [1:2] 37.29 -5.34
#> ..- attr(*, "names")= chr [1:2] "(Intercept)" "wt"
```

```

#> $ residuals      : Named num [1:32] -2.28 -0.92 -2.09 1.3 -0.2 ...
#> ..- attr(*, "names")= chr [1:32] "Mazda RX4" "Mazda RX4 Wag" "Datsun 710" "Hornet 4 Drive" ...
#> $ effects       : Named num [1:32] -113.65 -29.116 -1.661 1.631 0.111 ...
#> ..- attr(*, "names")= chr [1:32] "(Intercept)" "wt" "" "" ...
#> $ rank          : int 2
#> $ fitted.values: Named num [1:32] 23.3 21.9 24.9 20.1 18.9 ...
#> ..- attr(*, "names")= chr [1:32] "Mazda RX4" "Mazda RX4 Wag" "Datsun 710" "Hornet 4 Drive" ...
#> $ assign         : int [1:2] 0 1
#> $ qr             :List of 5
#>   ..$ qr    : num [1:32, 1:2] -5.657 0.177 0.177 0.177 0.177 ...
#>   ... .- attr(*, "dimnames")=List of 2
#>   ...   .$. : chr [1:32] "Mazda RX4" "Mazda RX4 Wag" "Datsun 710" "Hornet 4 Drive" ...
#>   ...   .$. : chr [1:2] "(Intercept)" "wt"
#>   ... .- attr(*, "assign")= int [1:2] 0 1
#>   ..$ qraux: num [1:2] 1.18 1.05
#>   ..$ pivot: int [1:2] 1 2
#>   ..$ tol  : num 1e-07
#>   ..$ rank : int 2
#>   ..- attr(*, "class")= chr "qr"
#> $ df.residual   : int 30
#> $ xlevels       : Named list()
#> $ call          : language lm(formula = mpg ~ wt, data = mtcars)
#> $ terms         :Classes 'terms', 'formula' language mpg ~ wt
#>   ... .- attr(*, "variables")= language list(mpg, wt)
#>   ... .- attr(*, "factors")= int [1:2, 1] 0 1
#>   ... .- attr(*, "dimnames")=List of 2
#>   ...   .$. : chr [1:2] "mpg" "wt"
#>   ...   .$. : chr "wt"
#>   ... .- attr(*, "term.labels")= chr "wt"
#>   ... .- attr(*, "order")= int 1
#>   ... .- attr(*, "intercept")= int 1
#>   ... .- attr(*, "response")= int 1
#>   ... .- attr(*, ".Environment")=<environment: R_GlobalEnv>
#>   ... .- attr(*, "predvars")= language list(mpg, wt)
#>   ... .- attr(*, "dataClasses")= Named chr [1:2] "numeric" "numeric"
#>   ...   .- attr(*, "names")= chr [1:2] "mpg" "wt"
#> $ model          :'data.frame': 32 obs. of 2 variables:
#>   ..$ mpg: num [1:32] 21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
#>   ..$ wt : num [1:32] 2.62 2.88 2.32 3.21 3.44 ...
#>   ... .- attr(*, "terms")=Classes 'terms', 'formula' language mpg ~ wt
#>   ...   .- attr(*, "variables")= language list(mpg, wt)
#>   ...   .- attr(*, "factors")= int [1:2, 1] 0 1
#>   ...   .- attr(*, "dimnames")=List of 2
#>   ...     .$. : chr [1:2] "mpg" "wt"
#>   ...     .$. : chr "wt"

```

```
#> ... . . - attr(*, "term.labels")= chr "wt"
#> ... . . - attr(*, "order")= int 1
#> ... . . - attr(*, "intercept")= int 1
#> ... . . - attr(*, "response")= int 1
#> ... . . - attr(*, ".Environment")=<environment: R_GlobalEnv>
#> ... . . - attr(*, "predvars")= language list(mpg, wt)
#> ... . . - attr(*, "dataClasses")= Named chr [1:2] "numeric" "numeric"
#> ... . . . - attr(*, "names")= chr [1:2] "mpg" "wt"
#> - attr(*, "class")= chr "lm"
```

7.2.4 Challenges

Challenge 1.

What are the four basic types of atomic vectors? How does a list differ from an atomic vector?

Challenge 2.

Why is `1 == "1"` true? Why is `-1 < FALSE` true? Why is `"one" < 2` false?

Challenge 3.

Create three vectors and combine them into a list. Assign them names.

Challenge 4.

If `x` is a list, what is the class of `x[1]`? How about `x[[1]]`?

7.3 Factors

Factors are special vectors that represent *categorical* data: variables that have a fixed and known set of possible values. Think: Democrat, Republican, Independent; Male, Female, Other; etc.

It is important that R knows whether it is dealing with a continuous or a categorical variable, as the statistical models you will develop in the future treat both types differently.

Historically, factors were much easier to work with than characters. As a result, many of the functions in base R automatically convert characters to factors. This means that factors often pop up in places where they're not actually helpful.

7.3.1 Creating Factors

To create factors in R, you use the function `factor()`. The first thing that you have to do is create a vector that contains all the observations that belong to a limited number of categories. For example, `party_vector` contains the partyID of 5 different individuals:

```
party_vector <- c("Rep", "Rep", "Dem", "Rep", "Dem")
```

It is clear that there are two categories, or in R-terms **factor levels**, at work here: `Dem` and `Rep`.

The function `factor()` will encode the vector as a factor:

```
party_factor <- factor(party_vector)
party_vector
#> [1] "Rep" "Rep" "Dem" "Rep" "Dem"
party_factor
#> [1] Rep Rep Dem Rep Dem
#> Levels: Dem Rep
```

7.3.2 Summarizing a Factor

One of your favorite functions in R will be `summary()`. This will give you a quick overview of the contents of a variable. Let's compare using `summary()` on both the character vector and the factor:

```
summary(party_vector)
summary(party_factor)
```

7.3.3 Changing Factor Levels

When you create the factor, the factor levels are set to specific values. We can access those values with the `levels()` function.

```
levels(party_factor)
#> [1] "Dem" "Rep"
```

Any values *not* in the set of levels will be silently converted to `NA`. Let's say we want to add an Independent to our sample:

```
party_factor[5] <- "Ind"
#> Warning in `<-factor`(`*tmp*`, 5, value = "Ind"): invalid factor level,
#> NA generated
party_factor
#> [1] Rep Rep Dem Rep <NA>
#> Levels: Dem Rep
```

We first need to add “Ind” to our factor levels. This will allow us to add Independents to our sample:

```
levels(party_factor)
#> [1] "Dem" "Rep"
levels(party_factor) <- c("Dem", "Rep", "Ind")

party_factor[5] <- "Ind"
party_factor
#> [1] Rep Rep Dem Rep Ind
#> Levels: Dem Rep Ind
```

7.3.4 Factors are Integers

Factors are pretty much integers that have labels on them. Underneath, it's really numbers (1, 2, 3...).

```
str(party_factor)
#> Factor w/ 3 levels "Dem", "Rep", "Ind": 2 2 1 2 3
```

They are better than using simple integer labels because factors are self-describing. For example, `democrat` and `republican` are more descriptive than 1s and 2s.

However, **factors are NOT characters!!**

While factors look (and often behave) like character vectors, they are actually integers. Be careful when treating them like strings.

```
x <- c("a", "b", "b", "a")
x <- as.factor(x)
c(x, "c")
#> [1] "1" "2" "2" "1" "c"
```

For this reason, it's usually best to explicitly **convert** factors to character vectors if you need string-like behaviour.

```
x <- c("a", "b", "b", "a")
x <- as.factor(x)
x <- as.character(x)
c(x, "c'')
#> [1] "a"   "b"   "b"   "a"   "c'"
```

7.3.5 Challenges

Challenge 1.

What happens to a factor when you modify its levels?

```
f1 <- factor(letters)
levels(f1) <- rev(levels(f1))
f1
#> [1] z y x w v u t s r q p o n m l k j i h g f e d c b a
#> Levels: z y x w v u t s r q p o n m l k j i h g f e d c b a
```

Challenge 2.

What does this code do? How do `f2` and `f3` differ from `f1`?

```
f2 <- rev(factor(letters))
f3 <- factor(letters, levels = rev(letters))
```

7.4 Matrices

Matrices are 2-d vectors. That is, they are a collection of elements of the same data type (numeric, character, or logical), arranged into a fixed number of rows and columns.

By definition, if you want to combine different types of data (one column numbers, another column characters), you want a **dataframe**, not a matrix.

7.4.1 Creating Matrices

We can create a matrix using the `matrix()` function. In this function, we assign dimensions to a vector, like this:

```
m <- matrix(1:6, nrow = 2, ncol = 3)
m
#>      [,1] [,2] [,3]
#> [1,]    1    3    5
#> [2,]    2    4    6
```

Notice that matrices fill column-wise. We can change this using the `byrow` argument:

```
m <- matrix(1:6, byrow = T, nrow = 2, ncol = 3)
m
#>      [,1] [,2] [,3]
```

```
#> [1,]    1    2    3
#> [2,]    4    5    6
```

Another way to create matrices is to bind columns or rows using `cbind()` and `rbind()`.

```
x <- 1:3
y <- 10:12
cbind(x, y)
#>      x  y
#> [1,] 1 10
#> [2,] 2 11
#> [3,] 3 12
# or
rbind(x, y)
#> [,1] [,2] [,3]
#> x     1     2     3
#> y     10    11    12
```

7.4.2 Matrix Dimensions

Use `dim()` to find out how many rows or columns are in a matrix (or dataframe)

```
dim(m)
#> [1] 2 3
```

We can transpose a matrix (or dataframe) with `t()`

```
m <- matrix(1:6, nrow = 2, ncol = 3)
m
#>      [,1] [,2] [,3]
#> [1,]    1    3    5
#> [2,]    2    4    6
t(m)
#>      [,1] [,2]
#> [1,]    1    2
#> [2,]    3    4
#> [3,]    5    6
```

7.4.3 Matrix Names

Just like vectors or lists, we can give matrices names that describe the rows and columns

```
m <- matrix(1:6, nrow = 2, ncol = 3)

rownames(m) <- c("row1", "row2")
colnames(m) <- c("A", "B", "C")

m
#>      A B C
#> row1 1 3 5
#> row2 2 4 6
```

7.4.4 Challenge

Take a look at the vector I've created about box office sales for the first three Harry Potter movies:

```
# Box office sales (in millions!)
philosophers_stone <- c(66.1, 317.6, 657.2)
chamber_secrets <- c(54.7, 261.9, 616.9)
prisoner_azkaban <- c(45.6, 249.5, 547.1)

# Vectors region and titles, used for naming
region <- c("UK", "US", "Other")
titles <- c("Philosopher's Stone", "Chamber of Secrets", "Prisoner of Azkaban")
```

Your challenge is to:

1. Combine the first three vectors into a matrix
2. Add names for the matrix's rows (`titles`) and columns (`region`)
3. Use `rowSums()` to find the total Worldwide Box Office sales for each movie.

7.5 Dataframes

A dataframe is a very important data type in R. It's pretty much the *de facto* data structure for most tabular data and it's also what we use for statistics.

Let's say we're working with the following survey data:

- ‘Are you married?’ or ‘yes/no’ questions (`logical`)
- ‘How old are you?’ (`numeric`)
- ‘What is your opinion on Trump?’ or other ‘open-ended’ questions (`character`)
- ...

A matrix won't work here because the dataset contains different data types.

A dataframe is a 2-dimentional data structure containing heterogeneous data types. Each column is a variable of a dataset, and the rows are observations.

NB: You might have heard of “tibbles,” used in the `tidyverse` suite of packages. Tibbles are like dataframes 2.0, tweaking some of the behavior of dataframes to make life easier for data analysis. For now, just think of tibbles and dataframes as the same thing and don’t worry about the difference.

7.5.1 Creating Dataframes

R contains a number of built-in datasets that are stored as dataframes. For example, the `mtcars` dataset contains information on automobile design and performance for 32 automobiles:

```
class(mtcars)
#> [1] "data.frame"
head(mtcars)
#>          mpg cyl disp  hp drat    wt  qsec vs am gear carb
#> Mazda RX4     21.0   6 160 110 3.90 2.62 16.5  0  1    4    4
#> Mazda RX4 Wag 21.0   6 160 110 3.90 2.88 17.0  0  1    4    4
#> Datsun 710    22.8   4 108  93 3.85 2.32 18.6  1  1    4    1
#> Hornet 4 Drive 21.4   6 258 110 3.08 3.21 19.4  1  0    3    1
#> Hornet Sportabout 18.7   8 360 175 3.15 3.44 17.0  0  0    3    2
#> Valiant       18.1   6 225 105 2.76 3.46 20.2  1  0    3    1
```

We also create dataframes when we import data through `read.csv` or other data file input. We’ll talk more about importing data later in the class.

We can create a dataframe from scratch using `data.frame()`. This function takes vectors as input:

```
# Definition of vectors
name <- c("Mercury", "Venus", "Earth", "Mars", "Jupiter", "Saturn", "Uranus", "Neptune")
type <- c("Terrestrial planet", "Terrestrial planet", "Terrestrial planet", "Terrestrial planet", "Gas giant", "Gas giant", "Gas giant", "Gas giant")
diameter <- c(0.382, 0.949, 1, 0.532, 11.209, 9.449, 4.007, 3.883)
rings <- c(FALSE, FALSE, FALSE, FALSE, TRUE, TRUE, TRUE, TRUE)

planets <- data.frame(name, type, diameter, rings)
planets
#>      name           type   diameter rings
#> 1 Mercury Terrestrial planet 0.382 FALSE
#> 2 Venus  Terrestrial planet 0.949 FALSE
#> 3 Earth  Terrestrial planet 1.000 FALSE
#> 4 Mars   Terrestrial planet 0.532 FALSE
#> 5 Jupiter Gas giant 11.209  TRUE
#> 6 Saturn Gas giant  9.449  TRUE
```

```
#> 7 Uranus          Gas giant    4.007 TRUE
#> 8 Neptune         Gas giant    3.883 TRUE
```

Beware: `data.frame()`'s default behaviour turns strings into factors. Use `stringAsFactors = FALSE` to suppress this behaviour as needed:

```
planets <- data.frame(name, type, diameter, rings, stringsAsFactors = F)
planets
#>      name           type   diameter   rings
#> 1 Mercury Terrestrial planet    0.382 FALSE
#> 2 Venus  Terrestrial planet    0.949 FALSE
#> 3 Earth   Terrestrial planet   1.000 FALSE
#> 4 Mars    Terrestrial planet   0.532 FALSE
#> 5 Jupiter        Gas giant   11.209 TRUE
#> 6 Saturn         Gas giant    9.449 TRUE
#> 7 Uranus         Gas giant    4.007 TRUE
#> 8 Neptune        Gas giant    3.883 TRUE
```

7.5.2 The Structure of Dataframes

Under the hood, a dataframe is a list of equal-length vectors. This makes it a 2-dimensional structure, so it shares properties of both the matrix and the list.

```
vec1 <- 1:3
vec2 <- c("a", "b", "c")
df <- data.frame(vec1, vec2)

str(df)
#> 'data.frame':   3 obs. of  2 variables:
#>   $ vec1: int  1 2 3
#>   $ vec2: Factor w/ 3 levels "a","b","c": 1 2 3
```

The `length()` of a dataframe is the length of the underlying list and so is the same as `ncol()`; `nrow()` gives the number of rows.

```
vec1 <- 1:3
vec2 <- c("a", "b", "c")
df <- data.frame(vec1, vec2)

# these two are equivalent - number of columns
length(df)
#> [1] 2
ncol(df)
#> [1] 2

# get number of rows
```

```
nrow(df)
#> [1] 3

# get number of both columns and rows
dim(df)
#> [1] 3 2
```

7.5.3 Naming Dataframes

Like matrices, dataframes have `colnames()`, and `rownames()`. However, since dataframes are really lists (of vectors) under the hood `names()` and `colnames()` are the same thing.

```
vec1 <- 1:3
vec2 <- c("a", "b", "c")
df <- data.frame(vec1, vec2)

# these two are equivalent
names(df)
#> [1] "vec1" "vec2"
colnames(df)
#> [1] "vec1" "vec2"

# change the colnames
colnames(df) <- c("Number", "Character")
df
#>   Number Character
#> 1      1          a
#> 2      2          b
#> 3      3          c

names(df) <- c("Number", "Character")
df
#>   Number Character
#> 1      1          a
#> 2      2          b
#> 3      3          c

# change the rownames
rownames(df)
#> [1] "1" "2" "3"
rownames(df) <- c("donut", "pickle", "pretzel")
df
#>       Number Character
#> donut      1          a
```

```
#> pickle      2      b  
#> pretzel    3      c
```

7.5.4 Coercing Dataframes

Coerce an object to a dataframe with `as.data.frame()`:

- A vector will create a one-column dataframe.
- A list will create one column for each element; it's an error if they're not all the same length.
- A matrix will create a data frame with the same number of columns and rows as the matrix.

7.5.5 Challenges

Challenge 1.

Create a 3x2 data frame called `basket`. The first column should contain the names of 3 fruits. The second column should contain the price of those fruits.

Challenge 2.

Now give your dataframe appropriate column and row names.

Challenge 3.

Add a third column called `color`, that tells me what color each fruit is.

7.5.6 Quiz

You can check your answers in `answers`.

1. How is a list different from an vector?
2. What are the four common types of vectors?
3. What are names? How do you get them and set them?
4. How is a matrix different from a data frame?

7.5.7 Answers

1. The elements of a list can be any type (even a list); the elements of an atomic vector are all of the same type.
2. The four common types of vector are logical, integer, double (sometimes called numeric), and character.
3. Names allow you to attach labels to values. You can get and set individual names with `names(x)` and `names(x) <- c("x", "y", ...)`.
4. Every element of a matrix must be the same type; in a data frame, the different columns can have different types.

Chapter 8

Subsetting

When working with data, you'll need to subset objects early and often. Luckily, R's subsetting operators are powerful and fast. Mastery of subsetting allows you to succinctly express complex operations in a way that few other languages can match. Subsetting is hard to learn because you need to master a number of interrelated concepts:

- The three subsetting operators: `[`, `[[`, and `$`.
- The four types of subsetting.
- The important differences in behaviour for different objects (e.g., vectors, lists, factors, matrices, and data frames).
- The use of subsetting in conjunction with assignment.

This unit helps you master subsetting by starting with the simplest type of subsetting: subsetting an atomic vector with `[`. It then gradually extends your knowledge, first to more complicated data types (like dataframes and lists), and then to the other subsetting operators, `[[` and `$`. You'll then learn how subsetting and assignment can be combined to modify parts of an object, and, finally, you'll see a large number of useful applications.

8.1 Subsetting Vectors

It's easiest to learn how subsetting works for vectors, and then how it generalises to higher dimensions and other more complicated objects. We'll start with `[`, the most commonly used operator.

8.1.1 Subsetting Types

Let's explore the different types of subsetting with a simple vector, `x`.

```
x <- c(2.1, 4.2, 3.3, 5.4)
```

Note that the number after the decimal point gives the original position in the vector.

There are four things you can use to subset a vector:

1. Positive integers return elements at the specified positions:

```
(x <- c(2.1, 4.2, 3.3, 5.4))
#> [1] 2.1 4.2 3.3 5.4
x[1]
#> [1] 2.1
```

We can also index multiple values by passing a vector of integers:

```
(x <- c(2.1, 4.2, 3.3, 5.4))
#> [1] 2.1 4.2 3.3 5.4
x[c(3, 1)]
#> [1] 3.3 2.1

# Duplicated indices yield duplicated values
x[c(1, 1)]
#> [1] 2.1 2.1
```

Note that you *have* to use `c` inside the `[` for this to work!

More examples:

```
# `order(x)` gives the index positions of smallest to largest values.
(x <- c(2.1, 4.2, 3.3, 5.4))
#> [1] 2.1 4.2 3.3 5.4
order(x)
#> [1] 1 3 2 4

# use this to order values.
x[order(x)]
#> [1] 2.1 3.3 4.2 5.4
x[c(1, 3, 2, 4)]
#> [1] 2.1 3.3 4.2 5.4
```

2. Negative integers omit elements at the specified positions:

```
x <- c(2.1, 4.2, 3.3, 5.4)
x[-1]
#> [1] 4.2 3.3 5.4
x[-c(3, 1)]
#> [1] 4.2 5.4
```

You can't mix positive and negative integers in a single subset:

```
x <- c(2.1, 4.2, 3.3, 5.4)
x[c(-1, 2)]
#> Error in x[c(-1, 2)]: only 0's may be mixed with negative subscripts
```

3. Character vectors return elements with matching names. This only works if the vector is named.

```
x <- c(2.1, 4.2, 3.3, 5.4)

# apply names
names(x) <- c("a", "b", "c", "d")

# subset using names
x[c("d", "c", "a")]
#> d   c   a
#> 5.4 3.3 2.1

# Like integer indices, you can repeat indices
x[c("a", "a", "a")]
#> a   a   a
#> 2.1 2.1 2.1

# Careful! Names are always matched exactly
x <- c(abc = 1, def = 2)
x[c("a", "d")]
#> <NA> <NA>
#> NA   NA
```

4. Logical vectors select elements where the corresponding logical value is TRUE.

```
x <- c(2.1, 4.2, 3.3, 5.4)
x[c(TRUE, TRUE, FALSE, FALSE)]
```

```
#> [1] 2.1 4.2
```

8.1.2 Conditional Subsetting

Logical subsetting is the most useful type of subsetting, because you use it to subset based on **conditional** or **comparative** statements.

The (logical) comparison operators known to R are:

- < for less than
- > for greater than
- <= for less than or equal to
- >= for greater than or equal to
- == for equal to each other
- != not equal to each other

The nice thing about R is that you can use these comparison operators also on vectors. For example:

```
x <- c(2.1, 4.2, 3.3, 5.4)
x > 3
#> [1] FALSE TRUE TRUE TRUE
```

This command tests for every element of the vector if the condition stated by the comparison operator is TRUE or FALSE. And it returns a logical vector!

We can now pass this statement between the square brackets that follow x to subset only those items that match TRUE:

```
x[x > 3]
#> [1] 4.2 3.3 5.4
```

You can combine conditional statements with & (and), | (or), and ! (not)

```
x <- c(2.1, 4.2, 3.3, 5.4)

# combining two conditional statements with &
x > 3 & x < 5
#> [1] FALSE TRUE TRUE FALSE
x[x > 3 & x < 5]
#> [1] 4.2 3.3

# combining two conditional statements with |
x < 3 | x > 5
#> [1] TRUE FALSE FALSE TRUE
x[x < 3 | x > 5]
#> [1] 2.1 5.4
```

```
# combining conditional statements with !
!x > 5
#> [1] TRUE TRUE TRUE FALSE
x[!x > 5]
#> [1] 2.1 4.2 3.3
```

Another way to generate implicit conditional statements is using the `%in%` operator, which tests whether an item is in a set:

```
x <- c(2.1, 4.2, 3.3, 5.4)

# generate implicit logical vectors through the %in% operator
x %in% c(3.3, 4.2)
#> [1] FALSE TRUE TRUE FALSE
x[x %in% c(3.3, 4.2)]
#> [1] 4.2 3.3
```

8.1.3 Challenge

Subset `country.vector` below to return every value EXCEPT “Canada” and “Brazil” `{-}`

```
country.vector<-c("Afghanistan", "Canada", "Sierra Leone", "Denmark", "Japan", "Brazil")

# Do it using positive integers

# Do it using negative integers

# Do it using a logical vector

# Do it using a conditional statement (and an implicit logical vector)
```

Solution:

```
country.vector<-c("Afghanistan", "Canada", "Sierra Leone", "Denmark", "Japan", "Brazil")

# Do it using positive integers
country.vector[c(1, 3, 4, 5)]

# Do it using negative integers
country.vector[-c(2, 6)]

# Do it using a logical vector
country.vector[c(TRUE, FALSE, TRUE, TRUE, TRUE, FALSE)]

# Do it using a conditional statement (and an implicit logical vector)
```

```
country.vector[!country.vector %in% c("Canada", "Brazil")]
```

8.2 Subsetting Lists

Subsetting a list works in the same way as subsetting an atomic vector. However, there's one important difference: `[` will always return a list. `[[` and `$`, as described below, let you pull out the components of the list.

Let's illustrate with the following list `my_list`:

```
my_list <- list(a = 1:3, b = "a string", c = pi, d = list(-1, -5))
```

8.2.1 With [

`[` extracts a sub-list where the result will always be a list. Like with vectors, you can subset with a logical, integer, or character vector.

```
my_list[1:2]
#> $a
#> [1] 1 2 3
#>
#> $b
#> [1] "a string"
str(my_list[1:2])
#> List of 2
#> $ a: int [1:3] 1 2 3
#> $ b: chr "a string"

my_list[4]
#> $d
#> $d[[1]]
#> [1] -1
#>
#> $d[[2]]
#> [1] -5
str(my_list[4])
#> List of 1
#> $ d:List of 2
#> ..$ : num -1
#> ..$ : num -5

my_list["a"]
#> $a
```

```
#> [1] 1 2 3
str(my_list["a"])
#> List of 1
#> $ a: int [1:3] 1 2 3
```

8.2.2 With [[

`[[` extracts a single *component* from a list. In other words, it removes that hierarchy and returns whatever object is stored inside.

```
my_list[[1]]
#> [1] 1 2 3
str(my_list[[1]])
#> int [1:3] 1 2 3

# compare to
my_list[1]
#> $a
#> [1] 1 2 3
str(my_list[1])
#> List of 1
#> $ a: int [1:3] 1 2 3
```

The distinction between `[` and `[[` is really important for lists, because `[[` drills down into the list while `[` returns a new, smaller list.

“If list `x` is a train carrying objects, then `x[[5]]` is the object in car 5; `x[4:6]` is a train of cars 4-6.”

— ?

8.2.3 with \$

`$` is a shorthand for extracting named elements of a list. It works similarly to `[[` except that you don’t need to use quotes.

```
my_list$a
#> [1] 1 2 3

# same as
my_list[["a"]]
#> [1] 1 2 3
```

The `$` operator becomes especially helpful when applied to dataframes, explained more below.

8.2.4 Challenge

Take a look at the linear model below:

```
mod <- lm(mpg ~ wt, data = mtcars)
summary(mod)
#>
#> Call:
#> lm(formula = mpg ~ wt, data = mtcars)
#>
#> Residuals:
#>    Min     1Q Median     3Q    Max
#> -4.543 -2.365 -0.125  1.410  6.873
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 37.285     1.878   19.86 < 2e-16 ***
#> wt          -5.344     0.559   -9.56 1.3e-10 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 3.05 on 30 degrees of freedom
#> Multiple R-squared:  0.753, Adjusted R-squared:  0.745
#> F-statistic: 91.4 on 1 and 30 DF, p-value: 1.29e-10
```

Extract the R squared from the model summary.

Solution:

```
mod.sum <- summary(mod)
mod.sum$r.squared
#> [1] 0.753
```

8.3 Subsetting Matrices

Similar to vectors, you can use the square brackets [] to select one or multiple elements from a matrix. But whereas vectors have one dimension, matrices have two dimensions. We therefore have to use two subsetting vectors – one for rows to select, another for columns – separated by a comma.

Check out the following matrix:

```
a <- matrix(1:9, nrow = 3)
colnames(a) <- c("A", "B", "C")
a
#>      A B C
```

```
#> [1,] 1 4 7
#> [2,] 2 5 8
#> [3,] 3 6 9
```

We can subset this matrix by passing two subsetting vectors: one to select rows, another to select columns:

```
# selects the value at the first row and second column
a[1, 2]
#> B
#> 4

# selects first row, and the first and third columns
a[1, -2]
#> A C
#> 1 7

# selects first two rows, and the first and third columns
a[c(1,2), c(1, 3)]
#>      A C
#> [1,] 1 7
#> [2,] 2 8
```

Blank subsetting is also useful because it lets you keep all rows or all columns.

```
a[c(1, 2), ] # selects first two rows and all columns
#>      A B C
#> [1,] 1 4 7
#> [2,] 2 5 8
```

8.4 Subsetting Dataframes

Data from data frames can be addressed like matrices, using two vectors separated by a comma.

```
# Definition of vectors
name <- c("Mercury", "Venus", "Earth", "Mars", "Jupiter", "Saturn", "Uranus", "Neptune")
type <- c("Terrestrial planet", "Terrestrial planet", "Terrestrial planet", "Terrestrial planet",
diameter <- c(0.382, 0.949, 1, 0.532, 11.209, 9.449, 4.007, 3.883)
rings <- c(FALSE, FALSE, FALSE, FALSE, TRUE, TRUE, TRUE, TRUE)

planets <- data.frame(name, type, diameter, rings, stringsAsFactors = F)
planets
#>      name           type   diameter   rings
#> 1 Mercury   Terrestrial planet     0.382 FALSE
```

```
#> 2 Venus Terrestrial planet 0.949 FALSE
#> 3 Earth Terrestrial planet 1.000 FALSE
#> 4 Mars Terrestrial planet 0.532 FALSE
#> 5 Jupiter Gas giant 11.209 TRUE
#> 6 Saturn Gas giant 9.449 TRUE
#> 7 Uranus Gas giant 4.007 TRUE
#> 8 Neptune Gas giant 3.883 TRUE
```

Let's try some subsetting now.

```
# Print out diameter of Mercury (row 1, column 3)
planets[1, 3]
#> [1] 0.382

# Print out data for Mars (entire fourth row)
planets[4, ]
#> name type diameter rings
#> 4 Mars Terrestrial planet 0.532 FALSE

# Print first two rows of the first two columns
planets[1:2, 1:2]
#> name type
#> 1 Mercury Terrestrial planet
#> 2 Venus Terrestrial planet
```

8.4.1 Subsetting Names and \$

Instead of using numerics to select elements of a data frame, you can also use the variable names to select columns of a data frame.

Suppose you want to select the first three elements of the type column. One way to do this is

```
planets[1:3, 2]
#> [1] "Terrestrial planet" "Terrestrial planet" "Terrestrial planet"
```

A possible disadvantage of this approach is that you have to know (or look up) the column number of type, which gets hard if you have a lot of variables. It is often easier to just make use of the variable name:

```
planets[1:3, "type"]
#> [1] "Terrestrial planet" "Terrestrial planet" "Terrestrial planet"
```

You will often want to select an entire column, namely one specific variable from a data frame. If you want to select all elements of the variable “diameter”, for example, both of these will do the trick:

```
planets[,3]
#> [1] 0.382 0.949 1.000 0.532 11.209 9.449 4.007 3.883
planets[,"diameter"]
#> [1] 0.382 0.949 1.000 0.532 11.209 9.449 4.007 3.883
```

However, there is a short-cut. If your columns have names, you can use the \$ sign:

```
planets$diameter
#> [1] 0.382 0.949 1.000 0.532 11.209 9.449 4.007 3.883
```

Remember that datasets are really lists of vectors (one vector per column). Just as `list$name` selects the `name` element from the list, `df$name` selects the `name` column (vector) from the dataframe.

8.4.2 Conditional Subsetting

What if we want to subset the dataset based on some condition? Let's say we want to extract all the planets with a diameter greater than 3? We could inspect the dataset and record all the observations that fit that description, but that's tedious and error prone.

There's a better way! We can combine two powerful subsetting tools: the \$ operator and conditional subsetting.

First, we extract the `diameter` column.

```
diameters <- planets$diameter
```

Then, we find the elements that are greater than 3.

```
diameters > 3
#> [1] FALSE FALSE FALSE FALSE TRUE TRUE TRUE TRUE
```

It's a boolean vector! We can now use this inside `[,]` to extract all plants with `diameter > 3`.

Think: Are we subsetting row or columns here?

```
planets[diameters > 3, ]
#>      name      type diameter rings
#> 5 Jupiter Gas giant    11.21  TRUE
#> 6 Saturn  Gas giant     9.45  TRUE
#> 7 Uranus  Gas giant     4.01  TRUE
#> 8 Neptune Gas giant     3.88  TRUE

# same as
# planets[planets$diameter > 3, ]
```

Because it allows you to easily combine conditions from multiple columns, logical subsetting is probably the most commonly used technique for extracting rows out of a data frame.

8.4.3 List-Like and Matrix-Like Subsetting

Data frames possess the characteristics of both lists and matrices: if you subset with a single vector, they behave like lists, and return only the columns.

```
df <- data.frame(x = 4:6, y = 3:1, z = letters[1:3])

# Like a list:
df[c("x", "z")]
#>   x z
#> 1 4 a
#> 2 5 b
#> 3 6 c

# Like a matrix
df[, c("x", "z")]
#>   x z
#> 1 4 a
#> 2 5 b
#> 3 6 c
```

But there's an important difference when you select a single column: matrix subsetting simplifies by default, list subsetting does not.

```
df <- data.frame(x = 4:6, y = 3:1, z = letters[1:3])

# like a list
df["x"]
#>   x
#> 1 4
#> 2 5
#> 3 6
class(df["x"])
#> [1] "data.frame"

# like a matrix
df[, "x"]
#> [1] 4 5 6
class(df[, "x"])
#> [1] "integer"
```

8.4.4 Challenges

Challenge 1. Fix each of the following common data frame subsetting errors:

```
# check out what we're dealing with
mtcars

# fix
mtcars[mtcars$cyl == 4, ]
mtcars[-1:4, ]
mtcars[mtcars$cyl <= 5]
mtcars[mtcars$cyl == 4 | 6, ]
```

Solution:

```
mtcars[mtcars$cyl == 4, ]
#>          mpg cyl  disp  hp drat   wt qsec vs am gear carb
#> Datsun 710 22.8  4 108.0 93 3.85 2.32 18.6  1  1    4    1
#> Merc 240D  24.4  4 146.7 62 3.69 3.19 20.0  1  0    4    2
#> Merc 230   22.8  4 140.8 95 3.92 3.15 22.9  1  0    4    2
#> Fiat 128   32.4  4  78.7 66 4.08 2.20 19.5  1  1    4    1
#> Honda Civic 30.4  4  75.7 52 4.93 1.61 18.5  1  1    4    2
#> Toyota Corolla 33.9  4  71.1 65 4.22 1.83 19.9  1  1    4    1
#> Toyota Corona 21.5  4 120.1 97 3.70 2.46 20.0  1  0    3    1
#> Fiat X1-9    27.3  4  79.0 66 4.08 1.94 18.9  1  1    4    1
#> Porsche 914-2 26.0  4 120.3 91 4.43 2.14 16.7  0  1    5    2
#> Lotus Europa  30.4  4  95.1 113 3.77 1.51 16.9  1  1    5    2
#> Volvo 142E   21.4  4 121.0 109 4.11 2.78 18.6  1  1    4    2
mtcars[-c(1:4), ]
#>          mpg cyl  disp  hp drat   wt qsec vs am gear carb
#> Hornet Sportabout 18.7  8 360.0 175 3.15 3.44 17.0  0  0    3    2
#> Valiant           18.1  6 225.0 105 2.76 3.46 20.2  1  0    3    1
#> Duster 360         14.3  8 360.0 245 3.21 3.57 15.8  0  0    3    4
#> Merc 240D          24.4  4 146.7 62 3.69 3.19 20.0  1  0    4    2
#> Merc 230           22.8  4 140.8 95 3.92 3.15 22.9  1  0    4    2
#> Merc 280           19.2  6 167.6 123 3.92 3.44 18.3  1  0    4    4
#> Merc 280C          17.8  6 167.6 123 3.92 3.44 18.9  1  0    4    4
#> Merc 450SE         16.4  8 275.8 180 3.07 4.07 17.4  0  0    3    3
#> Merc 450SL         17.3  8 275.8 180 3.07 3.73 17.6  0  0    3    3
#> Merc 450SLC        15.2  8 275.8 180 3.07 3.78 18.0  0  0    3    3
#> Cadillac Fleetwood 10.4  8 472.0 205 2.93 5.25 18.0  0  0    3    4
#> Lincoln Continental 10.4  8 460.0 215 3.00 5.42 17.8  0  0    3    4
#> Chrysler Imperial  14.7  8 440.0 230 3.23 5.34 17.4  0  0    3    4
#> Fiat 128            32.4  4  78.7 66 4.08 2.20 19.5  1  1    4    1
#> Honda Civic          30.4  4  75.7 52 4.93 1.61 18.5  1  1    4    2
```

```

#> Toyota Corolla      33.9   4 71.1 65 4.22 1.83 19.9  1 1 4 1
#> Toyota Corona       21.5   4 120.1 97 3.70 2.46 20.0  1 0 3 1
#> Dodge Challenger    15.5   8 318.0 150 2.76 3.52 16.9  0 0 3 2
#> AMC Javelin         15.2   8 304.0 150 3.15 3.44 17.3  0 0 3 2
#> Camaro Z28          13.3   8 350.0 245 3.73 3.84 15.4  0 0 3 4
#> Pontiac Firebird    19.2   8 400.0 175 3.08 3.85 17.1  0 0 3 2
#> Fiat X1-9            27.3   4 79.0 66 4.08 1.94 18.9  1 1 4 1
#> Porsche 914-2        26.0   4 120.3 91 4.43 2.14 16.7  0 1 5 2
#> Lotus Europa          30.4   4 95.1 113 3.77 1.51 16.9  1 1 5 2
#> Ford Pantera L       15.8   8 351.0 264 4.22 3.17 14.5  0 1 5 4
#> Ferrari Dino         19.7   6 145.0 175 3.62 2.77 15.5  0 1 5 6
#> Maserati Bora         15.0   8 301.0 335 3.54 3.57 14.6  0 1 5 8
#> Volvo 142E            21.4   4 121.0 109 4.11 2.78 18.6  1 1 4 2
mtcars[mtcars$cyl <= 5,]
#>                 mpg cyl disp hp drat wt qsec vs am gear carb
#> Datsun 710           22.8   4 108.0 93 3.85 2.32 18.6  1 1 4 1
#> Merc 240D            24.4   4 146.7 62 3.69 3.19 20.0  1 0 4 2
#> Merc 230             22.8   4 140.8 95 3.92 3.15 22.9  1 0 4 2
#> Fiat 128              32.4   4 78.7 66 4.08 2.20 19.5  1 1 4 1
#> Honda Civic           30.4   4 75.7 52 4.93 1.61 18.5  1 1 4 2
#> Toyota Corolla        33.9   4 71.1 65 4.22 1.83 19.9  1 1 4 1
#> Toyota Corona          21.5   4 120.1 97 3.70 2.46 20.0  1 0 3 1
#> Fiat X1-9              27.3   4 79.0 66 4.08 1.94 18.9  1 1 4 1
#> Porsche 914-2          26.0   4 120.3 91 4.43 2.14 16.7  0 1 5 2
#> Lotus Europa            30.4   4 95.1 113 3.77 1.51 16.9  1 1 5 2
#> Volvo 142E              21.4   4 121.0 109 4.11 2.78 18.6  1 1 4 2
mtcars[mtcars$cyl == 4 | mtcars$cyl == 6, ]
#>                 mpg cyl disp hp drat wt qsec vs am gear carb
#> Mazda RX4             21.0   6 160.0 110 3.90 2.62 16.5  0 1 4 4
#> Mazda RX4 Wag          21.0   6 160.0 110 3.90 2.88 17.0  0 1 4 4
#> Datsun 710             22.8   4 108.0 93 3.85 2.32 18.6  1 1 4 1
#> Hornet 4 Drive         21.4   6 258.0 110 3.08 3.21 19.4  1 0 3 1
#> Valiant                18.1   6 225.0 105 2.76 3.46 20.2  1 0 3 1
#> Merc 240D               24.4   4 146.7 62 3.69 3.19 20.0  1 0 4 2
#> Merc 230                22.8   4 140.8 95 3.92 3.15 22.9  1 0 4 2
#> Merc 280                19.2   6 167.6 123 3.92 3.44 18.3  1 0 4 4
#> Merc 280C                17.8   6 167.6 123 3.92 3.44 18.9  1 0 4 4
#> Fiat 128                  32.4   4 78.7 66 4.08 2.20 19.5  1 1 4 1
#> Honda Civic                30.4   4 75.7 52 4.93 1.61 18.5  1 1 4 2
#> Toyota Corolla              33.9   4 71.1 65 4.22 1.83 19.9  1 1 4 1
#> Toyota Corona                21.5   4 120.1 97 3.70 2.46 20.0  1 0 3 1
#> Fiat X1-9                  27.3   4 79.0 66 4.08 1.94 18.9  1 1 4 1
#> Porsche 914-2                26.0   4 120.3 91 4.43 2.14 16.7  0 1 5 2
#> Lotus Europa                  30.4   4 95.1 113 3.77 1.51 16.9  1 1 5 2
#> Ferrari Dino                  19.7   6 145.0 175 3.62 2.77 15.5  0 1 5 6

```

```
#> Volvo 142E      21.4   4 121.0 109 4.11 2.78 18.6 1 1     4     2
```

Challenge 2. Why does `mtcars[1:20]` return an error? How does it differ from the similar `mtcars[1:20,]`?

8.5 Sub-assignment

8.5.1 Basics of Sub-assignment

All subsetting operators can be combined with assignment to modify selected values of the input vector.

```
x <- 1:5
x[c(1, 2)] <- 2:3
x
#> [1] 2 3 3 4 5
```

This is especially useful when conditionally modifying vectors. For example, let's say we wanted to replace all values less than 3 with NA.

```
x <- 1:5
x[x < 3] <- NA
x
#> [1] NA NA  3  4  5
```

This also works on dataframes. Let's say we wanted to modify our `planets` dataframe.

```
# Definition of vectors
name <- c("Mercury", "Venus", "Earth", "Mars", "Jupiter", "Saturn", "Uranus", "Neptune")
type <- c("Terrestrial planet", "Terrestrial planet", "Terrestrial planet", "Terrestrial planet",
diameter <- c(0.382, 0.949, 1, 0.532, 11.209, 9.449, 4.007, 3.883)
rings <- c(FALSE, FALSE, FALSE, FALSE, TRUE, TRUE, TRUE)

planets <- data.frame(name, type, diameter, rings, stringsAsFactors = F)
planets
#>      name           type diameter rings
#> 1 Mercury Terrestrial planet    0.382 FALSE
#> 2 Venus  Terrestrial planet    0.949 FALSE
#> 3 Earth   Terrestrial planet    1.000 FALSE
#> 4 Mars    Terrestrial planet    0.532 FALSE
#> 5 Jupiter   Gas giant    11.209  TRUE
#> 6 Saturn    Gas giant    9.449  TRUE
#> 7 Uranus    Gas giant    4.007  TRUE
#> 8 Neptune   Gas giant    3.883  TRUE
```

Let's say we want to replace the term "Terrestrial planet" with "TP". First we need to subset `type` for those elements:

```
planets$type == "Terrestrial planet"
#> [1] TRUE TRUE TRUE TRUE FALSE FALSE FALSE FALSE
```

Now we can re-assign the values of `type`:

```
planets$type[planets$type == "Terrestrial planet"]
#> [1] "Terrestrial planet" "Terrestrial planet" "Terrestrial planet"
#> [4] "Terrestrial planet"
planets$type[planets$type == "Terrestrial planet"] <- "TP"
planets
#>   name      type diameter rings
#> 1 Mercury    TP    0.382 FALSE
#> 2 Venus      TP    0.949 FALSE
#> 3 Earth      TP    1.000 FALSE
#> 4 Mars       TP    0.532 FALSE
#> 5 Jupiter Gas giant 11.209 TRUE
#> 6 Saturn Gas giant  9.449 TRUE
#> 7 Uranus Gas giant  4.007 TRUE
#> 8 Neptune Gas giant  3.883 TRUE
```

8.5.2 Recycling

When applying an operation to two vectors that requires them to be the same length, R automatically recycles, or repeats, the shorter one, until it is long enough to match the longer one.

```
df <- data.frame(x = 4:7, y = letters[1:4])

# r recycles values
df$x <- c(1, 2)
df
#>   x y
#> 1 1 a
#> 2 2 b
#> 3 1 c
#> 4 2 d

# sometimes this is helpful if you want to replace an entire vector to one value.
df$x <- df$x + 3
df
#>   x y
#> 1 4 a
#> 2 5 b
```

```
#> 3 4 c
#> 4 5 d
```

8.5.3 Applications

The basic principles described above give rise to a wide variety of useful applications. Some of the most important applications are described below. Many of these basic techniques are wrapped up into more concise functions (e.g., `subset()`, `merge()`, `plyr::arrange()`), but it is useful to understand how they are implemented with basic subsetting. This will allow you to adapt to new situations that are not dealt with by existing functions.

Ordering Columns

Consider we have this data frame:

```
df <- data.frame(
  Country = c("Iraq", "China", "Mexico", "Russia", "United Kingdom"),
  Region = c("Middle East", "Asia", "North America", "Eastern Europe", "Western Europe"),
  Language = c("Arabic", "Mandarin", "Spanish", "Russian", "English")
)
df
#>           Country          Region Language
#> 1         Iraq    Middle East   Arabic
#> 2        China      Asia Mandarin
#> 3       Mexico  North America  Spanish
#> 4       Russia Eastern Europe  Russian
#> 5 United Kingdom Western Europe  English
```

What if we wanted to reorder the columns so that `Region` is first? We can do so using subsetting with the names (or number) of the columns:

```
df <- data.frame(
  Country = c("Iraq", "China", "Mexico", "Russia", "United Kingdom"),
  Region = c("Middle East", "Asia", "North America", "Eastern Europe", "Western Europe"),
  Language = c("Arabic", "Mandarin", "Spanish", "Russian", "English")
)

# reorder columns using names
names(df)
#> [1] "Country"  "Region"    "Language"
df1 <- df[, c("Region", "Country", "Language")]
df1
#>           Region          Country Language
```

```

#> 1   Middle East      Iraq    Arabic
#> 2       Asia        China   Mandarin
#> 3 North America     Mexico  Spanish
#> 4 Eastern Europe    Russia Russian
#> 5 Western Europe United Kingdom English

# reorder columns using indices
names(df)
#> [1] "Country" "Region"  "Language"
df1 <- df[, c(2,1,3)]
df1
#>           Region      Country Language
#> 1   Middle East      Iraq    Arabic
#> 2       Asia        China   Mandarin
#> 3 North America     Mexico  Spanish
#> 4 Eastern Europe    Russia Russian
#> 5 Western Europe United Kingdom English

```

One helpful function is the `order` function. It takes a vector as input and returns an integer vector describing how the subsetted vector should be ordered:

```

x <- c("b", "c", "a")
order(x)
#> [1] 3 1 2
x[order(x)]
#> [1] "a" "b" "c"

```

Knowing this, we can use `order` to reorder our columns by alphabetical order.

Removing (or keeping) columns from data frames.

There are two ways to remove columns from a data frame. You can set individual columns to `NULL`:

```

df <- data.frame(
  Country = c("Iraq", "China", "Mexico", "Russia", "United Kingdom"),
  Region = c("Middle East", "Asia", "North America", "Eastern Europe", "Western Europe"),
  Language = c("Arabic", "Mandarin", "Spanish", "Russian", "English")
)

df$Language <- NULL

```

Or you can subset to return only the columns you want:

```

df <- data.frame(
  Country = c("Iraq", "China", "Mexico", "Russia", "United Kingdom"),
  Region = c("Middle East", "Asia", "North America", "Eastern Europe", "Western Europe")
)

```

```
Language = c("Arabic", "Mandarin", "Spanish", "Russian", "English")
)

df1 <- df[, c("Country", "Region")]
df1
#>      Country          Region
#> 1    Iraq    Middle East
#> 2    China        Asia
#> 3    Mexico   North America
#> 4    Russia  Eastern Europe
#> 5 United Kingdom Western Europe

# using negative integers
df2 <- df[, -3]
df2
#>      Country          Region
#> 1    Iraq    Middle East
#> 2    China        Asia
#> 3    Mexico   North America
#> 4    Russia  Eastern Europe
#> 5 United Kingdom Western Europe
```


Chapter 9

Working with Data

Insert some introduction here.

9.1 Project Workflow

One day...

- you will need to quit R, go do something else, and return to your analysis the next day.
- you will be working on multiple projects simultaneously, and you'll want to keep them separate.
- you will need to bring data from the outside world into R, and send numerical results and figures from R back out into the world.

This unit teaches these topics.

9.1.1 Store Analyses in Scripts, Not Workspaces.

R Studio automatically preserves your workspace (environment and command history) when you quit R, and re-loads it the next session. I recommend you turn this behavior off.

This will cause you some short-term pain, because now when you restart RStudio, it will not remember the results of the code that you ran last time. But this short-term pain will save you long-term agony, because it forces you to capture all important interactions in your scripts.

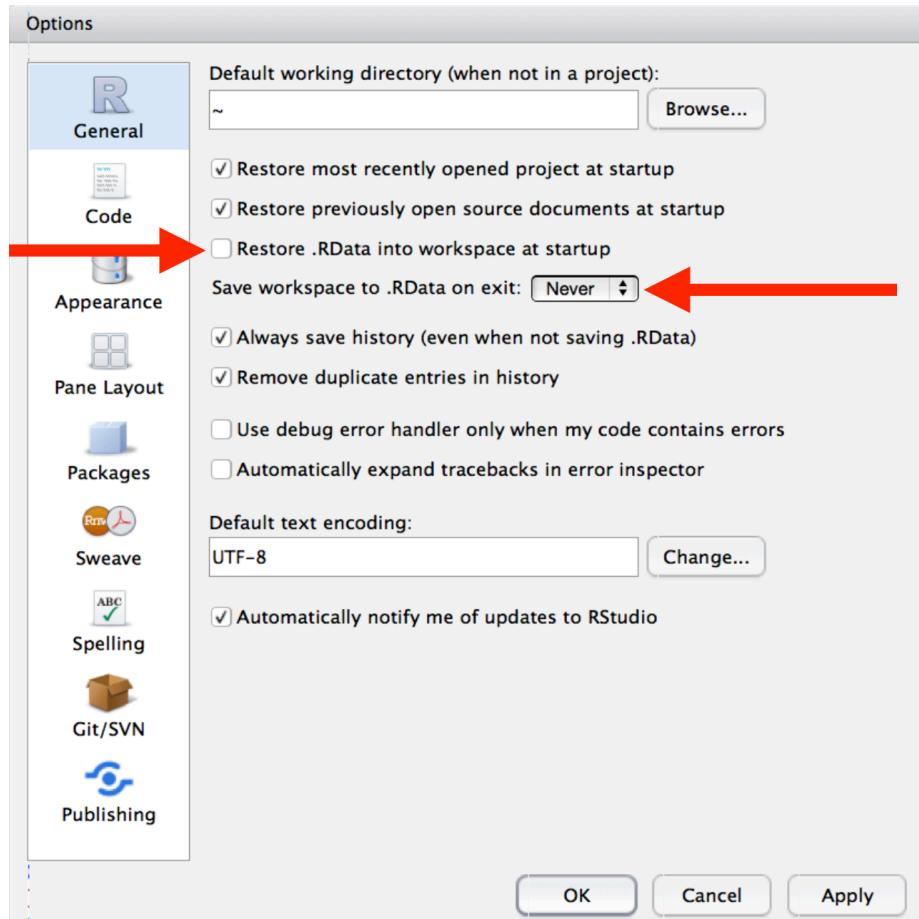


Figure 9.1:

9.1.2 Working Directories and Paths

Like many programming languages, R has a powerful notion of the **working directory**. This is where R looks for files that you ask it to load, and where it will put any files that you ask it to save.

RStudio shows your current working directory at the top of the console. You can print this out in R code by running `getwd()`:

```
getwd()  
#> [1] "/Users/petecuppernull/Desktop/course"
```

I do not recommend it, but you can set the working directory from within R:

```
setwd("/path/to/my/CoolProject")
```

The command above prints out a **path** to your working directory. Think of a path as an address. Paths are incredibly important in programming, but can be a little tricky. Let's go into a bit more detail.

Absolute Paths

Absolute paths are paths that point to the same place regardless of your current working directory. They always start with the **root directory** that holds everything else on your computer.

- In Windows, absolute paths start with a drive letter (e.g. C:) or two backslashes (e.g. \\servername).
- In Mac/Linux they start with a slash /. This is the leading slash in /users/rterman.

Inside the root directory are several other directories, which we call **subdirectories**. We know that the directory /home/rterman is stored inside /home because /home is the first part of its name. Similarly, we know that /home is stored inside the root directory / because its name begins with /.

Notice that there are two meanings for the / character. When it appears at the front of a file or directory name, > it refers to the root directory. When it appears *inside* a name, > it's just a separator.

Mac/Linux vs. Windows

There are two basic styles of paths: Mac/Linux and Windows. The main difference is how you separate the components of the path. Mac and Linux use slashes (e.g. plots/diamonds.pdf) and Windows uses backslashes (e.g. plots\diamonds.pdf).

R can work with either type, no matter what platform you're currently using. Unfortunately, backslashes mean something special to R, and to get a single backslash in the path, you need to type two backslashes! That makes life frustrating, so I recommend always using the Linux/Mac style with forward slashes.

Home Directory

Sometimes you'll see a ~ character in a path. * In Mac/Linux, the ~ is a convenient shortcut to your **home directory** (/users/rterman). * Windows doesn't really have the notion of a home directory, so it usually points to your documents directory (C:\Documents and Settings\rterman)

Absolute vs. Relative Paths

You should try not to use absolute paths in your scripts, because they hinder sharing: no one else will have exactly the same directory configuration as you. Another way to direct R to something is to give it a **relative path**.

Relative paths point to something relative to where you are, rather than from the root of the file system. For example, if your current working directory is /home/rterman, then the relative path data/un.csv directs to the full absolute path: /home/rterman/data/un.csv

9.1.3 R Projects

As a beginning R user, it's OK to let your home directory, documents directory, or any other weird directory on your computer be R's working directory.

But from this point forward, you should be organizing your projects into dedicated subdirectories, containing all the files associated with a project — input data, R scripts, results, figures.

This is such a common practice that RStudio has built-in support for this via **projects**.

Let's make a project together. Click **File > New Project**, then:

~

Think carefully about which subdirectory you put the project in. If you don't store it somewhere sensible, it will be hard to find in the future!

Once this process is complete, you'll get a new RStudio project. Check that the "home" directory of your project is the current working directory:

```
getwd()  
#> [1] "/Users/petecuppernull/Desktop/course"
```

Now whenever you refer to a file with a relative path, it will look for it there.

Go ahead and create a new R script and save it inside the project folder.

Quit RStudio. Inspect the folder associated with your project — notice the .Rproj file. Double-click that file to re-open the project. Notice you get back to where you left off: it's the same working directory and command history, and all the files you were working on are still open. Because you followed my instructions above, you will, however, have a completely fresh environment, guaranteeing that you're starting with a clean slate.

9.1.4 File Organization

You should be saving all your files associated with your project in one directory. Here's a basic organization structure that I recommend:

```
~~~
masters_thesis:
  masters_thesis.Rproj
  01_Clean.R
  02_Model.R
  03_Visualizations.R
  Data/
    raw/
      un-raw.csv
      worldbank-raw.csv
    cleaned/
      country-year.csv
  Results:
    regressions
      h1.txt
      h2.txt
    figures
      bivariate.pdf
      bar_plot.pdf
~~~
```

Here are some important tips:

- read raw data from the `Data` subdirectory. Don't ever change or overwrite the raw data!
- export cleaned and altered data into a separate directory.
- write separate scripts for each stage in the research pipeline. Keep scripts short and focused on one main purpose. If a script gets too long, that might be a sign you need to split it up.
- write scripts that reproduce your results and figures, and write them in the `Results` subdirectory.

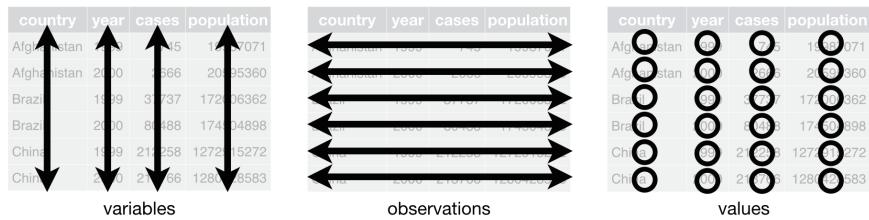


Figure 9.2:

Acknowledgements

This page is in part derived from the following sources:

1. R for Data Science licensed under Creative Commons Attribution-NonCommercial-NoDerivs 3.0

More Resources

- Gentzkow, Matthew and Jesse M. Shapiro. 2014. Code and Data for the Social Sciences: A Practitioner's Guide.

9.2 Introduction to Data

The upcoming weeks will be focused on using R for data cleaning and analysis. Let's first get on the same page with some terms:

- A **variable** is a quantity, quality, or property that you can measure.
- An **observation** is a set of measurements for the same unit. An observation will contain several values, each associated with a different variable. I'll sometimes refer to an observation as a **data point** or an **element**.
- A **value** is the state of a variable for a particular observation.
- **Tabular data** is a set of values, each associated with a variable and an observation. Tabular data has rows (observations) and columns (variables). Also called **rectangular** data or **spreadsheets**.

9.2.1 Where's my data?

To start, you first need to know where your data lives. Sometimes, the data is stored as a file on your computer, e.g. csv, Excel, SPSS, or some other file type. When the data is on your computer, we say the data is stored **locally**.

Data can also be stored externally on the Internet, in a package, or obtained through other sources. For example, some R packages contain datasets. The `nycflights13` package contains information on flights that departed NYC in 2013.

```
# not run
# install.packages("nycflights13")
library(nycflights13)
data(flights)
names(flights)
#> [1] "year"           "month"          "day"            "dep_time"
#> [5] "sched_dep_time" "dep_delay"       "arr_time"        "sched_arr_time"
#> [9] "arr_delay"      "carrier"         "flight"         "tailnum"
#> [13] "origin"         "dest"            "air_time"       "distance"
#> [17] "hour"           "minute"          "time_hour"
rm(flights)
#
```

Later in this course, we'll discuss how to obtain data from web APIs and websites. For now, the rest of the unit discusses data that is stored **locally**.

9.2.2 Data Storage

Ideally, your data should be stored in a certain file format. I recommend a `csv` (comma separated value) file, which formats spreadsheet (rectangular) data in a plain-text format. `csv` files are plain-text, and can be read into almost any statistical software program, including R. Try to avoid Excel files if you can.

Here are some other tips:

- When working with spreadsheets, the first row is usually reserved for the header, while the first column is used to identify the sampling unit (**unique identifier**, see below.)
- Avoid file names and variable names with blank spaces. This can cause errors when reading in data.
- If you want to concatenate words, insert a `.` or `_` in between to words instead of a space;
- Short names are preferred over longer names;
- Try to avoid using names that contain symbols such as `?, $, %, ^, &, *, (,), -, #, ?, ,, <, >, /, |, \, [,], {, and }`;

- make sure that any missing values in your data set are indicated with NA or blank fields (don't use 99 or 77)..

9.2.3 tidy Data

Datasets in the wild can often be messy. For example, check out the following data.

```
messy <- data.frame(
  county = c(36037, 36038, 36039, 36040, NA, 37001, 37002, 37003),
  state = c('NY', 'NY', 'NY', NA, NA, 'VA', 'VA', 'VA'),
  cnty_pop = c(3817735, 422999, 324920, 143432, NA, 3228290, 449499, 383888),
  state_pop = c(43320903, 43320903, NA, 43320903, 43320903, 7173000, 7173000, 7173000),
  region = c(1, 1, 1, 1, 1, 3, 3, 4)
)
messy
#>   county state cnty_pop state_pop region
#> 1 36037   NY  3817735  43320903     1
#> 2 36038   NY  422999   43320903     1
#> 3 36039   NY  324920      NA     1
#> 4 36040   <NA> 143432   43320903     1
#> 5    NA   <NA>      NA  43320903     1
#> 6 37001   VA  3228290  7173000     3
#> 7 37002   VA  449499  7173000     3
#> 8 37003   VA  383888  7173000     4
```

What a mess! How can the population of the state of New York be 43 million for one county but “missing” for another? If this is a dataset of counties, what does it mean when the “county” field is missing? If region is something like Census region, how can two counties in the same state be in different regions? And why is it that all the counties whose codes start with 36 are in New York except for one, where the state is unknown?

The goal should be to put our data in a tidy format. The two most important properties of tidy data are:

1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

If we follow these principles, our data should look like:

```
counties <- data.frame(
  county = c(36037, 36038, 36039, 36040, 37001, 37002, 37003),
  state = c('NY', 'NY', 'NY', 'NY', 'VA', 'VA', 'VA'),
  population = c(3817735, 422999, 324920, 143432, 3228290, 449499, 383888)
)
```

```

counties
#>   county state population
#> 1  36037   NY    3817735
#> 2  36038   NY    422999
#> 3  36039   NY    324920
#> 4  36040   NY    143432
#> 5  37001   VA    3228290
#> 6  37002   VA    449499
#> 7  37003   VA    383888

states <- data.frame(
  state = c("NY", "VA"),
  population = c(43320903, 7173000),
  region = c(1, 3)
)
states
#>   state population region
#> 1    NY     43320903      1
#> 2    VA     7173000      3

```

Now the ambiguity is gone. Every county has a population and a state. Every state has a population and a region. There are no missing states, no missing counties, and no conflicting definitions. The database is self-documenting. In fact, the database is now so clear that we can forget about names like `county_pop` and `state_pop` and just stick to “population.” Anyone would know which entity’s population you mean.

We’ll talk more about tidying data in later units.

9.2.4 Relational data

Collectively, multiple tables of data are called **relational data** because it is the relations, not just the individual datasets, that are important. Note that when we say relational database here, we are referring to how the data are structured, not to the use of any fancy software.

The main principle of relational data is that each table is structured around the same observational unit.

- counties contains data on counties.
- states contains data on states

County population is a property of a county, so it lives in the county table. State population is a property of a state, so it cannot live in the county table. If we had panel data on counties, we would need separate tables for things that vary at the county level (like state) and things that vary at the county-year level (like population).

9.2.5 Keys

The variables that connect each pair of tables are called **keys**. A key is a variable (or set of variables) that uniquely identifies an observation. It is also called a *unique identifier*.

- Keys are complete. They never take on missing values.
- Keys are unique. They are never duplicated across rows of a table.

In simple cases, a single variable is sufficient to identify an observation. In the example above, each county is identified with **county** (a numeric identifier); each state is identified with **state** (a two-letter string).

There are two types of keys:

- A **primary key** uniquely identifies an observation in its own table. For example, `counties$county` is a primary key because it uniquely identifies each county in the counties table.
- A **foreign key** uniquely identifies an observation in another table. For example, `counties$state` is a foreign key because it appears in the counties table where it matches each county to a unique state.

A primary key and the corresponding foreign key in another table form a **relation**.

Sometimes a table doesn't have an explicit primary key: each row is an observation, but no combination of variables reliably identifies it. If a table lacks a primary key, it's useful to add one.

Acknowledgements

This page is in part derived from the following sources:

1. R for Data Science licensed under Creative Commons Attribution-NonCommercial-NoDerivs 3.0
2. Gentzkow, Matthew and Jesse M. Shapiro. 2014. Code and Data for the Social Sciences: A Practitioner's Guide.

9.3 Importing and Exporting

9.3.1 Importing Data

Find Paths First

In order to import (or read) data into R, you first have to know where it is, and how to find it.

First, remember that you'll need to know the *current working directory* so that you know where R is looking for files. If you're using R Projects, that working directory will be the top-level directory of the project.

Second, you'll need to know where the data file is, relative to your working directory. If it's stored in the `Data/raw/` folder, the relative path to your file will be `Data/raw/file-name.csv`

Reading Tabular Data

The workhorse for reading into a data frame is `read.table()`, which allows any separator (CSV, tab-delimited, etc.). `read.csv()` is a special case of `read.table()` for CSV files.

The basic formula is:

```
# Basic CSV read: Import data with header row, values separated by ",",
mydataset <- read.csv(file=" ", stringsAsFactors=)
```

Here's a practical example, using the polityVI dataset:

```
#import polity
polity <- read.csv("data/polity.csv", stringsAsFactors = F)
polity[1:5, 1:5]
#>   cyear ccode scode    country year
#> 1 7001800 700 AFG Afghanistan 1800
#> 2 7001801 700 AFG Afghanistan 1801
#> 3 7001802 700 AFG Afghanistan 1802
#> 4 7001803 700 AFG Afghanistan 1803
#> 5 7001804 700 AFG Afghanistan 1804
```

We use `stringsAsFactors = F` in order to treat text columns as character vectors, not as factors. If we don't set this, the default is that all non-numerical columns will be encoded as factors. This behavior usually makes poor sense, and is due to historical reasons. At one point in time, factors were faster than character vectors, so R's `read.table()` set the default to read in text as factors.

`read.table()` has a number of other options:

```
# For importing tabular data with maximum customizeability
mydataset <- read.table(file=, header=, sep=, quote=, dec=, fill=, stringsAsFactors=)
```

Reading Excel Files

Don't use Microsoft Excel files (.xls or .xlsx). But if you must:

```
# Make sure you have installed the tidyverse suite (only necessary one time)
# install.packages("tidyverse") # Not Run
```

```
# Load the "readxl" package (necessary every new R session)
library(readxl)
```

`read_excel()` reads both `xls` and `xlsx` files and detects the format from the extension.

```
# Basic call
mydataset <- read_excel(path = , sheet = "")
```

Here's a real example:

```
# Example with .xlsx (single sheet)
air <- read_excel("data/airline_small.xlsx", sheet = 1)
air[1:5, 1:5]
#> # A tibble: 5 x 5
#>   Year Month DayofMonth DayOfWeek DepTime
#>   <dbl> <dbl>     <dbl>      <dbl> <chr>
#> 1  2005     11       22        2 1700
#> 2  2008      1        31        4 2216
#> 3  2005      7        17        7 905
#> 4  2008      9        23        2 859
#> 5  2005      3         5        6 827
```

Reading Stata (.dta) Files

There are many ways to read `.dta` files into R. I recommend using `haven` because it is part of the `tidyverse`.

```
library(haven)
air.dta <- read_dta("data/airline_small.dta")
air[1:5, 1:5]
#> # A tibble: 5 x 5
#>   Year Month DayofMonth DayOfWeek DepTime
#>   <dbl> <dbl>     <dbl>      <dbl> <chr>
#> 1  2005     11       22        2 1700
#> 2  2008      1        31        4 2216
#> 3  2005      7        17        7 905
#> 4  2008      9        23        2 859
#> 5  2005      3         5        6 827
```

For Really Big Data

If you have really big data, `read.csv()` will be too slow. In these cases, check out the following options:

- 1) `read_csv()` in the `readr` package is a faster, more helpful drop-in replacement for `read.csv()` that plays well with tidyverse packages (discussed in future lessons).
- 2) the `data.table` package is great for reading and manipulating large datasets (orders of gigabytes or 10s of gigabytes)

9.3.2 Exporting Data

You should never go from raw data to results in one script. Typically, you'll want to import raw data, clean it, and then export that cleaned dataset onto your computer. That cleaned dataset will then be imported into another script for analysis, in a modular fashion.

To export (or write) data from R onto your computer, you can create individual `.csv` files, or export many data objects into an `.RData` object.

Writing a csv Spreadsheet

To export an individual dataframe as a spreadsheet, use `write.csv()`

```
# Basic call
write.csv(x = , file = , row.names = , col.names = )
```

Let's write the `air` dataset as a csv.

```
# Basic call
write.csv(air, "data/airlines.csv", row.names = F)
```

Packaging Data into .RData

Sometimes, it's helpful to write several dataframes at once, to be used in later analysis. To do so, we use the `save()` function to create one file containing many R data objects.

```
# Basic call
save(..., file = )
```

Here's how we can write both `air` and `polity` into one file.

```
save(air, polity, file = "data/datasets.RData")
```

We can then read these datasets back into R using `load()`

```
# clear environment
rm(list=ls())
```

```
# load datasets
load("data/datasets.RData")
```

9.4 Exploring Data

9.4.1 The Gapminder Dataset

This lesson discusses how to perform basic exploratory data analysis.

For this unit, we'll be working with the "Gapminder" dataset, which is an excerpt of the data available at Gapminder.org. For each of 142 countries, the data provides values for life expectancy, GDP per capita, and population, every five years, from 1952 to 2007.

```
gap <- read.csv("data/gapminder.csv", stringsAsFactors = F)
```

9.4.2 Structure and Dimensions

The first things we want to know about a dataset are its dimensions and basic structure. For instance, we can look at the number of rows and columns:

```
# get number of rows and columns:
dim(gap)
#> [1] 1704      6
```

We might also want to see the names of the columns:

```
# see column names
names(gap)
#> [1] "country"    "year"        "pop"         "continent"   "lifeExp"     "gdpPercap"
```

The `str` function is helpful to see an overview of the data's structure:

```
# see structure of data
str(gap)
#> 'data.frame': 1704 obs. of 6 variables:
#> $ country : chr "Afghanistan" "Afghanistan" "Afghanistan" "Afghanistan" ...
#> $ year    : int 1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 ...
#> $ pop     : num 8425333 9240934 10267083 11537966 13079460 ...
#> $ continent: chr "Asia" "Asia" "Asia" "Asia" ...
#> $ lifeExp : num 28.8 30.3 32 34 36.1 ...
#> $ gdpPercap: num 779 821 853 836 740 ...
```

Finally, I encourage you to actually peak at the data itself. The `head` function displays the first 6 rows of any dataframe.

```
head(gap)
#>   country year    pop continent lifeExp gdpPercap
#> 1 Afghanistan 1952 8425333     Asia    28.8    779
#> 2 Afghanistan 1957 9240934     Asia    30.3    821
#> 3 Afghanistan 1962 10267083    Asia    32.0    853
#> 4 Afghanistan 1967 11537966    Asia    34.0    836
#> 5 Afghanistan 1972 13079460    Asia    36.1    740
#> 6 Afghanistan 1977 14880372    Asia    38.4    786
```

9.4.3 Common Alterations

There are some very common alterations researchers make on their data: changing column names, assigning NA values, and changing column types.

Note that we will cover how to perform these functions using the `tidyverse` later in the course. However, these lines are very common, so it's good to know how they work:

1. change column names

```
names(gap)
#> [1] "country"    "year"        "pop"          "continent"   "lifeExp"    "gdpPercap"
names(gap) <- c("country", "year", "pop", "continent", "life.exp", "gdp.percap")
str(gap)
#> 'data.frame': 1704 obs. of 6 variables:
#> $ country : chr "Afghanistan" "Afghanistan" "Afghanistan" "Afghanistan" ...
#> $ year    : int 1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 ...
#> $ pop     : num 8425333 9240934 10267083 11537966 13079460 ...
#> $ continent : chr "Asia" "Asia" "Asia" "Asia" ...
#> $ life.exp : num 28.8 30.3 32 34 36.1 ...
#> $ gdp.percap: num 779 821 853 836 740 ...
```

2. Change some values to NA

```
gap$life.exp[gap$life.exp < 0] <- NA
```

3. Coerce columns to a specific type. For instance, let's change `continent` from character to factor.

```
summary(gap$continent)
#>   Length   Class    Mode
#>   1704 character character
gap$continent <- as.factor(gap$continent)
summary(gap$continent)
#>   Africa Americas     Asia   Europe  Oceania
#>   624      300       396     360      24
```

9.4.4 Summary statistics

We can get quick summary statistics using `summary`. Passing the entire data frame will summarize all columns:

```
summary(gap)
#>   country           year        pop      continent
#>   Length:1704      Min.   :1952   Min.   :6.00e+04  Africa   :624
#>   Class :character 1st Qu.:1966   1st Qu.:2.79e+06 Americas:300
#>   Mode  :character  Median :1980   Median :7.02e+06  Asia    :396
#>             Mean   :1980   Mean   :2.96e+07  Europe  :360
#>             3rd Qu.:1993   3rd Qu.:1.96e+07 Oceania : 24
#>             Max.   :2007   Max.   :1.32e+09
#>
#>   life.exp       gdp.per_cap
#>   Min.   :23.6   Min.   : 241
#>   1st Qu.:48.2   1st Qu.: 1202
#>   Median :60.7   Median : 3532
#>   Mean   :59.5   Mean   : 7215
#>   3rd Qu.:70.8   3rd Qu.: 9325
#>   Max.   :82.6   Max.   :113523
```

Passing a column with summarize that particular column:

```
summary(gap$year)
#>   Min. 1st Qu. Median   Mean 3rd Qu.   Max.
#>   1952  1966  1980  1980  1993  2007
```

Sometimes we need to do some basic checking for the number of observations or types of observations in our dataset. To do this quickly and easily, `table()` is our friend.

Let's look at the number of observations first by region, and then by both region and year.

```
table(gap$continent)
#>
#>   Africa Americas   Asia   Europe   Oceania
#>   624     300      396     360      24

table(gap$continent, gap$year)
#>
#>   1952 1957 1962 1967 1972 1977 1982 1987 1992 1997 2002 2007
#>   Africa 52    52    52    52    52    52    52    52    52    52    52
#>   Americas 25   25   25   25   25   25   25   25   25   25   25
#>   Asia 33    33    33    33    33    33    33    33    33    33    33
#>   Europe 30    30    30    30    30    30    30    30    30    30    30
#>   Oceania 2     2     2     2     2     2     2     2     2     2     2
```

We can even divide by the total number of rows to get proportion, percent, etc.

```
table(gap$continent)/nrow(gap)
#>
#>   Africa Americas      Asia Europe Oceania
#> 0.3662    0.1761    0.2324  0.2113  0.0141
table(gap$continent)/nrow(gap)*100
#>
#>   Africa Americas      Asia Europe Oceania
#> 36.62    17.61    23.24  21.13   1.41
```

9.4.5 Review of Subsetting

We learned about subsetting in the previous lesson. Let's do a quick review here:

```
# Extract first 10 rows
gap[1:10, ]
#>   country year      pop continent life.exp gdp.percap
#> 1 Afghanistan 1952 8425333     Asia    28.8    779
#> 2 Afghanistan 1957 9240934     Asia    30.3    821
#> 3 Afghanistan 1962 10267083     Asia    32.0    853
#> 4 Afghanistan 1967 11537966     Asia    34.0    836
#> 5 Afghanistan 1972 13079460     Asia    36.1    740
#> 6 Afghanistan 1977 14880372     Asia    38.4    786
#> 7 Afghanistan 1982 12881816     Asia    39.9    978
#> 8 Afghanistan 1987 13867957     Asia    40.8    852
#> 9 Afghanistan 1992 16317921     Asia    41.7    649
#> 10 Afghanistan 1997 22227415     Asia    41.8    635

# Extract country year for first 10 rows
gap[1:10, c("country", "year")]
#>   country year
#> 1 Afghanistan 1952
#> 2 Afghanistan 1957
#> 3 Afghanistan 1962
#> 4 Afghanistan 1967
#> 5 Afghanistan 1972
#> 6 Afghanistan 1977
#> 7 Afghanistan 1982
#> 8 Afghanistan 1987
#> 9 Afghanistan 1992
#> 10 Afghanistan 1997

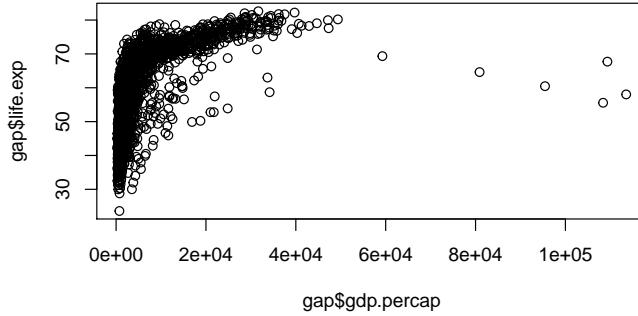
# Extract observations in Africa
africa <- gap[gap$continent=="Africa",]
```

```
# Find average life expectancy for observations in Africa
mean(gap$life.exp[gap$continent=="Africa"])
#> [1] 48.9
mean(africa$life.exp)
#> [1] 48.9
```

9.4.6 Basic Plotting

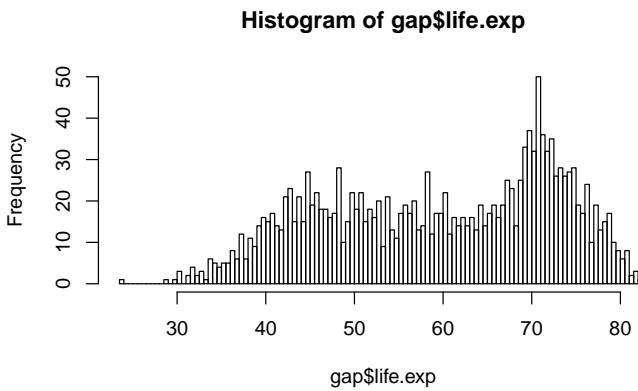
We'll go into plotting in greater detail soon, but let's touch on two common graphs. First, a scatterplot:

```
plot(gap$life.exp ~ gap$gdp.percap)
```



Finally, let's quickly take a look at a histogram of the variable nyt.count:

```
hist(gap$life.exp, breaks = 100)
```



9.4.7 Challenges

Challenge 1. Read the polity dataset.

```
polity <- read.csv("data/polity.csv", stringsAsFactors = F)
```

Challenge 2. Report the number and names of each variable in the dataset.

```
dim(polity)
#> [1] 16727    36
names(polity)
#> [1] "cyear"    "ccode"    "scode"    "country"   "year"      "flag"
#> [7] "fragment" "democ"    "autoc"    "polity"     "polity2"    "durable"
#> [13] "xrreg"    "xrcomp"   "xropen"   "xconst"    "parreg"    "parcomp"
#> [19] "exrec"    "exconst"  "polcomp"  "prior"     "emonth"   "eday"
#> [25] "eyear"    "eprec"    "interim"  "bmonth"   "bday"     "byear"
#> [31] "bprec"    "post"     "change"   "d4"       "sf"       "regtrans"
```

Challenge 3. Extract the 5th row from the polity dataset.

```
polity[5, ]
#>      cyear ccode scode      country year flag fragment democ autoc polity
#> 5 7001804    700 AFG Afghanistan 1804     0    NA     1     7    -6
#> polity2 durable xrreg xrcomp xropen xconst parreg parcomp exrec exconst
#> 5      -6     NA     3     1     1     1     3     3     1     1
#> polcomp prior emonth eday eyear eprec interim bmonth bday byear bprec
#> 5        6     NA     NA     NA     NA     NA     NA     NA     NA     NA
#> post change d4 sf regtrans
#> 5     NA     NA     NA     NA
```

Challenge 4. Extract the last row from the polity dataset.

Challenge 5. Count the percentage of observations with a value of polity2 greater than 8 in the gapminder dataset.

(Hint: if using sum(), read the help file..)

Challenge 6. Set all of the values of `democ` and `autac` columns less than `-10` to `NA`.

(Hint: You should first copy the `polity` object and work on the copy so that the original dataset is unchanged (or just read the data into R again afterwards to get a clean copy)

Chapter 10

Data Transformation

10.1 Introduction

10.1.1 tidyverse

It is often said that 80% of data analysis is spent on the process of cleaning and preparing the data. (Dasu and Johnson, 2003)

For most applied researchers, data preparation usually involves 3 main steps.

1. *Transforming* data frames, e.g. filtering, summarizing, and conducting calculations across groups.
2. *Tidying* data into the appropriate format.
3. *Merging* or linking several datasets to create a bigger dataset.

The `tidyverse` is a suite of packages designed specifically to help with these steps. These are by no means the only packages out there for data wrangling, but they are increasingly popular for their readable, straightforward syntax and sensible default behaviors.

In this chapter, we're going to focus on how to use the `dplyr` package for data transformation tasks.

10.1.2 Gapminder

For this unit, we'll be working with the "Gapminder" dataset again.

```
gap <- read.csv("data/gapminder-FiveYearData.csv", stringsAsFactors = TRUE)
kable(head(gap))
```

country

```
year
pop
continent
lifeExp
gdpPercap
Afghanistan
1952
8425333
Asia
28.8
779
Afghanistan
1957
9240934
Asia
30.3
821
Afghanistan
1962
10267083
Asia
32.0
853
Afghanistan
1967
11537966
Asia
34.0
836
Afghanistan
1972
```

```
13079460
```

```
Asia
```

```
36.1
```

```
740
```

```
Afghanistan
```

```
1977
```

```
14880372
```

```
Asia
```

```
38.4
```

```
786
```

10.1.3 Why dplyr?

So far, you've seen the basics of manipulating data frames, e.g. subsetting and basic calculations. For instance, we can use base R functions to calculate summary statistics across groups of observations, e.g., the mean GDP per capita within each region:

```
mean(gap[gap$continent == "Africa", "gdpPercap"])
#> [1] 2194
mean(gap[gap$continent == "Americas", "gdpPercap"])
#> [1] 7136
mean(gap[gap$continent == "Asia", "gdpPercap"])
#> [1] 7902
```

But this isn't ideal because it involves a fair bit of repetition. Repeating yourself will cost you time, both now and later, and potentially introduce some nasty bugs.

Luckily, the `dplyr` package provides a number of very useful functions for manipulating dataframes. These functions will save you time by reducing repetition. As an added bonus, you might even find the `dplyr` grammar easier to read.

Here, we're going to cover 6 of the most commonly used `dplyr` functions. We'll also cover pipes (`%>%`), which are used to combine them.

1. `select()`
2. `filter()`
3. `group_by()`
4. `summarize()`
5. `mutate()`
6. `arrange()`

If you have have not installed this package earlier, please do so now:

```
# not run  
# install.packages('dplyr')
```

Now let's load the package:

```
library(dplyr)
```

10.2 dplyr Functions

10.2.1 Select Columns with `select`

Imagine that we just received the gapminder dataset, but are only interested in a few variables in it. We could use the `select()` function to keep only the variables we select.

```
year_country_gdp <- select(gap, year, country, gdpPercap)  
kable(head(year_country_gdp))
```

```
year  
country  
gdpPercap  
1952  
Afghanistan  
779  
1957  
Afghanistan  
821  
1962  
Afghanistan  
853  
1967  
Afghanistan  
836  
1972  
Afghanistan
```

```
740
```

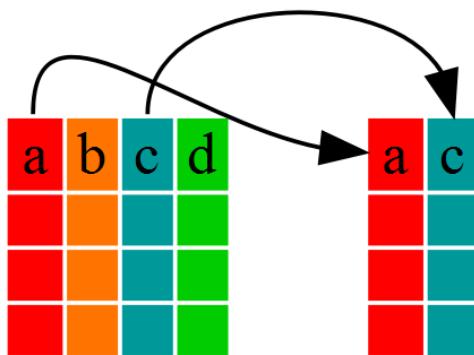
```
1977
```

```
Afghanistan
```

```
786
```

```
knitr::include_graphics(path = "img/dplyr-fig1.png")
```

`select(data.frame,a,c)`



If we open up `year_country_gdp`, we'll see that it only contains the year, country and gdpPercap. This is equivalent to the base R subsetting function:

```
year_country_gdp_base <- gap[,c("year", "country", "gdpPercap")]
kable(head(year_country_gdp))
```

```
year
```

```
country
```

```
gdpPercap
```

```
1952
```

```
Afghanistan
```

```
779
```

```
1957
```

```
Afghanistan
```

821

1962

Afghanistan

853

1967

Afghanistan

836

1972

Afghanistan

740

1977

Afghanistan

786

But, as we will see, `dplyr` makes for much more readable, efficient code because of its *pipe* operator.

10.2.2 The Pipe

```
knitr::include_graphics(path = "img/pipe.jpg")
```



Above, we used what's called 'normal' grammar, but the strengths of `dplyr` lie in combining several functions using *pipes*. Since the pipes grammar is unlike anything we've seen in R before, let's repeat what we've done above using pipes.

In typical base R code, a simple operation might be written like:

```
# NOT run
cupcakes <- bake(pour(mix(ingredients)))
```

A computer has no trouble understanding this and your cupcakes will be made just fine, but a person has to read right to left to understand the order of operations - the opposite of how most western languages are read - making it harder to understand what is being done!

To be more readable without pipes, we might break up this code into intermediate objects:

```
## NOT run
batter <- mix(ingredients)
muffin_tin <- pour(batter)
cupcakes <- bake(muffin_tin)
```

But, this can clutter our environment with a lot of variables that aren't very useful to us. Plus, these variables are often named very similar things

(e.g. step, step1, step2...) which can lead to confusion and the creation of hard-to-track-down bugs.

Enter the Pipe...

The *pipe* makes it easier to read code by laying out operations from left to right – each line can be read like a line of a recipe for the perfect data frame!

Pipes take the input on the left side of the `%>%` symbol and pass it in as the first argument to the function on the right side.

With pipes, our cupcake example might be written like:

```
## NOT run
cupcakes <- ingredients %>%
  mix() %>%
  pour() %>%
  bake()
```

Tips for Piping

1. Remember that you don't assign anything within the pipes – that is, you should not use `<-` inside the piped operation. Only use this at the beginning of your code if you want to save the output.
2. Remember to add the pipe `%>%` at the end of each line involved in the piped operation. A good rule of thumb: since RStudio will automatically indent lines of code that are part of a piped operation, if the line isn't indented, it probably hasn't been added to the pipe. If you have an error in a piped operation, always check to make sure the pipe is connected as you expect.
3. In RStudio, the hotkey for the pipe is Ctrl + Shift + M.

select & Pipe (%>%)

Since the pipe grammar is unlike anything we've seen in R before, let's repeat what we did above with the gapminder dataset using pipes:

```
year_country_gdp <- gap %>% select(year, country, gdpPerCap)
```

Let's walk through it step by step.

First, we summon the gapminder data frame and pass it on to the next step using the pipe symbol `%>%`.

The second step is the `select()` function. In this case, we don't specify which data object we use in the call to `select()` since we've piped it in from the previous line.

Fun Fact: There is a good chance you have encountered pipes before in the shell. In R, a pipe symbol is `%>%` while in the shell it is `|`. But the concept is the same!

10.2.3 Filter Rows with `filter`

Now let's say we're only interested in African countries. We can combine `select` and `filter` to select only the observations where `continent` is `Africa`.

```
year_country_gdp_africa <- gap %>%
  filter(continent == "Africa") %>%
  select(year, country, gdpPercap)
```

As with last time, first we pass the gapminder dataframe to the `filter()` function, then we pass the filtered version of the gapminder dataframe to the `select()` function.

To clarify, both the `select` and `filter` functions subset the data frame. The difference is that `select` extracts certain columns, while `filter` extracts certain rows.

Note: The order of operations is very important in this case. If we used `select` first, `filter` would not be able to find the variable `continent` since we would have removed it in the previous step.

10.2.4 Calculate Across Groups with `group_by`

A common task you'll encounter when working with data is running calculations on different groups within the data. For instance, what if we wanted to calculate the mean GDP per capita for each continent?

In base R, you would have to run the `mean()` function for each subset of data:

```
mean(gap$gdpPercap[gap$continent == "Africa"])
#> [1] 2194
mean(gap$gdpPercap[gap$continent == "Americas"])
#> [1] 7136
mean(gap$gdpPercap[gap$continent == "Asia"])
#> [1] 7902
mean(gap$gdpPercap[gap$continent == "Europe"])
#> [1] 14469
mean(gap$gdpPercap[gap$continent == "Oceania"])
#> [1] 18622
```

That's a lot of repetition! To make matters worse, what if we wanted to add these values to our original data frame as a new column? We would have to write something like this:

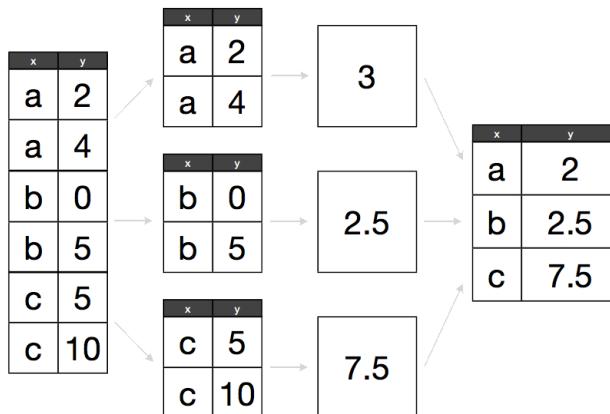
```
gap$mean.continent.GDP <- NA
gap$mean.continent.GDP[gap$continent == "Africa"] <- mean(gap$gdpPercap[gap$continent ==
gap$mean.continent.GDP[gap$continent == "Americas"] <- mean(gap$gdpPercap[gap$continent ==
gap$mean.continent.GDP[gap$continent == "Asia"] <- mean(gap$gdpPercap[gap$continent ==
gap$mean.continent.GDP[gap$continent == "Europe"] <- mean(gap$gdpPercap[gap$continent ==
gap$mean.continent.GDP[gap$continent == "Oceania"] <- mean(gap$gdpPercap[gap$continent ==
```

You can see how this can get pretty tedious, especially if we want to calculate more complicated or refined statistics. We could use loops or apply functions, but these can be difficult, slow, and error-prone.

split-apply-combine

The abstract problem we're encountering here is known as “split-apply-combine”:

```
knitr::include_graphics(path = "img/splitapply.png")
```



We want to *split* our data into groups (in this case continents), *apply* some calculations on that group, then *combine* the results together afterwards.

Luckily, `dplyr` offers a much cleaner, straight-forward solution to this problem.

First, let's remove the column we just made.

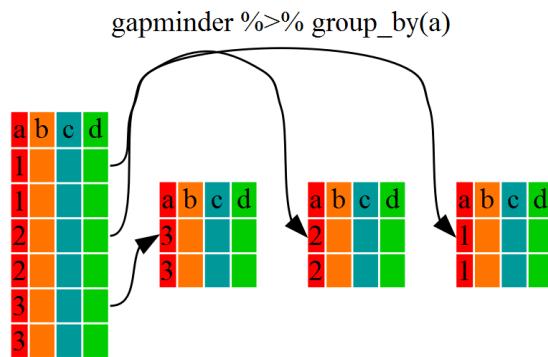
```
gap <- gap %>% select(-mean.continent.GDP) # drop a column with -
# OR
gap$mean.continent.GDP <- NULL
```

10.2.4.1 group_by

We've already seen how `filter()` can help us select observations that meet certain criteria (in the above: `continent == "Africa"`). More helpful, however, is the `group_by()` function, which will essentially use every unique criteria that we could have used in `filter()`.

A `grouped_df` can be thought of as a `list` where each item in the `list` is a `data.frame` which contains only the rows that correspond to a particular value for `continent` (at least in the example above).

```
knitr:::include_graphics(path = "img/dplyr-fig2.png")
```



10.2.5 Summarize Across Groups with summarize

`group_by()` on its own is not particularly interesting. It's much more exciting used in conjunction with the `summarize()` function.

This will allow us to create new variable(s) by applying transformations to variables in each of our groups (continent-specific data frames).

In other words, using the `group_by()` function, we split our original data frame into multiple pieces, to which we then apply summary functions (e.g. `mean()` or `sd()`) within `summarize()`.

The output is a new data frame reduced in size, with one row per group.

```
gdp_bycontinents <- gap %>%
  group_by(continent) %>%
  summarize(mean_gdpPercap = mean(gdpPercap))
kable(head(gdp_bycontinents))
```

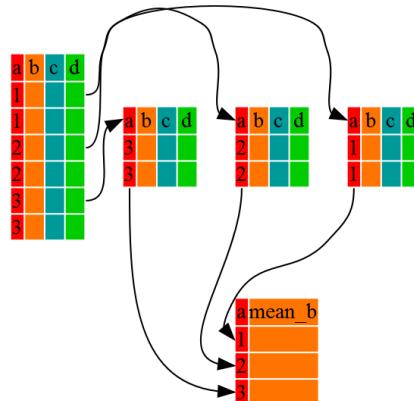
continent

mean_gdpPercap

```
Africa
2194
Americas
7136
Asia
7902
Europe
14469
Oceania
18622
```

```
knitr::include_graphics(path = "img/dplyr-fg3.png")
```

gapminder %>% group_by(a) %>% summarize(mean_b=mean(b))



That allowed us to calculate the mean gdpPercap for each continent.

But it gets even better – the function `group_by()` allows us to group by multiple variables. Let's group by `year` and `continent`.

```
gdp_bycontinents_bbyyear <- gap %>%
  group_by(continent, year) %>%
  summarize(mean_gdpPercap = mean(gdpPercap))
kable(head(gdp_bycontinents_bbyyear))
```

continent

year

```
mean_gdpPercap
```

```
Africa
```

```
1952
```

```
1253
```

```
Africa
```

```
1957
```

```
1385
```

```
Africa
```

```
1962
```

```
1598
```

```
Africa
```

```
1967
```

```
2050
```

```
Africa
```

```
1972
```

```
2340
```

```
Africa
```

```
1977
```

```
2586
```

That is already quite powerful, but it gets even better! You're not limited to defining 1 new variable in `summarize()`.

```
gdp_pop_bycontinents_byyear <- gap %>%
  group_by(continent, year) %>%
  summarize(mean_gdpPercap = mean(gdpPercap),
            sd_gdpPercap = sd(gdpPercap),
            mean_pop = mean(pop),
            sd_pop = sd(pop))
kable(head(gdp_pop_bycontinents_byyear))
```

```
continent
```

```
year
```

```
mean_gdpPercap
```

```
sd_gdpPercap
```

```
mean_pop
```

sd_pop

Africa

1952

1253

983

4570010

6317450

Africa

1957

1385

1135

5093033

7076042

Africa

1962

1598

1462

5702247

7957545

Africa

1967

2050

2848

6447875

8985505

Africa

1972

2340

3287

7305376

10130833

```
Africa
```

```
1977
```

```
2586
```

```
4142
```

```
8328097
```

```
11585184
```

10.2.6 Add New Variables with `mutate`

What if we wanted to add these values to our original data frame instead of creating a new object?

For this, we can use the `mutate()` function, which is similar to `summarize()` except that it creates new variables in the same dataframe that you pass into it.

```
gapminder_with_extra_vars <- gap %>%
  group_by(continent, year) %>%
  mutate(mean_gdpPercap = mean(gdpPercap),
        sd_gdpPercap = sd(gdpPercap),
        mean_pop = mean(pop),
        sd_pop = sd(pop))
kable(head(gapminder_with_extra_vars))
```

```
country
```

```
year
```

```
pop
```

```
continent
```

```
lifeExp
```

```
gdpPercap
```

```
mean_gdpPercap
```

```
sd_gdpPercap
```

```
mean_pop
```

```
sd_pop
```

```
Afghanistan
```

```
1952
```

```
8425333
```

Asia
28.8
779
5195
18635
42283556
1.13e+08
Afghanistan
1957
9240934
Asia
30.3
821
5788
19507
47356988
1.28e+08
Afghanistan
1962
10267083
Asia
32.0
853
5729
16416
51404763
1.36e+08
Afghanistan
1967
11537966
Asia

```

34.0
836
5971
14063
57747361
1.53e+08
Afghanistan
1972
13079460
Asia
36.1
740
8187
19088
65180977
1.74e+08
Afghanistan
1977
14880372
Asia
38.4
786
7791
11816
72257987
1.92e+08

```

We can also use `mutate()` to create new variables prior to (or even after) summarizing the information.

```

gdp_pop_bycontinents_byyear <- gap %>%
  mutate(gdp_billion = gdpPercap*pop/10^9) %>%
  group_by(continent, year) %>%
  summarize(mean_gdpPercap = mean(gdpPercap),

```

```
sd_gdpPercap = sd(gdpPercap),  
mean_pop = mean(pop),  
sd_pop = sd(pop),  
mean_gdp_billion = mean(gdp_billion),  
sd_gdp_billion = sd(gdp_billion)  
kable(head(gdp_pop_bycontinents_byyear))
```

continent
year
mean_gdpPercap
sd_gdpPercap
mean_pop
sd_pop
mean_gdp_billion
sd_gdp_billion
Africa
1952
1253
983
4570010
6317450
5.99
11.4
Africa
1957
1385
1135
5093033
7076042
7.36
14.5
Africa
1962

1598

1462

5702247

7957545

8.79

17.2

Africa

1967

2050

2848

6447875

8985505

11.44

23.2

Africa

1972

2340

3287

7305376

10130833

15.07

30.4

Africa

1977

2586

4142

8328097

11585184

18.70

38.1

mutate vs. summarize

It can be confusing to decide whether to use `mutate` or `summarize`. The key distinction is whether you want the output to have one row for each group or one row for each row in the original data frame:

- `mutate`: creates new columns with as many rows as the original data frame
- `summarize`: creates a data frame with as many rows as groups

Note that if you use an aggregation function such as `mean()` within `mutate()` without using `group_by()`, you'll simply do the summary over all the rows of the input data frame.

And if you use an aggregation function such as `mean()` within `summarize()` without using `group_by()`, you'll simply create an output data frame with one row (i.e., the whole input data frame is a single group).

10.2.7 Arrange Rows with `arrange`

As a last step, let's say we want to sort the rows in our data frame according to values in a certain column. We can use the `arrange()` function to do this. For instance, let's organize our rows by `year` (recent first), and then by `continent`.

```
gapminder_with_extra_vars <- gap %>%
  group_by(continent, year) %>%
  mutate(mean_gdpPercap = mean(gdpPercap),
        sd_gdpPercap = sd(gdpPercap),
        mean_pop = mean(pop),
        sd_pop = sd(pop)) %>%
  arrange(desc(year), continent)
kable(head(gapminder_with_extra_vars))
```

country	year	pop	continent	lifeExp	gdpPercap	mean_gdpPercap	sd_gdpPercap	mean_pop	sd_pop
Afghanistan	1952	27.6	Asia	21.8	779	779	158	4375	158
Afghanistan	1957	27.6	Asia	21.8	779	779	158	4375	158
Afghanistan	1962	27.6	Asia	22.2	779	779	158	4375	158
Afghanistan	1967	27.6	Asia	22.5	779	779	158	4375	158
Afghanistan	1972	27.6	Asia	22.9	779	779	158	4375	158

Algeria

2007

33333216

Africa

72.3

6223

3089

3618

17875763

24917726

Angola

2007

12420476

Africa

42.7

4797

3089

3618

17875763

24917726

Benin

2007

8078314

Africa

56.7

1441

3089

3618

17875763

24917726

Botswana

2007
1639131
Africa
50.7
12570
3089
3618
17875763
24917726
Burkina Faso
2007
14326203
Africa
52.3
1217
3089
3618
17875763
24917726
Burundi
2007
8390505
Africa
49.6
430
3089
3618
17875763
24917726

10.3 dplyr and “Non-Standard Evaluation”

You may run across the term “non-standard evaluation”. The use of data frame variables without quotes around them is an example of this.

Why is this strange?

```
gap %>% select(continent, year) %>% tail()
```

Compare it to:

```
gap[ , c('continent', 'year')]
gap[ , continent]
```

Because `continent` and `year` are not variables our current environment, `dplyr` does some fancy stuff behind the scenes to save us from typing the quotes.

This is fine if you have a data analysis workflow, but if you want to write a function that, for example, selects an arbitrary set of columns, you’ll run into trouble.

```
## here's a helper function that computes the mean of a variable, stratifying by a grouping variable
grouped_mean <- function(data, group_var, summary_var) {
  data %>%
    group_by(group_var) %>%
    summarise(mean = mean(summary_var))
}
gap %>% grouped_mean(continent, lifeExp)
gap %>% grouped_mean('continent', 'lifeExp')
```

See the `rlang` or `seplyr` packages for how one can deal with this problem in this context of using functions.

10.4 Challenges

Challenge 1. Use `dplyr` to create a data frame containing the median `lifeExp` for each continent.

```
gap %>%
  group_by(continent) %>%
  summarize(median_lifeexp = median(lifeExp))
#> # A tibble: 5 x 2
#>   continent median_lifeexp
#>   <fct>        <dbl>
#> 1 Africa          47.8
#> 2 Americas        67.0
```

```
#> 3 Asia          61.8
#> 4 Europe        72.2
#> 5 Oceania       73.7
```

Challenge 2. Use `dplyr` to add a column to the gapminder dataset that contains the total population of the continent of each observation in a given year. For example, if the first observation is Afghanistan in 1952, the new column would contain the population of Asia in 1952.

```
gap %>%
  group_by(continent, year) %>%
  mutate(continent_pop = sum(pop))
#> # A tibble: 1,704 x 7
#> # Groups:   continent, year [60]
#>   country      year     pop continent lifeExp gdpPercap continent_pop
#>   <fct>      <int>   <dbl> <fct>    <dbl>    <dbl>      <dbl>
#> 1 Afghanistan  1952  8425333 Asia      28.8     779.  1395357352.
#> 2 Afghanistan  1957  9240934 Asia      30.3     821.  1562780599
#> 3 Afghanistan  1962 10267083 Asia      32.0     853.  1696357182
#> 4 Afghanistan  1967 11537966 Asia      34.0     836.  1905662900
#> 5 Afghanistan  1972 13079460 Asia      36.1     740.  2150972248
#> 6 Afghanistan  1977 14880372 Asia      38.4     786.  2384513556
#> # ... with 1,698 more rows
```

Challenge 3. Use `dplyr` to: (a) add a column called `gdpPercap_diff` that contains the difference between the observation's `gdpPercap` and the mean `gdpPercap` of the continent in that year, (b) arrange the dataframe by the column you just created, in descending order (so that the relatively richest country-years are listed first).

hint: You might have to `ungroup()` before you `arrange()`.

```
gap %>%
  group_by(continent, year) %>%
  mutate(mean_gdpPercap = mean(gdpPercap)) %>%
  ungroup() %>%
  mutate(gdpPercap_diff = gdpPercap - mean_gdpPercap) %>%
  select(-mean_gdpPercap) %>%
  arrange(desc(gdpPercap_diff))
#> # A tibble: 1,704 x 7
#>   country year     pop continent lifeExp gdpPercap gdpPercap_diff
#>   <fct>   <int>   <dbl> <fct>    <dbl>    <dbl>      <dbl>
#> 1 Kuwait   1957  212846 Asia      58.0    113523.     107735.
```

```
#> 2 Kuwait 1952 160000 Asia      55.6 108382. 103187.  
#> 3 Kuwait 1972 841934 Asia     67.7 109348. 101160.  
#> 4 Kuwait 1962 358266 Asia     60.5 95458. 89729.  
#> 5 Kuwait 1967 575003 Asia     64.6 80895. 74924.  
#> 6 Kuwait 1977 1140357 Asia    69.3 59265. 51474.  
#> # ... with 1,698 more rows
```

Acknowledgments

Some of these materials in this module were adapted from:

- Software Carpentry)
- R bootcamp at UC Berkeley

Chapter 11

Tidying Data

Even before we conduct analysis or calculations, we need to put our data into the correct format. The goal here is to rearrange a messy dataset into one that is **tidy**.

The two most important properties of tidy data are:

- 1) Each column is a variable.
- 2) Each row is an observation.

Tidy data is easier to work with because you have a consistent way of referring to variables (as column names) and observations (as row indices). The data then becomes easier to manipulate, visualize, and model.

For more on the concept of *tidy* data, read Hadley Wickham's paper [here](#)

11.1 Wide vs. Long Formats

“Tidy datasets are all alike but every messy dataset is messy in its own way.” – Hadley Wickham

Tabular datasets can be arranged in many ways. For instance, consider the data below. Each data set displays information on heart rates observed in individuals across 3 different time periods. But the data are organized differently in each table.

```
wide <- data.frame(  
  name = c("Wilbur", "Petunia", "Gregory"),  
  time1 = c(67, 80, 64),  
  time2 = c(56, 90, 50),  
  time3 = c(70, 67, 101))
```

```
)  
kable(wide)  
  
name  
time1  
time2  
time3  
Wilbur  
67  
56  
70  
Petunia  
80  
90  
67  
Gregory  
64  
50  
101  
  
long <- data.frame(  
  name = c("Wilbur", "Petunia", "Gregory", "Wilbur", "Petunia", "Gregory", "Wilbur", "Petunia", "Gregory"),  
  time = c(1, 1, 1, 2, 2, 2, 3, 3, 3),  
  heartrate = c(67, 80, 64, 56, 90, 50, 70, 67, 10)  
)  
kable(long)  
  
name  
time  
heartrate  
Wilbur  
1  
67  
Petunia  
1
```

80

Gregory

1

64

Wilbur

2

56

Petunia

2

90

Gregory

2

50

Wilbur

3

70

Petunia

3

67

Gregory

3

10

Question: Which one of these do you think is the *tidy* format?

Answer: The first dataframe (the “wide” one) would not be considered *tidy* because values (i.e., heart rate) are spread across multiple columns.

We often refer to these different structures as “long” vs. “wide” formats. In the “long” format, you usually have 1 column for the observed variable and the other columns are ID variables.

For the “wide” format each row is often a site/subject/patient and you have multiple observation variables containing the same type of data. These can be either repeated observations over time, or observation of multiple variables (or a mix of both). In the above case, we had the same kind of data (heart rate) entered across 3 different columns, corresponding to three different time periods.

```
knitr::include_graphics(path = "img/tidyr-fig1.png")
```

wide vs long

ID	a1	a2	a3
1			
2			
3			

ID	ID2	A
1	a1	
2	a1	
3	a1	
1	a2	
2	a2	
3	a2	
1	a3	
2	a3	
3	a3	

You may find data input in the “wide” format to be simpler, and some other applications may prefer “wide” format data. However, many of R’s functions have been designed assuming you have “long” format data.

11.2 Tidying the Gapminder Data

Let's look at the structure of our original gapminder dataframe:

```
gap <- read.csv("data/gapminder-FiveYearData.csv", stringsAsFactors = TRUE)
kable(head(gap))
```

country

year

pop

continent

lifeExp

gdpPercap

Afghanistan

1952

8425333

Asia

28.8

779

Afghanistan

1957

9240934

Asia

30.3

821

Afghanistan

1962

10267083

Asia

32.0

853

Afghanistan

1967

```
11537966
Asia
34.0
836
Afghanistan
1972
13079460
Asia
36.1
740
Afghanistan
1977
14880372
Asia
38.4
786
```

Question: Is this data frame **wide** or **long**?

Answer: This data frame is somewhere in between the purely ‘long’ and ‘wide’ formats. We have 3 “ID variables” (`continent`, `country`, `year`) and 3 “Observation variables” (`pop`, `lifeExp`, `gdpPerCap`).

Despite not having ALL observations in 1 column, this intermediate format makes sense given that all 3 observation variables have different units. As we have seen, many of the functions in R are often vector based, and you usually do not want to do mathematical operations on values with different units.

On the other hand, there are some instances in which a purely long or wide format is ideal (e.g. plotting). Likewise, sometimes you’ll get data on your desk that is poorly organized, and you’ll need to `reshape` it.

11.3 `tidyR` Functions

Thankfully, the `tidyR` package will help you efficiently transform your data regardless of original format.

```
# Install the "tidyverse" package (only necessary one time)
# install.packages("tidyverse") # Not Run

# Load the "tidyverse" package (necessary every new R session)
library(tidyverse)
```

11.3.1 gather

Until now, we've been using the nicely formatted original gapminder dataset. This dataset is not quite wide and not quite long – it's something in the middle, but 'real' data (i.e. our own research data) will never be so well organized. Here let's start with the wide format version of the gapminder dataset.

```
gap_wide <- read.csv("data/gapminder_wide.csv", stringsAsFactors = FALSE)
kable(head(gap_wide))
```

continent

country

gdpPercap_1952

gdpPercap_1957

gdpPercap_1962

gdpPercap_1967

gdpPercap_1972

gdpPercap_1977

gdpPercap_1982

gdpPercap_1987

gdpPercap_1992

gdpPercap_1997

gdpPercap_2002

gdpPercap_2007

lifeExp_1952

lifeExp_1957

lifeExp_1962

lifeExp_1967

lifeExp_1972

lifeExp_1977
lifeExp_1982
lifeExp_1987
lifeExp_1992
lifeExp_1997
lifeExp_2002
lifeExp_2007
pop_1952
pop_1957
pop_1962
pop_1967
pop_1972
pop_1977
pop_1982
pop_1987
pop_1992
pop_1997
pop_2002
pop_2007
Africa
Algeria
2449
3014
2551
3247
4183
4910
5745
5681
5023
4797

5288

6223

43.1

45.7

48.3

51.4

54.5

58.0

61.4

65.8

67.7

69.2

71.0

72.3

9279525

10270856

11000948

12760499

14760787

17152804

20033753

23254956

26298373

29072015

31287142

33333216

Africa

Angola

3521

3828

4269

5523
5473
3009
2757
2430
2628
2277
2773
4797
30.0
32.0
34.0
36.0
37.9
39.5
39.9
39.9
40.6
41.0
41.0
42.7
4232095
4561361
4826015
5247469
5894858
6162675
7016384
7874230
8735988
9875024

10866106

12420476

Africa

Benin

1063

960

949

1036

1086

1029

1278

1226

1191

1233

1373

1441

38.2

40.4

42.6

44.9

47.0

49.2

50.9

52.3

53.9

54.8

54.4

56.7

1738315

1925173

2151895

2427334

2761407

3168267

3641603

4243788

4981671

6066080

7026113

8078314

Africa

Botswana

851

918

984

1215

2264

3215

4551

6206

7954

8647

11004

12570

47.6

49.6

51.5

53.3

56.0

59.3

61.5

63.6

62.7
52.6
46.6
50.7
442308
474639
512764
553541
619351
781472
970347
1151184
1342614
1536536
1630347
1639131
Africa
Burkina Faso
543
617
723
795
855
743
807
912
932
946
1038
1217
32.0

34.9
37.8
40.7
43.6
46.1
48.1
49.6
50.3
50.3
50.6
52.3
4469979
4713416
4919632
5127935
5433886
5889574
6634596
7586551
8878303
10352843
12251209
14326203
Africa
Burundi
339
380
355
413
464
556

560
622
632
463
446
430
39.0
40.5
42.0
43.5
44.1
45.9
47.5
48.2
44.7
45.3
47.4
49.6
2445618
2667518
2961915
3330989
3529983
3834415
4580410
5126023
5809236
6121610
7021078
8390505

The first step towards getting our nice intermediate data format is to first convert from the wide to the long format.

The function `gather()` will ‘gather’ the observation variables into a single variable. This is sometimes called “melting” your data, because it melts the table from wide to long. Those data will be melted into two variables: one for the variable names, and the other for the variable values.

```
gap_long <- gap_wide %>%
  gather(obstype_year, obs_values, 3:38)
kable(head(gap_long))
```

```
continent
country
obstype_year
obs_values
Africa
Algeria
gdpPercap_1952
2449
Africa
Angola
gdpPercap_1952
3521
Africa
Benin
gdpPercap_1952
1063
Africa
Botswana
gdpPercap_1952
851
Africa
Burkina Faso
gdpPercap_1952
```

```
543
Africa
Burundi
gdpPercap_1952
339
```

Notice that we put 3 arguments into the `gather()` function:

1. The name the new column for the new ID variable (`obstype_year`),
2. The name for the new amalgamated observation variable (`obs_value`),
3. The indices of the old observation variables (3:38, signalling columns 3 through 38) that we want to gather into one variable. Notice that we don't want to melt down columns 1 and 2, as these are considered "ID" variables.

We can also select observation variables using:

- variable indices
- variable names (without quotes)
- `x:z` to select all variables between x and z
- `-y` to *exclude* y
- `starts_with(x, ignore.case = TRUE)`: all names that starts with x
- `ends_with(x, ignore.case = TRUE)`: all names that ends with x
- `contains(x, ignore.case = TRUE)`: all names that contain x

See the `select()` function in `dplyr` for more options.

For instance, here we do the same thing with (1) the `starts_with` function, and (2) the `-` operator:

```
# 1. with the starts_with() function
gap_long <- gap_wide %>%
  gather(obstype_year, obs_values, starts_with('pop'),
         starts_with('lifeExp'), starts_with('gdpPercap'))
kable(head(gap_long))
```

```
continent
country
obstype_year
obs_values
Africa
Algeria
pop_1952
9279525
```

```
Africa
Angola
pop_1952
4232095
Africa
Benin
pop_1952
1738315
Africa
Botswana
pop_1952
442308
Africa
Burkina Faso
pop_1952
4469979
Africa
Burundi
pop_1952
2445618
# 2. with the - operator
gap_long <- gap_wide %>%
  gather(obstype_year, obs_values, -continent, -country)
kable(head(gap_long))

continent
country
obstype_year
obs_values
Africa
Algeria
gdpPercap_1952
```

```
2449  
Africa  
Angola  
gdpPercap_1952  
3521  
Africa  
Benin  
gdpPercap_1952  
1063  
Africa  
Botswana  
gdpPercap_1952  
851  
Africa  
Burkina Faso  
gdpPercap_1952  
543  
Africa  
Burundi  
gdpPercap_1952  
339
```

However you choose to do it, notice that the output collapses all of the measured variables into two columns: one containing the new ID variable, the other containing the observation value for that row.

11.3.2 separate

You'll notice that in our long dataset, `obstype_year` actually contains 2 pieces of information, the observation type (`pop`, `lifeExp`, or `gdpPercap`) and the `year`.

We can use the `separate()` function to split the character strings into multiple variables:

```
gap_long_sep <- gap_long %>%
  separate(obstype_year, into = c('obs_type', 'year'), sep = "_") %>%
  mutate(year = as.integer(year))
kable(head(gap_long_sep))
```

continent
country
obs_type
year
obs_values
Africa
Algeria
gdpPercap
1952
2449
Africa
Angola
gdpPercap
1952
3521
Africa
Benin
gdpPercap
1952
1063
Africa
Botswana
gdpPercap
1952
851
Africa
Burkina Faso

```
gdpPercap
```

```
1952
```

```
543
```

```
Africa
```

```
Burundi
```

```
gdpPercap
```

```
1952
```

```
339
```

11.3.3 spread

The opposite of `gather()` is `spread()`. It spreads our observation variables back out to make a wider table. We can use this function to spread our `gap_long()` to the original “medium” format.

```
gap_medium <- gap_long_sep %>%
  spread(obs_type, obs_values)
kable(head(gap_medium))
```

```
continent
```

```
country
```

```
year
```

```
gdpPercap
```

```
lifeExp
```

```
pop
```

```
Africa
```

```
Algeria
```

```
1952
```

```
2449
```

```
43.1
```

```
9279525
```

```
Africa
```

```
Algeria
```

```
1957
```

```
3014  
45.7  
10270856  
Africa  
Algeria  
1962  
2551  
48.3  
11000948  
Africa  
Algeria  
1967  
3247  
51.4  
12760499  
Africa  
Algeria  
1972  
4183  
54.5  
14760787  
Africa  
Algeria  
1977  
4910  
58.0  
17152804
```

All we need is some quick fixes to make this dataset identical to the original `gapminder` dataset:

```
gap <- read.csv("data/gapminder-FiveYearData.csv")  
kable(head(gap))
```

```
country
year
pop
continent
lifeExp
gdpPercap
Afghanistan
1952
8425333
Asia
28.8
779
Afghanistan
1957
9240934
Asia
30.3
821
Afghanistan
1962
10267083
Asia
32.0
853
Afghanistan
1967
11537966
Asia
34.0
836
Afghanistan
```

```
1972  
13079460  
Asia  
36.1  
740  
Afghanistan  
1977  
14880372  
Asia  
38.4  
786  
# rearrange columns  
gap_medium <- gap_medium[, names(gap)]  
kable(head(gap_medium))
```

```
country  
year  
pop  
continent  
lifeExp  
gdpPercap  
Algeria  
1952  
9279525  
Africa  
43.1  
2449  
Algeria  
1957  
10270856  
Africa  
45.7
```

```
3014
Algeria
1962
11000948
Africa
48.3
2551
Algeria
1967
12760499
Africa
51.4
3247
Algeria
1972
14760787
Africa
54.5
4183
Algeria
1977
17152804
Africa
58.0
4910
# arrange by country, continent, and year
gap_medium <- gap_medium %>%
  arrange(country, continent, year)
kable(head(gap_medium))

country
year
```

```
pop  
continent  
lifeExp  
gdpPercap  
Afghanistan  
1952  
8425333  
Asia  
28.8  
779  
Afghanistan  
1957  
9240934  
Asia  
30.3  
821  
Afghanistan  
1962  
10267083  
Asia  
32.0  
853  
Afghanistan  
1967  
11537966  
Asia  
34.0  
836  
Afghanistan  
1972  
13079460
```

Asia
36.1
740
Afghanistan
1977
14880372
Asia
38.4
786

What we just told you will become obsolete...

`gather` and `spread` are being replaced by `pivot_longer` and `pivot_wider` in `tidyverse` 1.0.0, which use ideas from the `cdata` package to make reshaping easier to think about. In future classes, we'll migrate to those functions.

11.4 More tidyverse

`dplyr` and `tidyverse` have many more functions to help you wrangle and manipulate your data. See the Data Wrangling Cheat Sheet for more.

There are some other useful packages in the tidyverse:

- `ggplot2` for plotting (we'll cover this in the Visualization module.)
- `readr` and `haven` for reading in data
- `purrr` for working iterations.
- `stringr`, `lubridate`, `forcats` for manipulating strings, dates, and factors, respectively
- many many more! Take a peak at the tidyverse github page...

Pro Tip: To install and load the core tidyverse packages (includes `tidyverse`, `dplyr`, and `ggplot2`, among others), try:

```
## NOT run
# install.packages("tidyverse")
library(tidyverse)
```

11.5 Challenges

Challenge 1. Subset the results from challenge #3 (above) to select only the `country`, `year`, and `gdpPercap_diff` columns. Use `tidyverse` put it in wide format so that countries are rows and years are columns.

Challenge 2. Now turn the dataframe above back into the long format with three columns: `country`, `year`, and `gdpPercap_diff`.

Acknowledgments

Some of these materials in this module were adapted from:

- Software Carpentry
- R bootcamp at UC Berkeley

```
library(kableExtra)
```

Chapter 12

Relational Data

It's rare that data analysis involves only a single table of data. Typically, you have many tables of data, and you must combine them to answer the questions that you're interested in. Collectively, multiple tables of data are called **relational data** because it is the relations, not just the individual datasets, that are important.

Note that when we say relational database here, we are referring to how the data are structured, not to the use of any fancy software.

12.1 Why Relational Data

As social scientists, we're often working with data across different levels of analysis. The main principle of relational data is that each table is structured around the same observational unit.

Why is this important? Check out the following data.

```
messy <- data.frame(  
  county = c(36037, 36038, 36039, 36040, NA , 37001, 37002, 37003),  
  state = c('NY', 'NY', 'NY', NA, NA, 'VA', 'VA', 'VA'),  
  cnty_pop = c(3817735, 422999, 324920, 143432, NA, 3228290, 449499, 383888),  
  state_pop = c(43320903, 43320903, NA, 43320903, 43320903, 7173000, 7173000, 7173000),  
  region = c(1, 1, 1, 1, 1, 3, 3, 4)  
)  
  
kable(messy)
```

county
state

cnty_pop
state_pop
region
36037
NY
3817735
43320903
1
36038
NY
422999
43320903
1
36039
NY
324920
NA
1
36040
NA
143432
43320903
1
NA
NA
NA
43320903
1
37001
VA
3228290

```
7173000
```

```
3
```

```
37002
```

```
VA
```

```
449499
```

```
7173000
```

```
3
```

```
37003
```

```
VA
```

```
383888
```

```
7173000
```

```
4
```

What a mess! How can the population of the state of New York be 43 million for one county but “missing” for another? If this is a dataset of counties, what does it mean when the “county” field is missing? If region is something like Census region, how can two counties in the same state be in different regions? And why is it that all the counties whose codes start with 36 are in New York except for one, where the state is unknown?

If we follow the principles of relational data, each type of observational unit should form a table.

- counties contains data on counties.
- states contains data on states

So our data should look like:

```
counties <- data.frame(
  county = c(36037, 36038, 36039, 36040, 37001, 37002, 37003),
  state = c('NY', 'NY', 'NY', 'NY', 'VA', 'VA', 'VA'),
  county_pop = c(3817735, 422999, 324920, 143432, 3228290, 449499, 383888), stringsAsFactors = F
)
kable(counties)
```

```
county
```

```
state
```

```
county_pop
```

```
36037
```

```
NY
```

```
3817735
36038
NY
422999
36039
NY
324920
36040
NY
143432
37001
VA
3228290
37002
VA
449499
37003
VA
383888

states <- data.frame(
  state = c("NY", "VA"),
  state_pop = c(43320903, 7173000),
  region = c(1, 3), stringsAsFactors = F
)
kable(states)

state
state_pop
region
NY
43320903
1
VA
```

7173000

3

County population is a property of a county, so it lives in the county table. State population is a property of a state, so it cannot live in the county table. If we had panel data on counties, we would need separate tables for things that vary at the county level (like state) and things that vary at the county-year level (like population).

Now the ambiguity is gone. Every county has a population and a state. Every state has a population and a region. There are no missing states, no missing counties, and no conflicting definitions. The database is self-documenting.

12.2 Keys

The variables used to connect each pair of tables are called **keys**. A key is a variable (or set of variables) that uniquely identifies an observation. Also called a *unique identifier*.

- Keys are complete. They never take on missing values.
- Keys are unique. They are never duplicated across rows of a table.

In simple cases, a single variable is sufficient to identify an observation. In the example above, each county is identified with **county** (a numeric identifier); each state is identified with **state** (a two-letter string).

There are two types of keys:

- A **primary key** uniquely identifies an observation in its own table. For example, `counties$county` is a primary key because it uniquely identifies each county in the `counties` table.
- A **foreign key** uniquely identifies an observation in another table. For example, the `counties$state` is a foreign key because it appears in the `counties` table where it matches each county to a unique state.

Sometimes a table doesn't have an explicit primary key: each row is an observation, but no combination of variables reliably identifies it. If a table lacks a primary key, it's useful to add one with `mutate()` and `row_number()`. This is called a **surrogate key**.

A primary key and the corresponding foreign key in another table form a **relation**.

12.3 Joins

Data stored in the form we have outlined above is considered *normalized*. In general, we should try to keep data normalized as far into the code pipeline as we can. Storing normalized data means your data will be easier to understand and it will be harder to make costly mistakes.

At some point, however, we're going to have to merge (or **join**) the tables together to produce a single dataframe, and conduct analysis on that dataframe.

Let's say we wanted to merge tables `x` and `y`. A **join** allows you to combine variables from the two tables. It first matches observations by their keys, then copies across variables from one table to the other.

There are four join options:

1. An **inner join** keeps observations that appear in both tables.
2. A **left join** keeps all observations in `x`.
3. A **right join** keeps all observations in `y`.
4. A **full join** keeps all observations in `x` and all observations in `y`.

The most commonly used join is the `left_join()`: you use this whenever you look up additional data from another table, because it preserves the original observations even when there isn't a match. For example, a `left_join()` on `x` and `y` pulls in variables from `y` while preserving all the observations on `x`.

Let's say we want to combine the `countries` and `states` tables we created earlier.

```
counties_states <- counties %>%
  left_join(states, by = "state")
```

```
kable(counties_states)
```

county

state

county_pop

state_pop

region

36037

NY

3817735

43320903

1

36038	
NY	
422999	
43320903	
1	
36039	
NY	
324920	
43320903	
1	
36040	
NY	
143432	
43320903	
1	
37001	
VA	
3228290	
7173000	
3	
37002	
VA	
449499	
7173000	
3	
37003	
VA	
383888	
7173000	
3	

Notice there are two new columns: `state_pop` and `region`.

The left join should be your default join: use it unless you have a strong reason to prefer one of the others.

12.4 Defining Keys

In the example above, the two tables were joined by a single variable, and that variable has the same name in both tables. That constraint was encoded by `by = "key"`.

You can use other values for `by` to connect the tables in other ways:

1. The default, `by = NULL`, uses all variables that appear in both tables, what we might call a “natural join”.

For example, let’s say we wanted to add a column to the `gapminder` dataset that encodes the regime type of each country-year observation. We’ll get that data from the `polityVI` dataset.

```
gapminder <- read.csv("data/gapminder.csv", stringsAsFactors = F)
polity <- read.csv("data/polity_sub.csv", stringsAsFactors = F)
kable(head(polity))
```

```
country
year
polity2
Afghanistan
1800
-6
Afghanistan
1801
-6
Afghanistan
1802
-6
Afghanistan
1803
-6
Afghanistan
```

1804

-6

Afghanistan

1805

-6

We're now ready to join the tables. The common keys between them are `country` and `year`:

```
gap1 <- gapminder %>%
  left_join(polity)
#> Joining, by = c("country", "year")

kable(head(gap1))
```

country

year

pop

continent

lifeExp

gdpPercap

polity2

Afghanistan

1952

8425333

Asia

28.8

779

-10

Afghanistan

1957

9240934

Asia

30.3

821

-10
Afghanistan
1962
10267083
Asia
32.0
853
-10
Afghanistan
1967
11537966
Asia
34.0
836
-7
Afghanistan
1972
13079460
Asia
36.1
740
-7
Afghanistan
1977
14880372
Asia
38.4
786
-7

2. A character vector, `by = c("x", "y")`. This is like a natural join, but uses only some of the common variables.

3. A named character vector: `by = c("a" = "b")`. This will match variable `a` in table `x` to variable `b` in table `y`. The variables from `x` will be used in the output.

For example, let's add another variable to our `gapminder` dataset – physical integrity rights – from the CIRI dataset.

```
ciri <- read.csv("data/ciri_sub.csv", stringsAsFactors = F)
kable(head(ciri))
```

```
CTRY
YEAR
PHYSINT
Afghanistan
1981
0
Afghanistan
1982
0
Afghanistan
1983
0
Afghanistan
1984
0
Afghanistan
1985
0
Afghanistan
1986
0
```

Both datasets have country and year columns, but they are named differently.

```
gap2 <- gap1 %>%
  left_join(ciri, by = c("country" = "CTRY", "year" = "YEAR"))

kable(head(gap2))
```

country
year
pop
continent
lifeExp
gdpPercap
polity2
PHYSINT
Afghanistan
1952
8425333
Asia
28.8
779
-10
NA
Afghanistan
1957
9240934
Asia
30.3
821
-10
NA
Afghanistan
1962
10267083
Asia
32.0
853
-10

NA

Afghanistan

1967

11537966

Asia

34.0

836

-7

NA

Afghanistan

1972

13079460

Asia

36.1

740

-7

NA

Afghanistan

1977

14880372

Asia

38.4

786

-7

NA

Notice that PHYSINT is NA in the first 6 rows because the `ciri` dataset does not contain observations for Afghanistan in these years. But because we used `left_join()`, all observations in `gapminder` were preserved.

We can see some values for PHYSINT if we peek at the bottom of the dataset:

```
kable(tail(gap2))
```

country
year
pop
continent
lifeExp
gdpPercap
polity2
PHYSINT
1699
Zimbabwe
1982
7636524
Africa
60.4
789
4
5
1700
Zimbabwe
1987
9216418
Africa
62.4
706
-6
5
1701
Zimbabwe
1992
10704340
Africa

60.4

693

-6

5

1702

Zimbabwe

1997

11404948

Africa

46.8

792

-6

6

1703

Zimbabwe

2002

11926563

Africa

40.0

672

-4

2

1704

Zimbabwe

2007

12311143

Africa

43.5

470

-4

1

12.5 Duplicate Keys

So far we have assumed that the keys are unique. But that's not always the case. For example,

```
x <- data.frame(key = c(1, 2),
                  val_y = c("x1", "x2"))

y <- data.frame(key = c(1, 2, 2, 1),
                  val_x = c("y1", "y2", "y3", "y4"))

left_join(x, y, by = "key")
#>   key val_y val_x
#> 1   1     x1    y1
#> 2   1     x1    y4
#> 3   2     x2    y2
#> 4   2     x2    y3
```

Notice that this can sometimes cause unintended duplicates.

Acknowledgements

This page is in part derived from the following sources:

1. R for Data Science licensed under Creative Commons Attribution-NonCommercial-NoDerivs 3.0
2. Gentzkow, Matthew and Jesse M. Shapiro. 2014. Code and Data for the Social Sciences: A Practitioner's Guide.

“Make it informative, then make it pretty”

Chapter 13

Plotting

There are two major sets of tools for creating plots in R:

- 1. base, which come with all R installations.
- 2. ggplot2, a stand-alone package.

Note that other plotting facilities do exist (notably `lattice`), but base and `ggplot2` are by far the most popular.

13.1 The Dataset

For the following examples, we will be using the gapminder dataset we've used previously. Gapminder is a country-year dataset with information on life expectancy, among other things.

```
gap <- read.csv("data/gapminder-FiveYearData.csv", stringsAsFactors = F)
```

13.2 R Base Graphics

The `basic` call takes the following form:

```
plot(x=, y=)  
plot(x = gap$gdpPercap, y = gap$lifeExp)
```

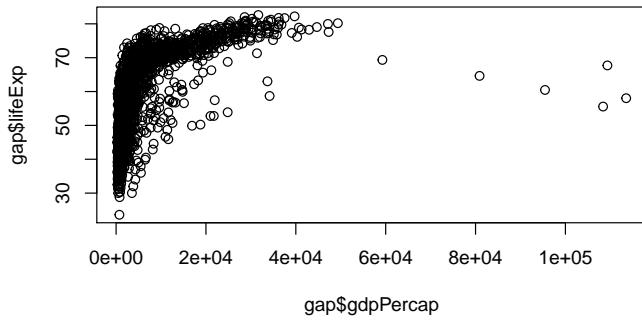
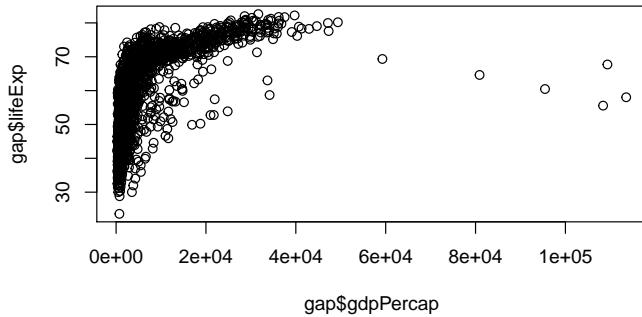


Figure 13.1:



13.2.1 Scatter and Line Plots

The “type” argument accepts the following character indicators.

- “p” – point/scatter plots (default plotting behavior)

```
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="p")
```

- “l” – line graphs

```
# Note that "line" does not create a smoothing line, just connected points
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="l")
```

- “b” – both line and point plots

```
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="b")
```

13.2.2 Histograms and Density Plots

Histograms display the frequency of different values of a variable.

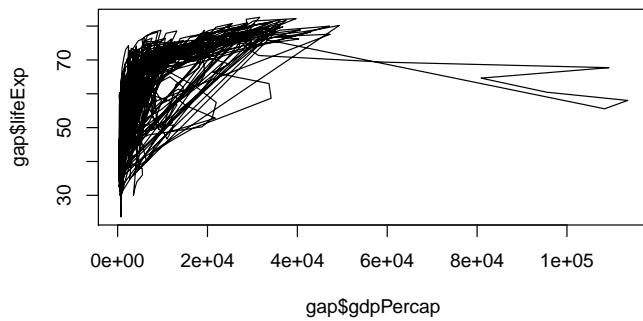


Figure 13.2:

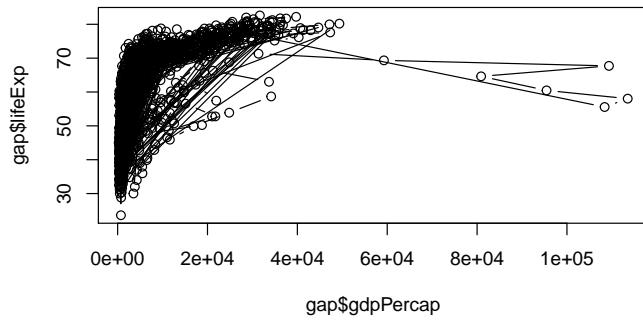
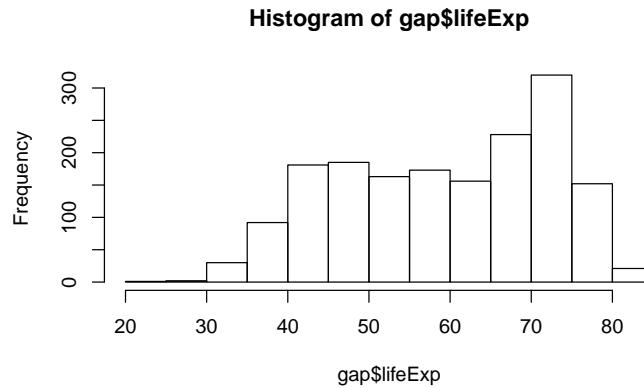


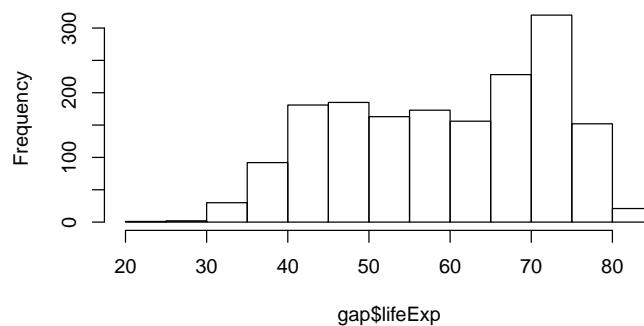
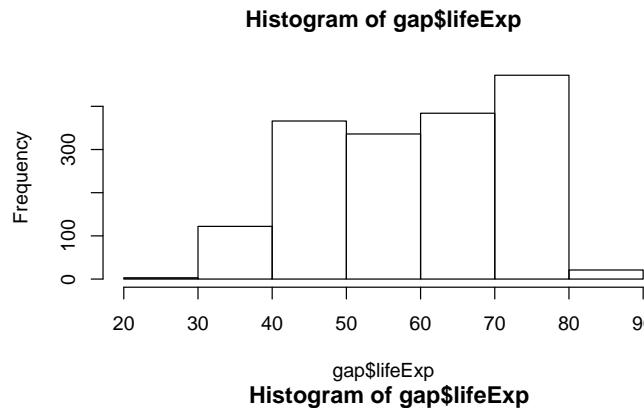
Figure 13.3:

```
hist(x=gap$lifeExp)
```



Histograms require a `breaks` argument, which determine the number of bins in the plot. Let's play around with different `breaks` values.

```
hist(x=gap$lifeExp, breaks=5)
hist(x=gap$lifeExp, breaks=10)
```



Density plots are similar, they visualize the distribution of data over a continu-

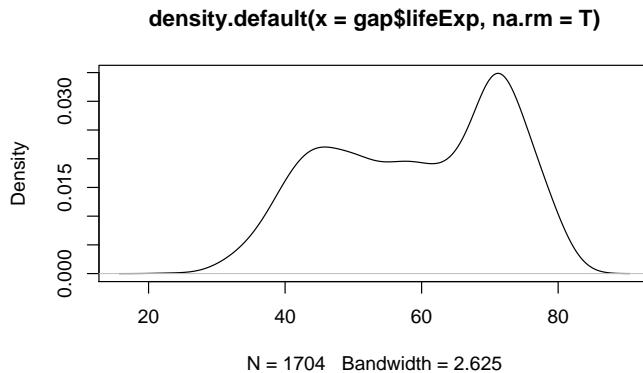


Figure 13.4:

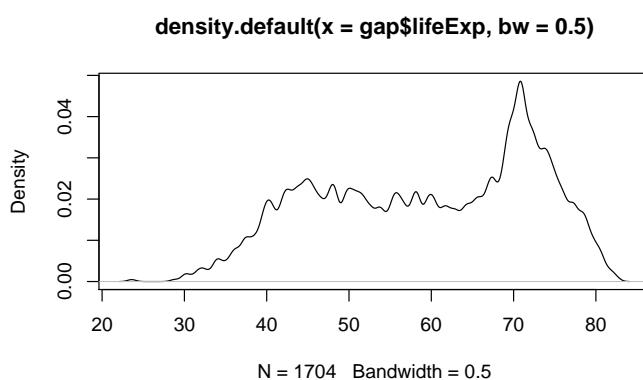
ous interval.

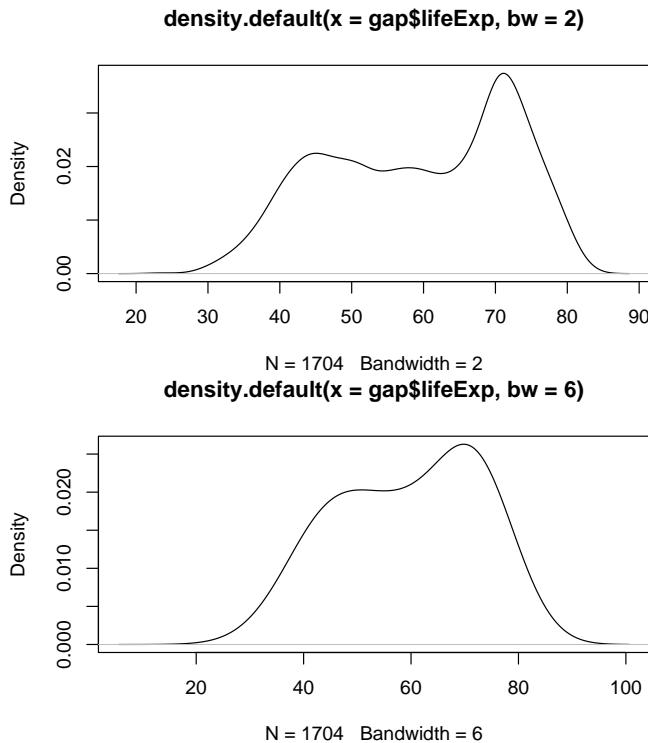
```
# Create a density object (NOTE: be sure to remove missing values)
age.density <- density(x=gap$lifeExp, na.rm=T)

# Plot the density object
plot(x=age.density)
```

Density passes a `bw` parameter, which determines the plot's "bandwidth".

```
# Plot the density object, bandwidth of 0.5
plot(x=density(x=gap$lifeExp, bw=.5))
# Plot the density object, bandwidth of 2
plot(x=density(x=gap$lifeExp, bw=2))
# Plot the density object, bandwidth of 6
plot(x=density(x=gap$lifeExp, bw=6))
```





13.2.3 Labels

Here's the basic call with popular labeling arguments:

```
plot(x=, y=, type="", xlab="", ylab="", main="")
```

From the previous example...

```
plot(x = gap$gdpPercap, y = gap$lifeExp, type="p", xlab="GDP per cap", ylab="Life Expe
```

13.2.4 Axis and Size Scaling

Currently it's hard to see the relationship between the points due to some strong outliers in GDP per capita. We can change the scale of units on the x-axis using scaling arguments.

Here's the basic call with popular scaling arguments

```
plot(x=, y=, type="", xlim=, ylim=, cex=)
```

From the previous example...

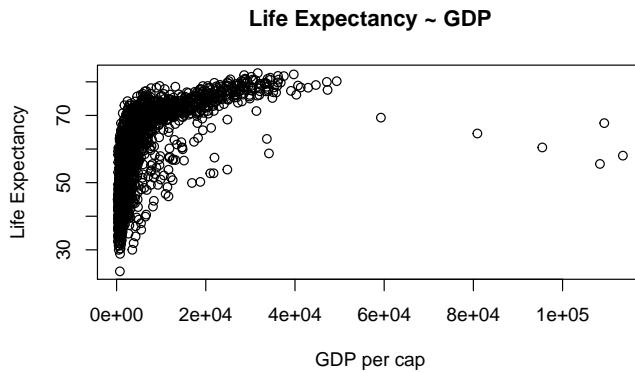


Figure 13.5:

```
# Create a basic plot
plot(x = gap$gdpPercap, y = gap$lifeExp, type="p")
# Limit gdp (x-axis) to between 1,000 and 20,000
plot(x = gap$gdpPercap, y = gap$lifeExp, xlim = c(1000,20000))
# Limit gdp (x-axis) to between 1,000 and 20,000, increase point size to 2
plot(x = gap$gdpPercap, y = gap$lifeExp, xlim = c(1000,20000), cex=2)
# Limit gdp (x-axis) to between 1,000 and 20,000, decrease point size to 0.5
plot(x = gap$gdpPercap, y = gap$lifeExp, xlim = c(1000,20000), cex=0.5)
```

13.2.5 Graphical Parameters

We can change the points with a number of graphical options:

```
plot(x=, y=, type="", col="", pch=, lty=, lwd=)
```

- Colors

```
colors()[1:20] # View first 20 elements of the color vector
#> [1] "white"          "aliceblue"       "antiquewhite"    "antiquewhite1"
#> [5] "antiquewhite2"  "antiquewhite3"  "antiquewhite4"  "aquamarine"
#> [9] "aquamarine1"   "aquamarine2"   "aquamarine3"   "aquamarine4"
#> [13] "azure"         "azure1"        "azure2"        "azure3"
#> [17] "azure4"        "beige"        "bisque"        "bisque1"
colors()[179] # View specific element of the color vector
#> [1] "gray26"
```

Another option: R Color Infographic

```
plot(x = gap$gdpPercap, y = gap$lifeExp, type="p", col=colors()[145]) # or col="gold3"
plot(x = gap$gdpPercap, y = gap$lifeExp, type="p", col="seagreen4") # or col=colors()[578]
```

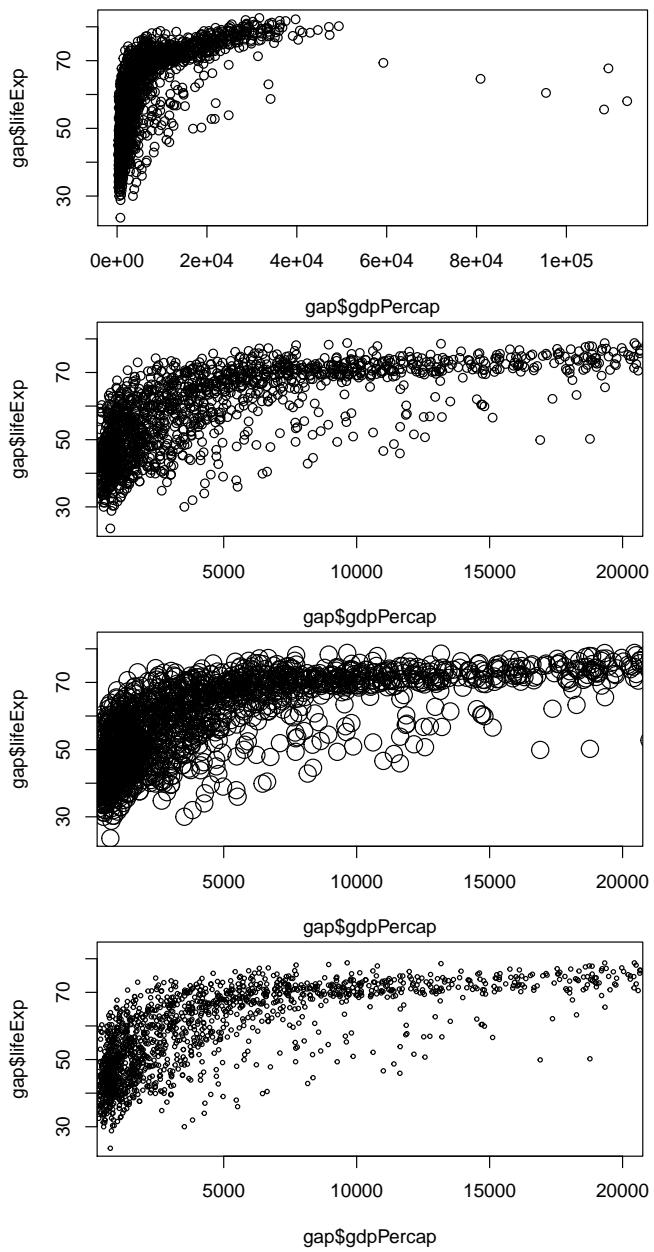


Figure 13.6:

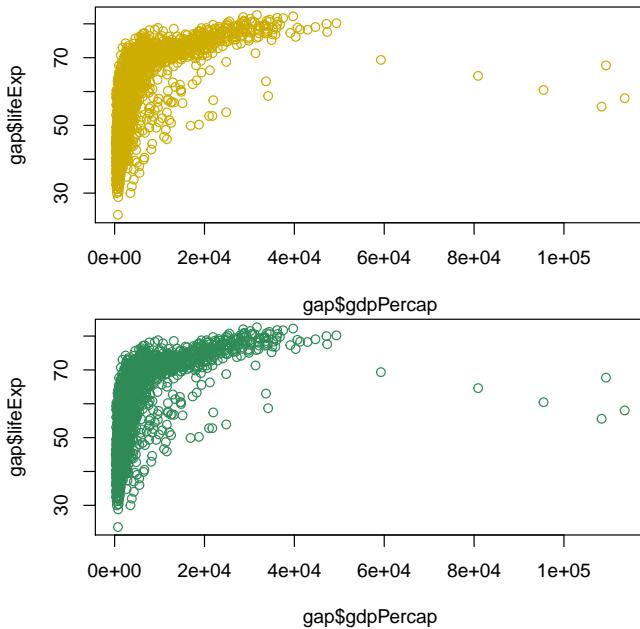


Figure 13.7:

- Point Styles and Widths

A Good Reference

```
# Change point style to crosses
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="p", pch=3)
# Change point style to filled squares
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="p", pch=15)
# Change point style to filled squares and increase point size to 3
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="p", pch=15, cex=3)
# Change point style to "w"
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="p", pch="w")
# Change point style to "$" and increase point size to 2
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="p", pch="$", cex=2)
```

- Line Styles and Widths

```
# Line plot with solid line
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="l", lty=1)
# Line plot with medium dashed line
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="l", lty=2)
# Line plot with short dashed line
plot(x = gap$gdpPerCap, y = gap$lifeExp, type="l", lty=3)
# Change line width to 2
```

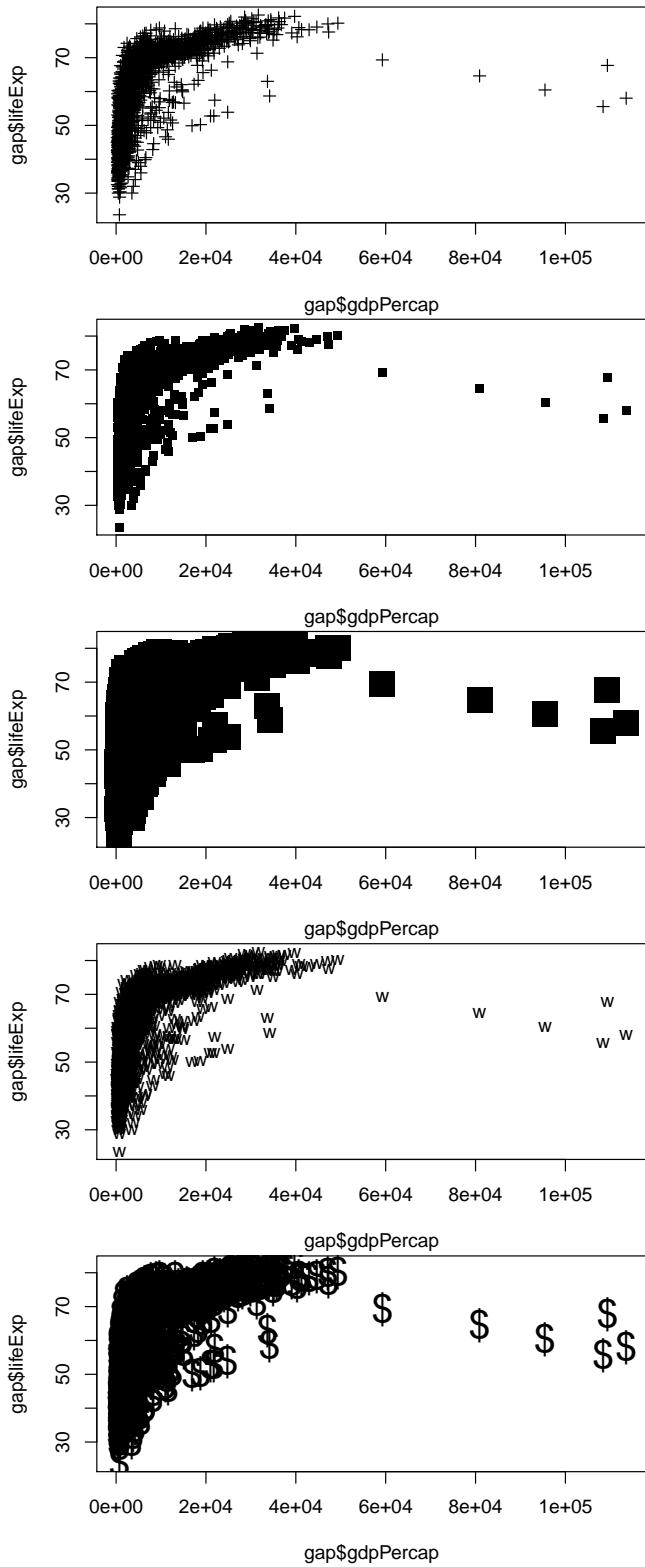


Figure 13.8:

```
plot(x = gap$gdpPercap, y = gap$lifeExp, type="l", lty=3, lwd=2)
# Change line width to 5
plot(x = gap$gdpPercap, y = gap$lifeExp, type="l", lwd=5)
# Change line width to 10 and use dash-dot
plot(x = gap$gdpPercap, y = gap$lifeExp, type="l", lty=4, lwd=10)
```

13.2.6 Annotations, Reference Lines, and Legends

- Text

We can add text to an arbitrary point on the graph like this:

```
# plot the line first
plot(x = gap$gdpPercap, y = gap$lifeExp, type="p")
# now add the label
text(x=40000, y=50, labels="Evens Out", cex = .75)
```

We can also add labels for every point by passing in a vector of text:

```
# first randomly select rows for a smaller gapaset
library(dplyr)
small <- gap %>% sample_n(100)

# plot the line first
plot(x = small$gdpPercap, y = small$lifeExp, type="p")
# now add the label
text(x = small$gdpPercap, y = small$lifeExp, labels = small$country)
```

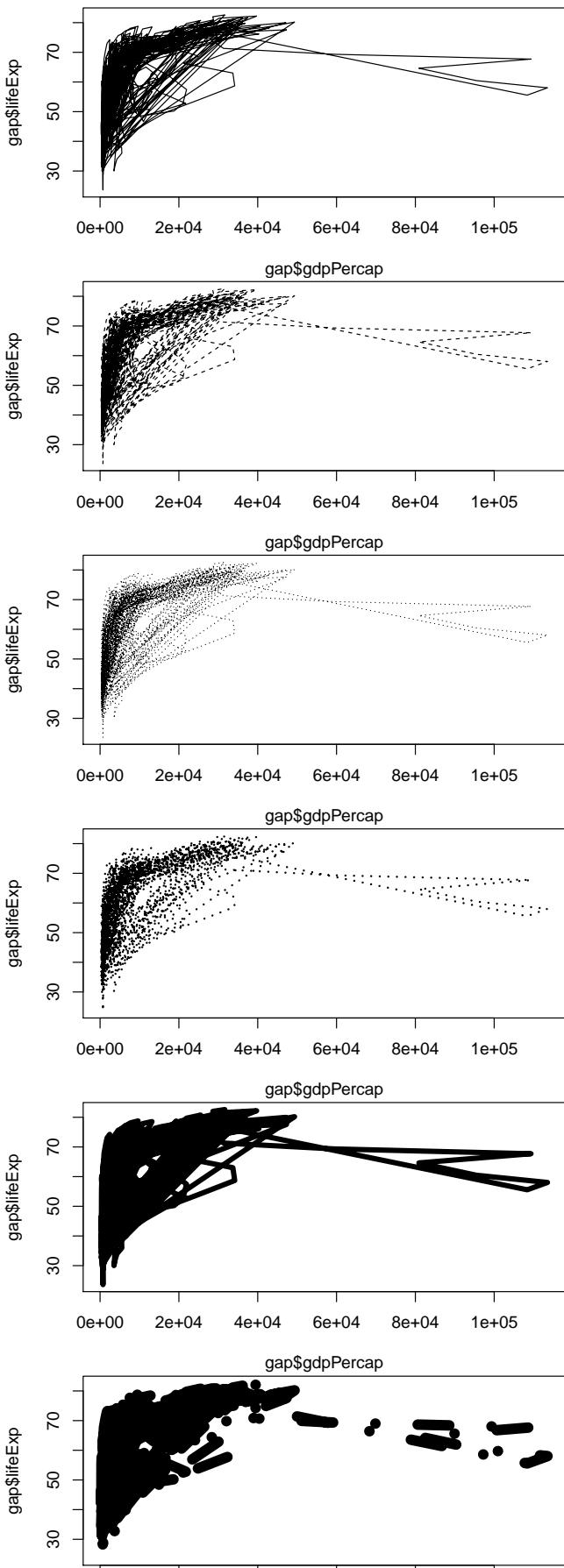
- Reference Lines

```
# plot the line
plot(x = gap$gdpPercap, y = gap$lifeExp, type="p")
# now the guides
abline(v=40000, h=75, lty=2)
```

13.3 ggplot2

Setup:

```
library(ggplot2)
gap <- read.csv("data/gapminder-FiveYearData.csv", stringsAsFactors = F)
```



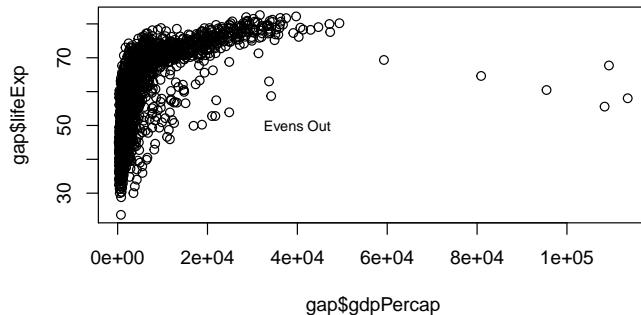


Figure 13.10:

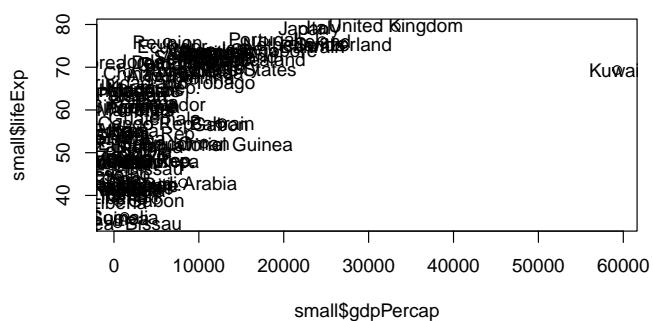


Figure 13.11:

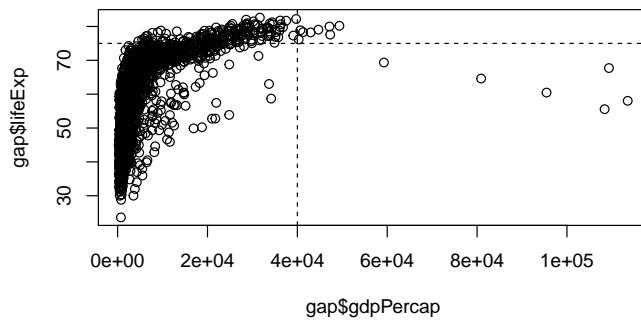


Figure 13.12:

Why `ggplot`?

- More elegant & compact code than R base graphics
- More aesthetically pleasing defaults than lattice
- Very powerful for exploratory data analysis
- Follows a grammar, just like any language.
- It defines basic components that make up a sentence. In this case, the grammar defines components in a plot.
- Grammar of graphics originally coined by Lee Wilkinson

13.3.1 Grammar

The general call for `ggplot2` looks like this:

```
ggplot(data=, aes(x=, y=), color=, size=) + geom_xxxx() + geom_yyyy()
```

The *grammar* involves some basic components:

1. **Data:** a `data.frame`
2. **Aesthetics:** How your data are represented visually, aka its “mapping”. Which variables are shown on x, y axes, as well as color, size, shape, etc.
3. **Geometry:** The geometric objects in a plot – points, lines, polygons, etc.

The key to understanding `ggplot2` is thinking about a figure in layers: just like you might do in an image editing program like Photoshop, Illustrator, or Inkscape.

Let's look at an example:

```
ggplot(data = gap, aes(x = gdpPercap, y = lifeExp)) +
  geom_point()
```

So the first thing we do is call the `ggplot` function. This function lets R know that we're creating a new plot, and any of the arguments we give the `ggplot` function are the global options for the plot: they apply to all layers on the plot.

We've passed in two arguments to `ggplot`. First, we tell `ggplot` what `data` we want to show on our figure, in this example the `gapminder` data we read in earlier.

For the second argument we passed in the `aes` function, which tells `ggplot` how variables in the data map to aesthetic properties of the figure, in this case the x and y locations. Here we told `ggplot` we want to plot the `lifeExp` column of the `gapminder` data frame on the x-axis, and the `gdpPercap` column on the y-axis.

Notice that we didn't need to explicitly pass `aes` these columns (e.g. `x = gapminder[, "lifeExp"]`), this is because `ggplot` is smart enough to know to look in the data for that column!

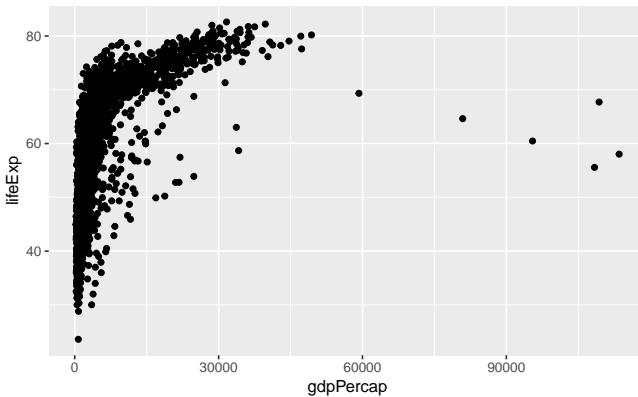
By itself, the call to `ggplot` isn't enough to draw a figure:

```
ggplot(data = gap, aes(x = gdpPercap, y = lifeExp))
```

We need to tell `ggplot` how we want to visually represent the data, which we do by adding a new `geom` layer. In our example, we used `geom_point`, which tells `ggplot` we want to visually represent the relationship between x and y as a scatterplot of points:

```
ggplot(data = gap, aes(x = gdpPercap, y = lifeExp)) +
  geom_point()

# same as
# my_plot <- ggplot(data = gap, aes(x = gdpPercap, y = lifeExp))
# my_plot + geom_point()
```



Challenge 1

Modify the example so that the figure visualises how life expectancy has changed over time:

Hint: the gapminder dataset has a column called `year`, which should appear on the x-axis.

YOUR CODE HERE

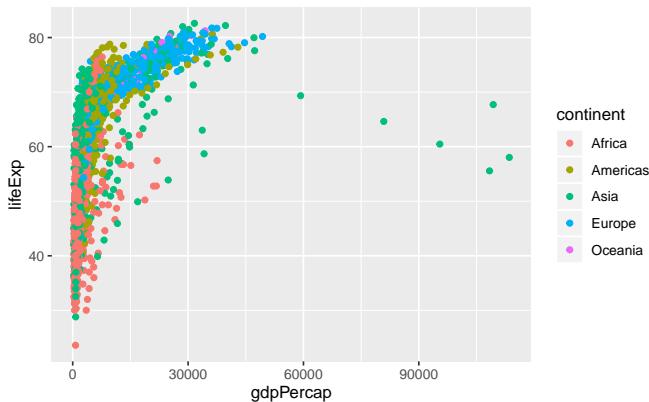
```
ggplot(data = gap, aes(x = year, y = lifeExp)) +
  geom_point()
```



13.3.2 Anatomy of aes

In the previous examples and challenge we've used the `aes` function to tell the scatterplot `geom` about the `x` and `y` locations of each point. Another aesthetic property we can modify is the point `color`.

```
ggplot(data = gap, aes(x = gdpPercap, y = lifeExp, color=continent)) +
  geom_point()
```



Normally, specifying options like `color="red"` or `size=10` for a given layer results in its contents being red and quite large. Inside the `aes()` function, however, these arguments are given entire variables whose values will then be displayed using different realizations of that aesthetic.

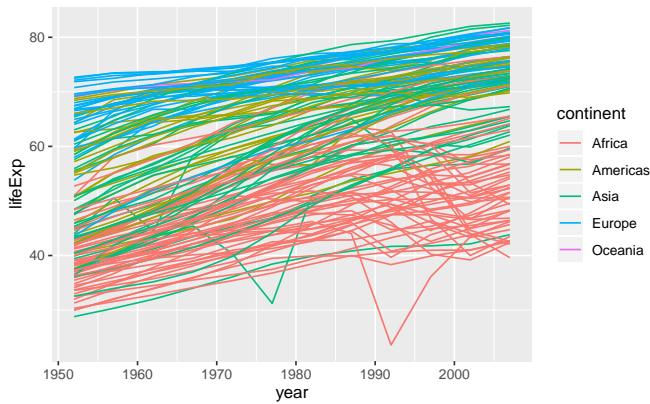
`Color` isn't the only aesthetic argument we can set to display variation in the data. We can also vary by shape, size, etc.

```
ggplot(data=, aes(x=, y=, by =, color=, linetype=, shape=, size=))
```

13.3.3 Layers

In the previous challenge, you plotted `lifeExp` over time. Using a scatterplot probably isn't the best for visualising change over time. Instead, let's tell `ggplot` to visualise the data as a line plot:

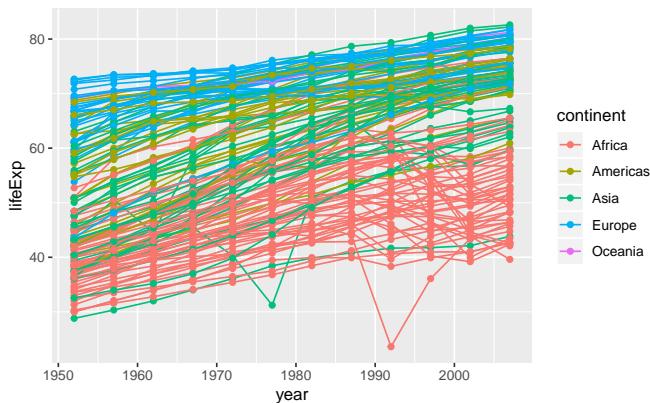
```
ggplot(data = gap, aes(x=year, y=lifeExp, by=country, color=continent)) +
  geom_line()
```



Instead of adding a `geom_point` layer, we've added a `geom_line` layer. We've also added the `by` aesthetic, which tells `ggplot` to draw a line for each country.

But what if we want to visualise both lines and points on the plot? We can simply add another layer to the plot:

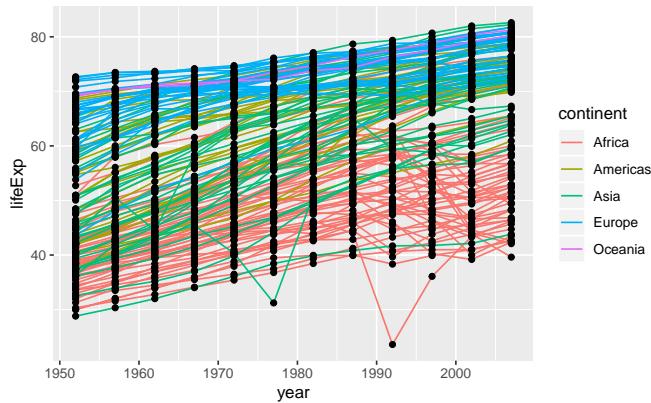
```
ggplot(data = gap, aes(x=year, y=lifeExp, by=country, color=continent)) +
  geom_line() +
  geom_point()
```



It's important to note that each layer is drawn on top of the previous layer. In this example, the points have been drawn on top of the lines. Here's a

demonstration:

```
ggplot(data = gap, aes(x=year, y=lifeExp, by=country)) +
  geom_line(aes(color=continent)) +
  geom_point()
```



In this example, the aesthetic mapping of `color` has been moved from the global plot options in `ggplot` to the `geom_line` layer so it no longer applies to the points. Now we can clearly see that the points are drawn on top of the lines.

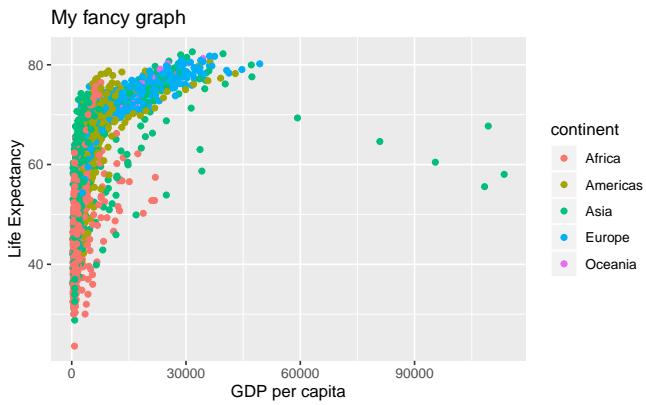
Challenge 2

Switch the order of the point and line layers from the previous example. What happened?

13.3.4 Labels

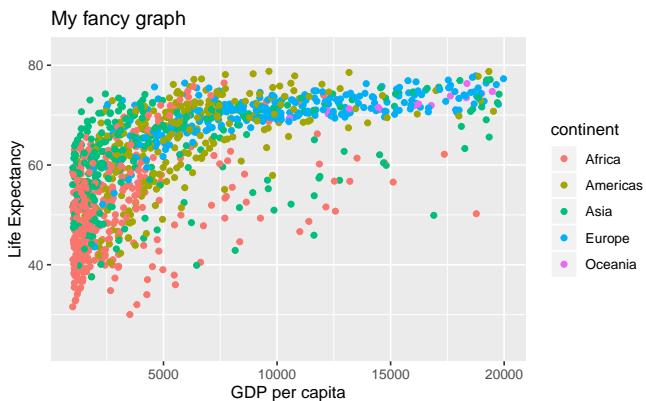
Labels are considered to be their own layers in `ggplot`.

```
# add x and y axis labels
ggplot(data = gap, aes(x = gdpPercap, y = lifeExp, color=continent)) +
  geom_point() +
  xlab("GDP per capita") +
  ylab("Life Expectancy") +
  ggtitle("My fancy graph")
```



So are scales:

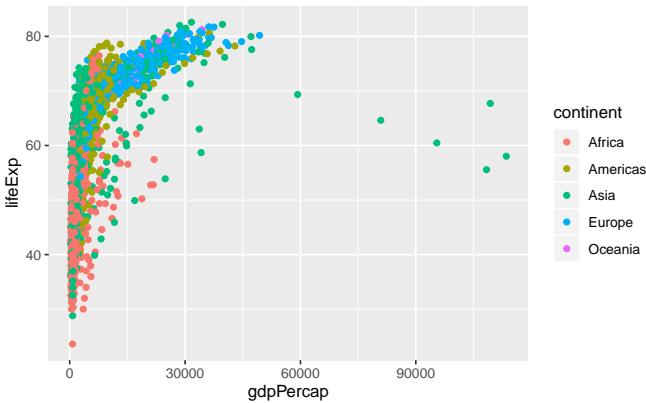
```
# limit x-axis from 1,000 to 20,000
ggplot(data = gap, aes(x = gdpPerCap, y = lifeExp, color=continent)) +
  geom_point() +
  xlab("GDP per capita") +
  ylab("Life Expectancy") +
  ggtitle("My fancy graph") +
  xlim(1000, 20000)
#> Warning: Removed 515 rows containing missing values (geom_point).
```



13.3.5 Transformations and Stats

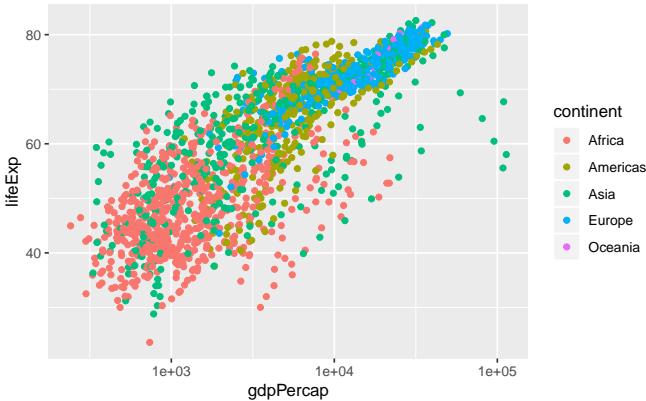
`ggplot` also makes it easy to overlay statistical models over the data. To demonstrate we'll go back to an earlier example:

```
ggplot(data = gap, aes(x = gdpPerCap, y = lifeExp, color=continent)) +
  geom_point()
```



We can change the scale of units on the x-axis using the `scale` functions. These control the mapping between the data values and visual values of an aesthetic.

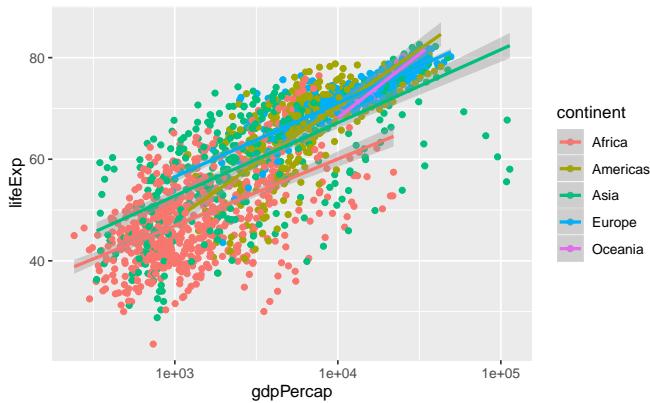
```
ggplot(data = gap, aes(x = gdpPerCap, y = lifeExp, color=continent)) +
  geom_point() +
  scale_x_log10()
```



The `log10` function applied a transformation to the values of the `gdpPerCap` column before rendering them on the plot, so that each multiple of 10 now only corresponds to an increase in 1 on the transformed scale, e.g. a GDP per capita of 1,000 is now 3 on the y axis, a value of 10,000 corresponds to 4 on the x-axis and so on. This makes it easier to visualise the spread of data on the x-axis.

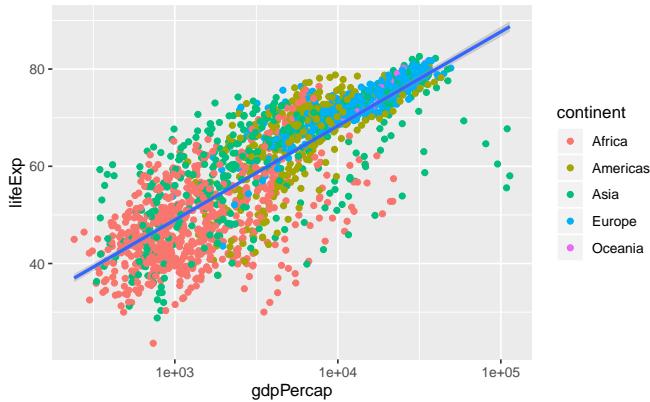
We can fit a simple relationship to the data by adding another layer, `geom_smooth`:

```
ggplot(data = gap, aes(x = gdpPerCap, y = lifeExp, color=continent)) +
  geom_point() +
  scale_x_log10() +
  geom_smooth(method="lm")
```



Note that we have 5 lines, one for each region, because of the **color** option is the global **aes** function. But if we move it, we get different results:

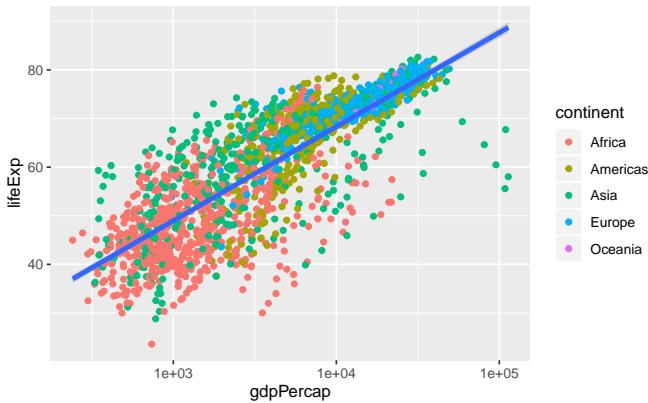
```
ggplot(data = gap, aes(x = gdpPercap, y = lifeExp)) +
  geom_point(aes(color=continent)) +
  scale_x_log10() +
  geom_smooth(method="lm")
```



So, there are two ways an aesthetic can be specified. Here, we set the **color** aesthetic by passing it as an argument to **geom_point**. Previously in the lesson, we used the **aes** function to define a *mapping* between data variables and their visual representation.

We can make the line thicker by setting the **size** aesthetic in the **geom_smooth** layer:

```
ggplot(data = gap, aes(x = gdpPercap, y = lifeExp)) +
  geom_point(aes(color=continent)) +
  scale_x_log10() +
  geom_smooth(method="lm", size = 1.5)
```



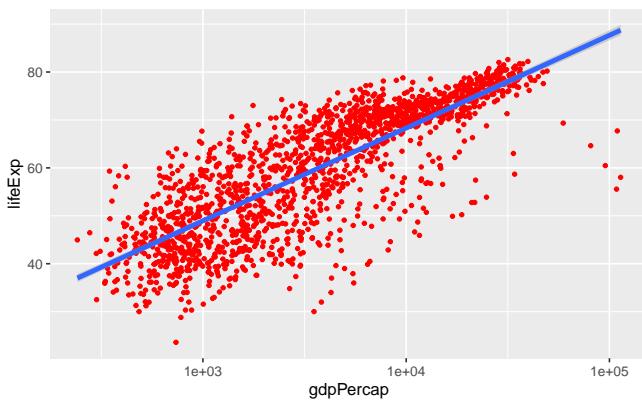
Challenge 3

Modify the color and size of the points on the point layer in the previous example so that they are fixed (i.e. not reflective of continent).

Hint: do not use the `aes` function.

```
# YOUR CODE HERE

ggplot(data = gap, aes(x = gdpPercap, y = lifeExp)) +
  geom_point(color = "red", size = 1) +
  scale_x_log10() +
  geom_smooth(method="lm", size = 1.5)
```



13.3.6 Facets

Earlier, we visualised the change in life expectancy over time across all countries in one plot. Alternatively, we can split this out over multiple panels by adding

a layer of **facet** panels:

```
ggplot(data = gap, aes(x = year, y = lifeExp, color=continent)) +
  geom_line() +
  facet_wrap(~ country)
```



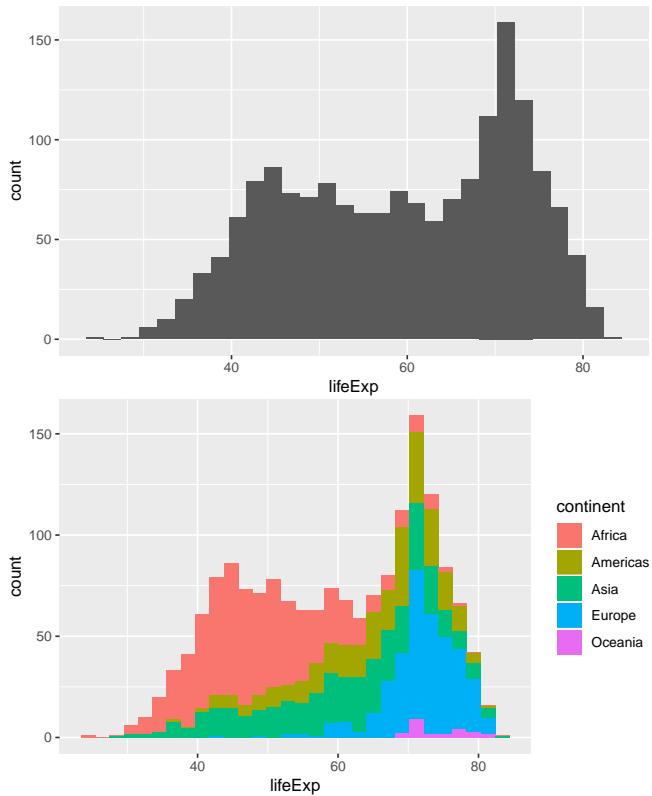
13.3.7 Putting Everything Together

Here are some other common **geom** layers:

bar plots

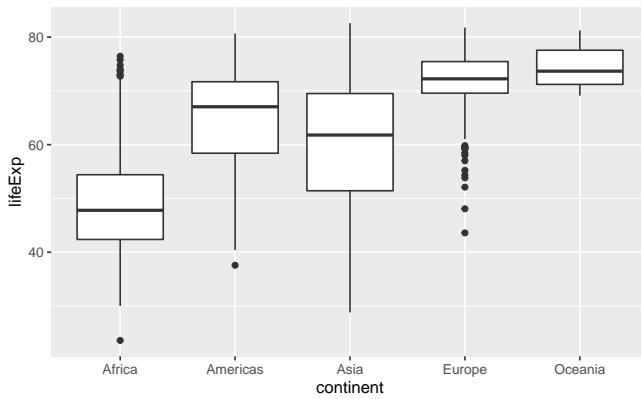
```
# count of lifeExp bins
ggplot(data = gap, aes(x = lifeExp)) +
  geom_bar(stat="bin")
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

# with color representing regions
ggplot(data = gap, aes(x = lifeExp, fill = continent)) +
  geom_bar(stat="bin")
#> `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



box plots

```
ggplot(data = gap, aes(x = continent, y = lifeExp)) +
  geom_boxplot()
```



This is just a taste of what you can do with `ggplot2`.

RStudio provides a really useful cheat sheet of the different layers available, and more extensive documentation is available on the [ggplot2 website](#).

Finally, if you have no idea how to change something, a quick Google search will usually send you to a relevant question and answer on Stack Overflow with reusable code to modify!

Challenge 4

Create a density plot of GDP per capita, filled by continent.

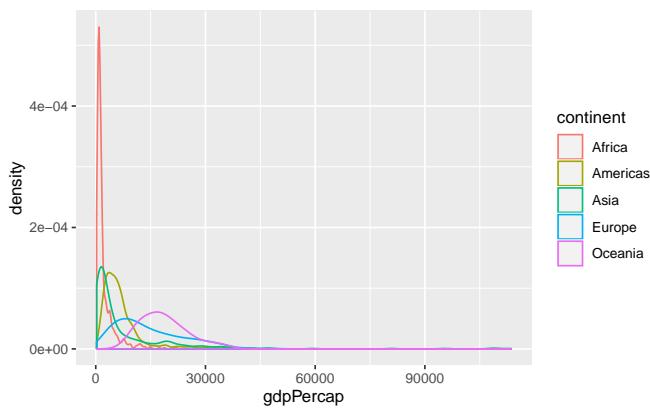
Advanced: - Transform the x-axis to better visualise the data spread. - Add a facet layer to panel the density plots by year.

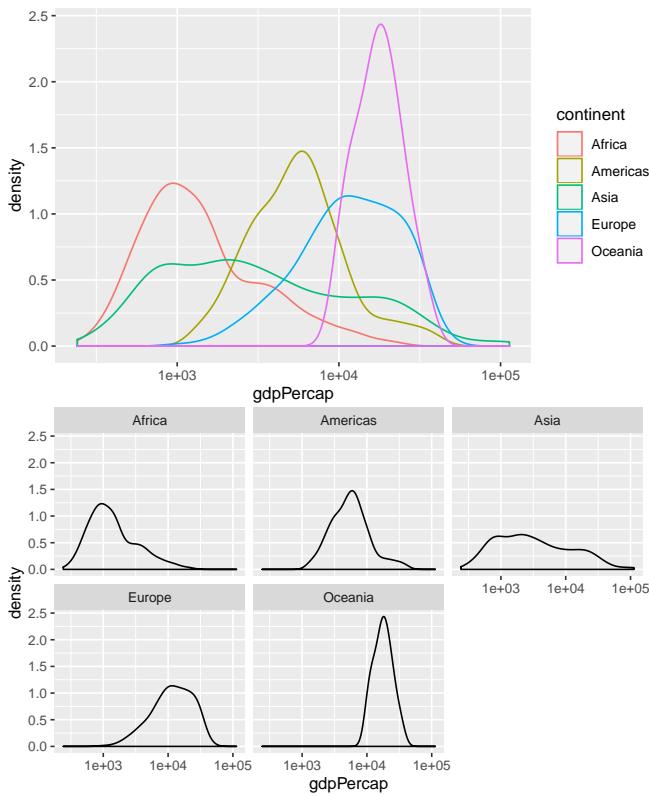
YOUR CODE HERE.

```
ggplot(gap, aes(x = gdpPercap)) +
  geom_density(aes(color = continent))

##Advanced
# Transform the x-axis to better visualise the data spread
ggplot(gap, aes(x = gdpPercap)) +
  geom_density(aes(color = continent)) +
  scale_x_log10()

#Add a facet layer to panel the density plots by year
ggplot(gap, aes(x = gdpPercap)) +
  geom_density() +
  facet_wrap(~ continent) +
  scale_x_log10()
```





13.4 Saving plots

There are two basic image types:

- 1) **Raster/Bitmap** (.png, .jpeg)

Every pixel of a plot contains its own separate coding; not so great if you want to resize the image.

```
jpeg(filename="example.png", width=, height=)
plot(x,y)
dev.off()
```

- 2) **Vector** (.pdf, .ps)

Every element of a plot is encoded with a function that gives its coding conditional on several factors; this is great for resizing.

```
pdf(filename="example.pdf", width=, height=)
plot(x,y)
dev.off()
```

Exporting with ggplot

```
# Assume we saved our plot is an object called example.plot
ggsave(filename="example.pdf", plot=example.plot, scale=, width=, height=)
```


Chapter 14

Statistical Inferences

```
# setup
gap <- read.csv("data/gapminder-FiveYearData.csv", stringsAsFactors = TRUE)
```

14.1 Statistical Distributions

Since R was developed by statisticians, it handles distributions and simulation seamlessly.

All commonly-used distributions have functions in R. Each distribution has a family of functions:

- **d** - probability density/mass function, e.g. `dnorm()`
- **r** - generate a random value, e.g., `rnorm()`
- **p** - cumulative distribution function, e.g., `pnorm()`
- **q** - quantile function (inverse CDF), e.g., `qnorm()`

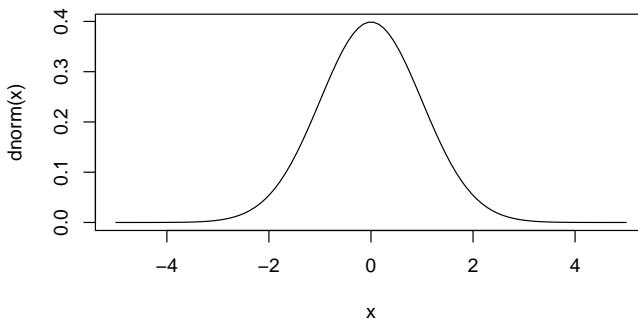
Let's see some of these functions in action with the normal distribution (mean 0, standard deviation 1)

```
dnorm(1.96) # probability density of 1.96 from normal distribution
#> [1] 0.0584
rnorm(1:10) # get 10 random values from the normal distribution
#> [1] -1.40004  0.25532 -2.43726 -0.00557  0.62155  1.14841 -1.82182
#> [8] -0.24733 -0.24420 -0.28271
pnorm(1.96) # cumulative distribution function
#> [1] 0.975
qnorm(.975) # inverse cumulative distribution function
#> [1] 1.96
```

We can also use these functions on other distributions: * `rnorm()` # normal distribution * `runif()` # uniform distribution * `rbinom()` # binomial distribution * `rpois()` # poisson distribution * `rbeta()` # beta distribution * `rgamma()` # gamma distribution * `rt()` # student t distribution * `rchisq()`. # chi-squared distribution

```
rbinom(0:10, size = 10, prob = 0.3)
#> [1] 2 4 4 2 6 4 1 3 4 4 1
dt(5, df = 1)
#> [1] 0.0122

x <- seq(-5, 5, length = 100)
plot(x, dnorm(x), type = 'l')
```



14.1.1 Sampling and Simulation

We can draw a sample with or without replacement with `sample`.

```
sample(1:nrow(gap), 20, replace = FALSE)
#> [1] 385 513 1084 815 735 1201 1611 307 368 1153 846 1087 1118 163
#> [15] 1294 1300 1673 1638 657 778
```

`dplyr` has a helpful `select_n` function that samples rows of a dataframe.

```
small <- sample_n(gap, 20)
nrow(small)
#> [1] 20
```

Here's an example of some code that would be part of a bootstrap.

```
gap <- read.csv("data/gapminder-FiveYearData.csv", stringsAsFactors = F)

# actual mean
mean(gap$lifeExp, na.rm = TRUE)
#> [1] 59.5

# here's a bootstrap sample:
```

```
smp <- sample_n(gap, size = nrow(gap), replace = TRUE)
mean(smp$lifeExp, na.rm = TRUE)
#> [1] 59.2
```

14.1.2 Random Seeds

A few key facts about generating random numbers:

- Random numbers on a computer are *pseudo-random*; they are generated deterministically from a very, very, very long sequence that repeats
- The *seed* determines where you are in that sequence

To replicate any work involving random numbers, make sure to set the seed first. The seed can be arbitrary – pick your favorite number.

```
set.seed(1)
vals <- sample(1:nrow(gap), 10)
vals
#> [1] 453 634 975 1545 343 1527 1605 1122 1067 105

vals <- sample(1:nrow(gap), 10)
vals
#> [1] 351 301 1170 654 1309 846 1219 1684 645 1318

set.seed(1)
vals <- sample(1:nrow(gap), 10)
vals
#> [1] 453 634 975 1545 343 1527 1605 1122 1067 105
```

14.1.3 Challenges

Challenge 1. Generate 100 random Poisson values with a population mean of 5. How close is the mean of those 100 values to the value of 5?

```
poisson <- rpois(100, 5)
mean(poisson)
#> [1] 5.1
```

Challenge 2. What is the 95th percentile of a chi-square distribution with 1 degree of freedom?

```
qchisq(.95, df = 1)
#> [1] 3.84
```

Challenge 3. What's the probability of getting a value greater than 5 if you draw from a standard normal distribution? What about a t distribution with 1 degree of freedom?

```
pnorm(5, 0, 1, FALSE)
#> [1] 2.87e-07

pt(5, df = 1, lower.tail = FALSE)
#> [1] 0.0628
```

14.2 Inferences and Regressions

Once we've imported our data, summarized it, carried out group-wise operations, and perhaps reshaped it, we may also want to attempt causal inference.

This often requires doing the following:

- 1) Carrying out Classical Hypothesis Tests
- 2) Estimating Regressions

```
# setup
gap <- read.csv("data/gapminder-FiveYearData.csv", stringsAsFactors = F)
```

14.2.1 Statistical Tests

Let's say we're interested in whether the life expectancy in 1967 is different than in 1977.

```
# pull out life expectancy by different years
life.exp.1967 <- gap$lifeExp[gap$year==1967]
life.exp.1977 <- gap$lifeExp[gap$year==1977]
```

One can test for differences in distributions in either:

- 1) Their means using t-tests:

```
# t test of means
t.test(x = life.exp.1967, y = life.exp.1977)
```

```
#>
#> Welch Two Sample t-test
#>
#> data: life.exp.1967 and life.exp.1977
#> t = -3, df = 300, p-value = 0.005
#> alternative hypothesis: true difference in means is not equal to 0
#> 95 percent confidence interval:
#> -6.57 -1.21
#> sample estimates:
#> mean of x mean of y
#>      55.7      59.6
```

- 2) Their entire distributions using ks-tests

```
# ks tests of distributions
ks.test(x = life.exp.1967, y = life.exp.1977)
#> Warning in ks.test(x = life.exp.1967, y = life.exp.1977): p-value will be
#> approximate in the presence of ties
#>
#> Two-sample Kolmogorov-Smirnov test
#>
#> data: life.exp.1967 and life.exp.1977
#> D = 0.2, p-value = 0.008
#> alternative hypothesis: two-sided
```

14.2.2 Regressions and Linear Models

Running regressions in R is generally straightforward. There are two basic, catch-all regression functions in R:

- *glm* fits a generalized linear model with your choice of family/link function (gaussian, logit, poisson, etc.)
- *lm* is just a standard linear regression (equivalent to *glm* with family = gaussian(link = “identity”))

The basic *glm* call looks something like this:

```
glm(formula = y ~ x1 + x2 + x3 + ..., family = familyname(link = "linkname"), data = )
```

There are a bunch of families and links to use (?family for a full list), but some essentials are: *binomial(link = “logit”)*, *gaussian(link = “identity”)*, and *poisson(link = “log”)*

If you’re using *lm*, the call looks the same but without the *family* argument.

- Example: suppose we want to regress the life expectancy on the GDP per capita and the population, as well as the continent and year. The *lm* call

would be something like this:

```
reg <- lm(formula = lifeExp ~ log(gdpPercap) + log(pop) + continent + year, data = gap)
```

Missing values

Missing values obviously cannot convey any information about the relationship between the variables. Most modeling functions will drop any rows that contain missing values.

14.2.3 Regression Output

When we store this regression in an object, we get access to several items of interest.

1. All components contained in the regression output:

```
names(reg)
#> [1] "coefficients"   "residuals"      "effects"       "rank"
#> [5] "fitted.values"  "assign"        "qr"           "df.residual"
#> [9] "contrasts"     "xlevels"       "call"          "terms"
#> [13] "model"
```

2. Regression coefficients

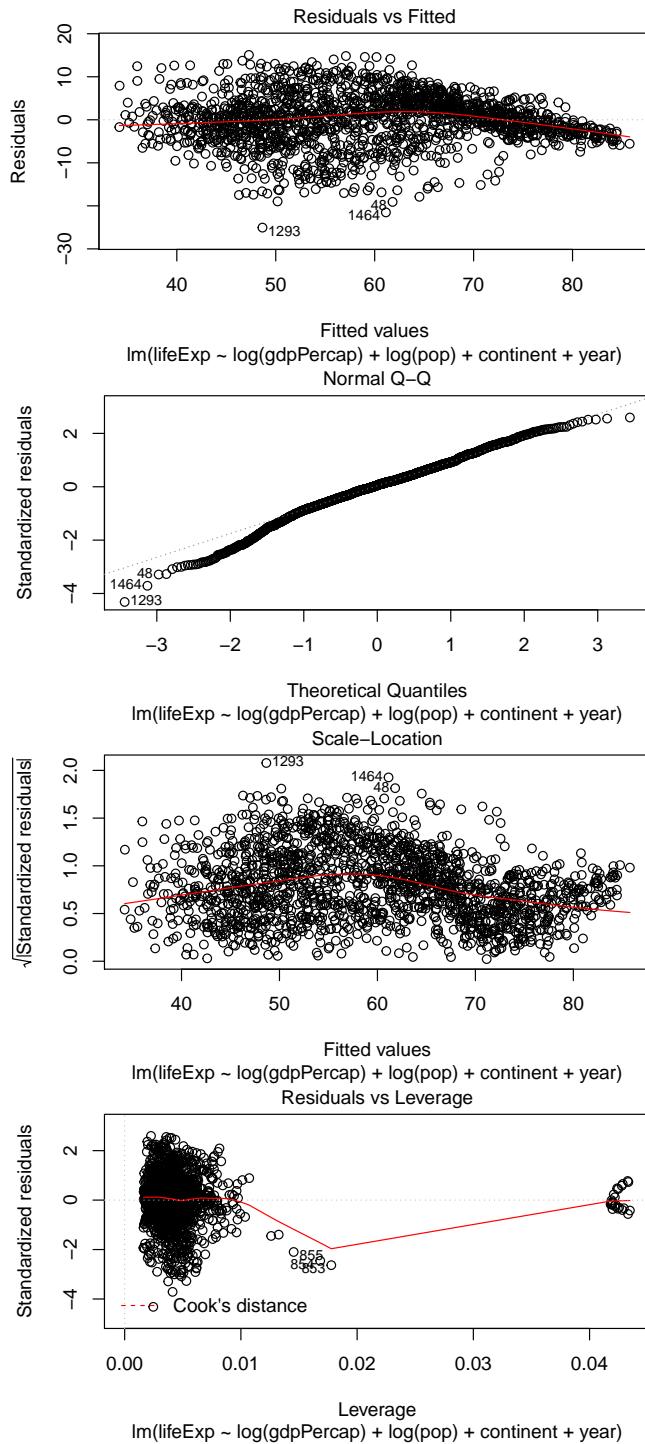
```
reg$coefficients
#> (Intercept)    log(gdpPercap)      log(pop) continentAmericas
#> -460.813        5.076            0.153             8.745
#> continentAsia  continentEurope  continentOceania      year
#>      6.825        12.281          12.540            0.238
```

3. Regression degrees of freedom

```
reg$df.residual
#> [1] 1696
```

4. Standard (diagnostic) plots for a regression

```
plot(reg)
```



R also has a helpful `summary` method for regression objects.

```
summary(reg)
#>
#> Call:
#> lm(formula = lifeExp ~ log(gdpPercap) + log(pop) + continent +
#>      year, data = gap)
#>
#> Residuals:
#>    Min     1Q Median     3Q    Max
#> -25.057 -3.286  0.329  3.706 15.065
#>
#> Coefficients:
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -4.61e+02  1.70e+01 -27.15 <2e-16 ***
#> log(gdpPercap) 5.08e+00  1.63e-01  31.19 <2e-16 ***
#> log(pop)       1.53e-01  9.67e-02   1.58   0.11
#> continentAmericas 8.75e+00  4.77e-01  18.35 <2e-16 ***
#> continentAsia    6.83e+00  4.23e-01  16.13 <2e-16 ***
#> continentEurope   1.23e+01  5.29e-01  23.20 <2e-16 ***
#> continentOceania  1.25e+01  1.28e+00   9.79 <2e-16 ***
#> year             2.38e-01  8.93e-03  26.61 <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 5.81 on 1696 degrees of freedom
#> Multiple R-squared:  0.798, Adjusted R-squared:  0.798
#> F-statistic: 960 on 7 and 1696 DF, p-value: <2e-16
```

We can also extract useful things from the summary object:

```
# Store summary method results
summ_reg <- summary(reg)

# View summary method results objects
objects(summ_reg)
#> [1] "adj.r.squared" "aliased"          "call"           "coefficients"
#> [5] "cov.unscaled"  "df"               "fstatistic"     "r.squared"
#> [9] "residuals"     "sigma"            "terms"

# View table of coefficients
summ_reg$coefficients
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept) -460.813  16.97028 -27.15 3.96e-135
#> log(gdpPercap) 5.076   0.16272  31.19 3.37e-169
#> log(pop)      0.153   0.09668   1.58 1.14e-01
#> continentAmericas 8.745   0.47660  18.35 9.61e-69
```

```
#> continentAsia      6.825   0.42320  16.13  1.49e-54
#> continentEurope    12.281   0.52924  23.20  1.12e-103
#> continentOceania   12.540   1.28114  9.79  4.80e-22
#> year                0.238   0.00893  26.61  1.06e-130
```

14.2.4 Interactions

There are also some useful shortcuts for regressing on interaction terms:

1. `x1:x2` interacts all terms in `x1` with all terms in `x2`

```
mod.1 <- lm(lifeExp ~ log(gdpPercap) + log(pop) + continent:factor(year), data = gap)
summary(mod.1)

#>
#> Call:
#> lm(formula = lifeExp ~ log(gdpPercap) + log(pop) + continent:factor(year),
#>      data = gap)
#>
#> Residuals:
#>   Min     1Q Median     3Q    Max
#> -26.568 -2.553  0.004  2.915 15.567
#>
#> Coefficients: (1 not defined because of singularities)
#>                               Estimate Std. Error t value Pr(>|t|)    
#> (Intercept)                  27.1838  4.6849   5.80  7.8e-09  
#> log(gdpPercap)               5.0795  0.1605  31.65 < 2e-16  
#> log(pop)                     0.0789  0.0943   0.84  0.40251  
#> continentAfrica:factor(year) 1952 -24.1425  4.1125  -5.87 5.2e-09  
#> continentAmericas:factor(year) 1952 -16.4465  4.1663  -3.95 8.2e-05  
#> continentAsia:factor(year) 1952  -19.3347  4.1408  -4.67 3.3e-06  
#> continentEurope:factor(year) 1952  -7.0918  4.1352  -1.71 0.08654  
#> continentOceania:factor(year) 1952  -6.0635  5.6511  -1.07 0.28344  
#> continentAfrica:factor(year) 1957  -22.4964  4.1098  -5.47 5.1e-08  
#> continentAmericas:factor(year) 1957 -14.3673  4.1643  -3.45 0.00057  
#> continentAsia:factor(year) 1957  -17.1743  4.1375  -4.15 3.5e-05  
#> continentEurope:factor(year) 1957  -5.9094  4.1327  -1.43 0.15293  
#> continentOceania:factor(year) 1957  -5.6300  5.6503  -1.00 0.31921  
#> continentAfrica:factor(year) 1962  -21.0139  4.1069  -5.12 3.5e-07  
#> continentAmericas:factor(year) 1962 -12.3135  4.1630  -2.96 0.00314  
#> continentAsia:factor(year) 1962  -15.5626  4.1351  -3.76 0.00017  
#> continentEurope:factor(year) 1962  -5.0542  4.1308  -1.22 0.22130  
#> continentOceania:factor(year) 1962  -5.3122  5.6498  -0.94 0.34723  
#> continentAfrica:factor(year) 1967  -19.7034  4.1035  -4.80 1.7e-06  
#> continentAmericas:factor(year) 1967 -10.9324  4.1613  -2.63 0.00869  
#> continentAsia:factor(year) 1967  -13.1569  4.1327  -3.18 0.00148
```

```

#> continentEurope:factor(year)1967    -4.9134    4.1291   -1.19  0.23423
#> continentOceania:factor(year)1967  -5.7712    5.6492   -1.02  0.30712
#> continentAfrica:factor(year)1972   -18.1469   4.1007   -4.43  1.0e-05
#> continentAmericas:factor(year)1972 -9.6537    4.1595   -2.32  0.02042
#> continentAsia:factor(year)1972    -11.6014   4.1293   -2.81  0.00502
#> continentEurope:factor(year)1972   -4.9763    4.1275   -1.21  0.22813
#> continentOceania:factor(year)1972  -5.8094    5.6487   -1.03  0.30389
#> continentAfrica:factor(year)1977   -16.1848   4.0996   -3.95  8.2e-05
#> continentAmericas:factor(year)1977 -8.3382    4.1580   -2.01  0.04509
#> continentAsia:factor(year)1977    -10.1220   4.1270   -2.45  0.01428
#> continentEurope:factor(year)1977   -4.5523    4.1267   -1.10  0.27013
#> continentOceania:factor(year)1977  -5.1232    5.6485   -0.91  0.36454
#> continentAfrica:factor(year)1982   -14.1933   4.0990   -3.46  0.00055
#> continentAmericas:factor(year)1982 -6.5921    4.1577   -1.59  0.11304
#> continentAsia:factor(year)1982    -7.6001    4.1257   -1.84  0.06564
#> continentEurope:factor(year)1982   -4.1185    4.1262   -1.00  0.31837
#> continentOceania:factor(year)1982  -4.0553    5.6483   -0.72  0.47288
#> continentAfrica:factor(year)1987   -12.1850   4.0995   -2.97  0.00300
#> continentAmericas:factor(year)1987 -4.7157    4.1577   -1.13  0.25687
#> continentAsia:factor(year)1987    -5.6914    4.1249   -1.38  0.16785
#> continentEurope:factor(year)1987   -3.7298    4.1258   -0.90  0.36613
#> continentOceania:factor(year)1987  -3.5164    5.6480   -0.62  0.53364
#> continentAfrica:factor(year)1992   -11.8028   4.0994   -2.88  0.00404
#> continentAmericas:factor(year)1992 -3.2855    4.1575   -0.79  0.42949
#> continentAsia:factor(year)1992    -4.3823    4.1241   -1.06  0.28811
#> continentEurope:factor(year)1992   -2.5151    4.1262   -0.61  0.54225
#> continentOceania:factor(year)1992  -1.9804    5.6480   -0.35  0.72590
#> continentAfrica:factor(year)1997   -11.9577   4.0986   -2.92  0.00358
#> continentAmericas:factor(year)1997 -2.1611    4.1566   -0.52  0.60319
#> continentAsia:factor(year)1997    -3.5016    4.1228   -0.85  0.39583
#> continentEurope:factor(year)1997   -2.0843    4.1256   -0.51  0.61348
#> continentOceania:factor(year)1997  -1.4478    5.6478   -0.26  0.79771
#> continentAfrica:factor(year)2002   -12.5237   4.0972   -3.06  0.00227
#> continentAmericas:factor(year)2002 -0.9898    4.1564   -0.24  0.81180
#> continentAsia:factor(year)2002    -2.6798    4.1221   -0.65  0.51571
#> continentEurope:factor(year)2002   -1.5734    4.1252   -0.38  0.70294
#> continentOceania:factor(year)2002  -0.4735    5.6477   -0.08  0.93320
#> continentAfrica:factor(year)2007   -11.6568   4.0948   -2.85  0.00447
#> continentAmericas:factor(year)2007 -0.6931    4.1550   -0.17  0.86754
#> continentAsia:factor(year)2007    -2.2008    4.1202   -0.53  0.59332
#> continentEurope:factor(year)2007   -1.5284    4.1247   -0.37  0.71102
#> continentOceania:factor(year)2007      NA      NA      NA      NA
#>
#> (Intercept)                      ***
#> log(gdpPerCap)                   ***

```

```
#> log(pop)
#> continentAfrica:factor(year)1952    ***
#> continentAmericas:factor(year)1952 ***
#> continentAsia:factor(year)1952      ***
#> continentEurope:factor(year)1952    .
#> continentOceania:factor(year)1952
#> continentAfrica:factor(year)1957    ***
#> continentAmericas:factor(year)1957 ***
#> continentAsia:factor(year)1957      ***
#> continentEurope:factor(year)1957
#> continentOceania:factor(year)1957
#> continentAfrica:factor(year)1962    ***
#> continentAmericas:factor(year)1962  **
#> continentAsia:factor(year)1962      ***
#> continentEurope:factor(year)1962
#> continentOceania:factor(year)1962
#> continentAfrica:factor(year)1967    ***
#> continentAmericas:factor(year)1967 **
#> continentAsia:factor(year)1967      **
#> continentEurope:factor(year)1967
#> continentOceania:factor(year)1967
#> continentAfrica:factor(year)1972    ***
#> continentAmericas:factor(year)1972 *
#> continentAsia:factor(year)1972      **
#> continentEurope:factor(year)1972
#> continentOceania:factor(year)1972
#> continentAfrica:factor(year)1977    ***
#> continentAmericas:factor(year)1977 *
#> continentAsia:factor(year)1977      *
#> continentEurope:factor(year)1977
#> continentOceania:factor(year)1977
#> continentAfrica:factor(year)1982    ***
#> continentAmericas:factor(year)1982 .
#> continentAsia:factor(year)1982      .
#> continentEurope:factor(year)1982
#> continentOceania:factor(year)1982
#> continentAfrica:factor(year)1987    **
#> continentAmericas:factor(year)1987
#> continentAsia:factor(year)1987      *
#> continentEurope:factor(year)1987
#> continentOceania:factor(year)1987
#> continentAfrica:factor(year)1992    **
#> continentAmericas:factor(year)1992
#> continentAsia:factor(year)1992      *
#> continentEurope:factor(year)1992
```

```

#> continentOceania:factor(year)1992
#> continentAfrica:factor(year)1997  **
#> continentAmericas:factor(year)1997
#> continentAsia:factor(year)1997
#> continentEurope:factor(year)1997
#> continentOceania:factor(year)1997
#> continentAfrica:factor(year)2002  **
#> continentAmericas:factor(year)2002
#> continentAsia:factor(year)2002
#> continentEurope:factor(year)2002
#> continentOceania:factor(year)2002
#> continentAfrica:factor(year)2007  **
#> continentAmericas:factor(year)2007
#> continentAsia:factor(year)2007
#> continentEurope:factor(year)2007
#> continentOceania:factor(year)2007
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 5.65 on 1642 degrees of freedom
#> Multiple R-squared:  0.816, Adjusted R-squared:  0.809
#> F-statistic: 119 on 61 and 1642 DF, p-value: <2e-16

```

2. $x_1 \times x_2$ produces the cross of x_1 and x_2 , or $x_1 + x_2 + x_1 \cdot x_2$

```

mod.2 <- lm(lifeExp ~ log(gdpPercap) + log(pop) + continent*factor(year), data = gap)
summary(mod.2)

#>
#> Call:
#> lm(formula = lifeExp ~ log(gdpPercap) + log(pop) + continent *
#>     factor(year), data = gap)
#>
#> Residuals:
#>    Min      1Q  Median      3Q     Max
#> -26.568 -2.553  0.004  2.915  15.567
#>
#> Coefficients:
#>             Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 3.0413   2.0741   1.47  0.14275
#> log(gdpPercap) 5.0795   0.1605  31.65 < 2e-16
#> log(pop)      0.0789   0.0943   0.84  0.40251
#> continentAmericas 7.6960   1.3932   5.52 3.9e-08
#> continentAsia   4.8078   1.2657   3.80  0.00015
#> continentEurope 17.0508   1.3295  12.83 < 2e-16
#> continentOceania 18.0790   4.0890   4.42  1.0e-05
#> factor(year)1957 1.6461   1.1078   1.49  0.13747

```

```
#> factor(year)1962           3.1286  1.1084  2.82  0.00482
#> factor(year)1967           4.4392  1.1097  4.00  6.6e-05
#> factor(year)1972           5.9956  1.1113  5.39  7.9e-08
#> factor(year)1977           7.9578  1.1124  7.15  1.3e-12
#> factor(year)1982           9.9492  1.1134  8.94  < 2e-16
#> factor(year)1987          11.9575  1.1138 10.74  < 2e-16
#> factor(year)1992          12.3398  1.1146 11.07  < 2e-16
#> factor(year)1997          12.1848  1.1161 10.92  < 2e-16
#> factor(year)2002          11.6188  1.1181 10.39  < 2e-16
#> factor(year)2007          12.4857  1.1212 11.14  < 2e-16
#> continentAmericas:factor(year)1957  0.4330  1.9438  0.22  0.82375
#> continentAsia:factor(year)1957   0.5142  1.7776  0.29  0.77241
#> continentEurope:factor(year)1957 -0.4638  1.8313 -0.25  0.80010
#> continentOceania:factor(year)1957 -1.2126  5.7552 -0.21  0.83315
#> continentAmericas:factor(year)1962  1.0043  1.9438  0.52  0.60546
#> continentAsia:factor(year)1962   0.6435  1.7777  0.36  0.71741
#> continentEurope:factor(year)1962  -1.0911  1.8315 -0.60  0.55142
#> continentOceania:factor(year)1962  -2.3774  5.7552 -0.41  0.67960
#> continentAmericas:factor(year)1967  1.0750  1.9438  0.55  0.58033
#> continentAsia:factor(year)1967   1.7387  1.7777  0.98  0.32819
#> continentEurope:factor(year)1967  -2.2608  1.8317 -1.23  0.21728
#> continentOceania:factor(year)1967  -4.1468  5.7552 -0.72  0.47130
#> continentAmericas:factor(year)1972  0.7972  1.9438  0.41  0.68176
#> continentAsia:factor(year)1972   1.7377  1.7779  0.98  0.32851
#> continentEurope:factor(year)1972  -3.8801  1.8322 -2.12  0.03435
#> continentOceania:factor(year)1972  -5.7415  5.7552 -1.00  0.31862
#> continentAmericas:factor(year)1977  0.1505  1.9439  0.08  0.93828
#> continentAsia:factor(year)1977   1.2549  1.7784  0.71  0.48050
#> continentEurope:factor(year)1977  -5.4183  1.8329 -2.96  0.00316
#> continentOceania:factor(year)1977  -7.0175  5.7553 -1.22  0.22290
#> continentAmericas:factor(year)1982  -0.0948  1.9439 -0.05  0.96110
#> continentAsia:factor(year)1982   1.7854  1.7788  1.00  0.31567
#> continentEurope:factor(year)1982  -6.9759  1.8336 -3.80  0.00015
#> continentOceania:factor(year)1982  -7.9409  5.7553 -1.38  0.16785
#> continentAmericas:factor(year)1987  -0.2267  1.9440 -0.12  0.90720
#> continentAsia:factor(year)1987   1.6858  1.7796  0.95  0.34363
#> continentEurope:factor(year)1987  -8.5955  1.8350 -4.68  3.0e-06
#> continentOceania:factor(year)1987  -9.4104  5.7554 -1.64  0.10223
#> continentAmericas:factor(year)1992  0.8213  1.9441  0.42  0.67276
#> continentAsia:factor(year)1992   2.6127  1.7803  1.47  0.14243
#> continentEurope:factor(year)1992  -7.7631  1.8346 -4.23  2.5e-05
#> continentOceania:factor(year)1992  -8.2567  5.7555 -1.43  0.15160
#> continentAmericas:factor(year)1997  2.1006  1.9443  1.08  0.28012
#> continentAsia:factor(year)1997   3.6483  1.7812  2.05  0.04070
#> continentEurope:factor(year)1997  -7.1773  1.8358 -3.91  9.6e-05
```

```

#> continentOceania:factor(year)1997 -7.5691  5.7557 -1.32 0.18867
#> continentAmericas:factor(year)2002  3.8379  1.9442  1.97 0.04854
#> continentAsia:factor(year)2002     5.0361  1.7814  2.83 0.00476
#> continentEurope:factor(year)2002   -6.1005  1.8369 -3.32 0.00092
#> continentOceania:factor(year)2002  -6.0287  5.7558 -1.05 0.29506
#> continentAmericas:factor(year)2007  3.2677  1.9444  1.68 0.09303
#> continentAsia:factor(year)2007     4.6483  1.7823  2.61 0.00919
#> continentEurope:factor(year)2007   -6.9223  1.8378 -3.77 0.00017
#> continentOceania:factor(year)2007  -6.4222  5.7558 -1.12 0.26468
#>
#> (Intercept)
#> log(gdpPerCap)          ***
#> log(pop)
#> continentAmericas       ***
#> continentAsia           ***
#> continentEurope          ***
#> continentOceania         ***
#> factor(year)1957
#> factor(year)1962          **
#> factor(year)1967          ***
#> factor(year)1972          ***
#> factor(year)1977          ***
#> factor(year)1982          ***
#> factor(year)1987          ***
#> factor(year)1992          ***
#> factor(year)1997          ***
#> factor(year)2002          ***
#> factor(year)2007          ***
#> continentAmericas:factor(year)1957
#> continentAsia:factor(year)1957
#> continentEurope:factor(year)1957
#> continentOceania:factor(year)1957
#> continentAmericas:factor(year)1962
#> continentAsia:factor(year)1962
#> continentEurope:factor(year)1962
#> continentOceania:factor(year)1962
#> continentAmericas:factor(year)1967
#> continentAsia:factor(year)1967
#> continentEurope:factor(year)1967
#> continentOceania:factor(year)1967
#> continentAmericas:factor(year)1972
#> continentAsia:factor(year)1972
#> continentEurope:factor(year)1972    *
#> continentOceania:factor(year)1972
#> continentAmericas:factor(year)1977

```

```
#> continentAsia:factor(year)1977
#> continentEurope:factor(year)1977 ** 
#> continentOceania:factor(year)1977
#> continentAmericas:factor(year)1982
#> continentAsia:factor(year)1982
#> continentEurope:factor(year)1982 *** 
#> continentOceania:factor(year)1982
#> continentAmericas:factor(year)1987
#> continentAsia:factor(year)1987
#> continentEurope:factor(year)1987 *** 
#> continentOceania:factor(year)1987
#> continentAmericas:factor(year)1992
#> continentAsia:factor(year)1992
#> continentEurope:factor(year)1992 *** 
#> continentOceania:factor(year)1992
#> continentAmericas:factor(year)1997
#> continentAsia:factor(year)1997 * 
#> continentEurope:factor(year)1997 *** 
#> continentOceania:factor(year)1997
#> continentAmericas:factor(year)2002 *
#> continentAsia:factor(year)2002 ** 
#> continentEurope:factor(year)2002 *** 
#> continentOceania:factor(year)2002
#> continentAmericas:factor(year)2007 .
#> continentAsia:factor(year)2007 ** 
#> continentEurope:factor(year)2007 *** 
#> continentOceania:factor(year)2007
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 5.65 on 1642 degrees of freedom
#> Multiple R-squared: 0.816, Adjusted R-squared: 0.809
#> F-statistic: 119 on 61 and 1642 DF, p-value: <2e-16
```

Note that we wrapped the `year` variables into a `factor()` function. By default, R breaks up our variables into their different factor levels (as it will do whenever your regressors have factor levels).

If your data aren't factorized, you can tell `lm/glm` to factorize a variable (i.e. create dummy variables on the fly) by writing `factor()`

```
glm(formula = y ~ x1 + x2 + factor(x3), family = family(link = "link"),
     data = )
```

14.2.5 Formatting Regression Tables

Most papers report the results of regression analysis in some kind of table. Typically, this table includes the values of coefficients, standard errors, and significance levels from one or more models.

The `stargazer` package provides excellent tools to make and format regression tables automatically. It can also output summary statistics from a dataframe:

```
library(stargazer)
stargazer(gap, type = "text")
#>
#> -----
#> Statistic   N      Mean       St. Dev.      Min  Pctl(25)  Pctl(75)  ...
#> -----
#> year        1,704  1,980.000    17.300     1,952  1,966.0  1,993.0  2
#> pop         1,704  29,601,212.000 106,157,897.000 60,011  2,793,664 19,585,222.0 1,318
#> lifeExp     1,704    59.500      12.900     23.600  48.200    70.800    82
#> gdpPercap   1,704   7,215.000    9,857.000    241.000 1,202.000  9,325.000   113,
#> -----
```

Let's say we want to report the results from three different models:

```
mod.1 <- lm(lifeExp ~ log(gdpPercap) + log(pop), data = gap)
mod.2 <- lm(lifeExp ~ log(gdpPercap) + log(pop) + continent, data = gap)
mod.3 <- lm(lifeExp ~ log(gdpPercap) + log(pop) + continent + year, data = gap)
```

`stargazer` can produce well-formatted tables that hold regression analysis results from all these models side-by-side.

```
stargazer(mod.1, mod.2, mod.3, title = "Regression Results", type = "text")
#>
#> Regression Results
#> -----
#>                                         Dependent variable:
#>                                         -----
#>                                         lifeExp
#>                                         (2)
#>                                         (1)
#> -----
#> log(gdpPercap)          8.340***      6.590***      5
#>                               (0.143)      (0.182)
#>
#> log(pop)                1.280***      0.866***      8
#>                               (0.111)      (0.111)
#>
#> continentAmericas       6.170***      6.170***      8
#>                               (0.555)
```

```

#> continentAsia          4.670***   6.830***  

#>                           (0.494)  (0.423)  

#>  

#> continentEurope         8.560***  12.300***  

#>                           (0.608)  (0.529)  

#>  

#> continentOceania       8.350***  12.500***  

#>                           (1.510)  (1.280)  

#>  

#> year                   0.238***  (0.009)  

#>  

#>  

#> Constant                -28.800*** -12.000*** -461.000***  

#>                           (2.080)   (2.270)   (17.000)  

#>  

#> -----  

#> Observations            1,704      1,704      1,704  

#> R2                      0.677      0.714      0.798  

#> Adjusted R2             0.677      0.713      0.798  

#> Residual Std. Error     7.340 (df = 1701)    6.920 (df = 1697)    5.810 (df = 1696)  

#> F Statistic              1,786.000*** (df = 2; 1701) 707.000*** (df = 6; 1697) 960.000*** (df = 7; 1696)  

#> ======  

#> Note: *p<0.1; **p<0.05; ***p<0.01

```

Customization

`stargazer` is incredibly customizable. Let's say we wanted to:

- re-name our explanatory variables;
- remove information on the “Constant”;
- only keep the number of observations from the summary statistics; and
- style the table to look like those in American Journal of Political Science.

```

stargazer(mod.1, mod.2, mod.3, title = "Regression Results", type = "text",
           covariate.labels = c("GDP per capita, logged", "Population, logged", "Americas", "Asia",
           omit = "Constant",
           keep.stat="n", style = "ajps")
#>
#> Regression Results
#> -----
#>                               lifeExp
#>                         Model 1  Model 2  Model 3
#> -----
#> GDP per capita, logged 8.340*** 6.590*** 5.080***
```

```

#>                               (0.143)  (0.182)  (0.163)
#> Population, logged      1.280*** 0.866***  0.153
#>                               (0.111)  (0.111)  (0.097)
#> Americas                  6.170*** 8.740*** 
#>                               (0.555)  (0.477)
#> Asia                      4.670*** 6.830*** 
#>                               (0.494)  (0.423)
#> Europe                     8.560*** 12.300*** 
#>                               (0.608)  (0.529)
#> Oceania                    8.350*** 12.500*** 
#>                               (1.510)  (1.280)
#> Year                       0.238*** 
#>                               (0.009)
#> N                           1704     1704     1704
#> -----
#> ***p < .01; **p < .05; *p < .1

```

Check out `?stargazer` to see more options.

Output Types

Once we like the look of our table, we can output/export it in a number of ways. The `type` argument specifies what output the command should produce. Possible values are:

- "latex" for LaTeX code,
- "html" for HTML code,
- "text" for ASCII text output (what we used above).

Let's say we're using LaTeX to typeset our paper. We can output our regression table in LaTeX:

```

stargazer(mod.1, mod.2, mod.3, title = "Regression Results", type = "latex",
           covariate.labels = c("GDP per capita, logged", "Population, logged", "Americas",
           omit = "Constant",
           keep.stat="n", style = "ajps")
#>
#> % Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: h
#> % Date and time: Wed, Oct 09, 2019 - 11:51:44
#> \begin{table}[!htbp] \centering
#>   \caption{Regression Results}
#>   \label{r}
#>   \begin{tabular}{@{\extracolsep{5pt}}lccc}
#>     \hline
#>     \multicolumn{3}{c}{\textbf{Model 1}} & \textbf{Model 2} & \textbf{Model 3} \\
#>     \hline
#>     Constant & 0.000 & 0.000 & 0.000 \\
#>     GDP per capita, logged & 1.280*** & 0.866*** & 0.153 \\
#>     Population, logged & (0.111) & (0.111) & (0.097) \\
#>     Americas & 6.170*** & 8.740*** \\
#>     Asia & (0.555) & (0.477) \\
#>     Europe & 4.670*** & 6.830*** \\
#>     Oceania & (0.494) & (0.423) \\
#>     Year & 8.560*** & 12.300*** \\
#>     (0.608) & (0.529) \\
#>     N & 8.350*** & 12.500*** \\
#>     (1.510) & (1.280) \\
#>     & 0.238*** \\
#>     & (0.009) \\
#>     \hline
#>   \end{tabular}
#> \hline
#> ***p < .01; **p < .05; *p < .1

```

```
#> \hline \\[-1.8ex]
#> GDP per capita, logged & 8.340$^{***}$ & 6.590$^{***}$ & 5.080$^{***}$ \\
#> & (0.143) & (0.182) & (0.163) \\
#> Population, logged & 1.280$^{***}$ & 0.866$^{***}$ & 0.153 \\
#> & (0.111) & (0.111) & (0.097) \\
#> Americas & & 6.170$^{***}$ & 8.740$^{***}$ \\
#> & & (0.555) & (0.477) \\
#> Asia & & 4.670$^{***}$ & 6.830$^{***}$ \\
#> & & (0.494) & (0.423) \\
#> Europe & & 8.560$^{***}$ & 12.300$^{***}$ \\
#> & & (0.608) & (0.529) \\
#> Oceania & & 8.350$^{***}$ & 12.500$^{***}$ \\
#> & & (1.510) & (1.280) \\
#> Year & & & 0.238$^{***}$ \\
#> & & & (0.009) \\
#> N & 1704 & 1704 & 1704 \\
#> \hline \\[-1.8ex]
#> \multicolumn{4}{l}{$^{\ast\ast\ast}p < .01; ^{\ast\ast}p < .05; ^{\ast}p < .1$} \\
#> \end{tabular}
#> \end{table}
```

To include the produced tables in our paper, we can simply insert this stargazer LaTeX output into the publication's TeX source.

Alternatively, you can use the `out` argument to save the output in a `.tex` or `.txt` file:

```
stargazer(mod.1, mod.2, mod.3, title = "Regression Results", type = "latex",
          covariate.labels = c("GDP per capita, logged", "Population, logged", "Americas", "Asia",
          omit = "Constant",
          keep.stat="n", style = "ajps",
          out = "regression-table.txt")
```

To include stargazer tables in Microsoft Word documents (e.g., `.doc` or `.docx`), use the following procedure:

- Use the `out` argument to save output into an `.html` file.
- Open the resulting file in your web browser.
- Copy and paste the table from the web browser to your Microsoft Word document.

```
stargazer(mod.1, mod.2, mod.3, title = "Regression Results", type = "html",
          covariate.labels = c("GDP per capita, logged", "Population, logged", "Americas", "Asia",
          omit = "Constant",
          keep.stat="n", style = "ajps",
          out = "regression-table.html")
```

14.2.6 Challenges

Challenge 1. Fit two linear regression models from the gapminder data, where the outcome is `lifeExp` and the explanatory variables are `log(pop)`, `log(gdpPercap)`, and `year`. In one model, treat `year` as a numeric variable. In the other, factorize the `year` variable. How do you interpret each model?

```
model1 <- lm(lifeExp ~ log(pop) + log(gdpPercap) + year, data = gap)
model2 <- lm(lifeExp ~ log(pop) + log(gdpPercap) + factor(year), data = gap)
```

Challenge 2. Fit a logistic regression model where the outcome is whether `lifeExp` is greater than or less than 60 years, exploring the use of different predictors.

```
library(dplyr)

gap <- gap %>%
  mutate(lifeExp60 = as.logical(lifeExp >= 60))

logit_model <- glm(lifeExp60 ~ log(pop) + log(gdpPercap) + year, family = "binomial",
```

Challenge 3. Using `stargazer`, format a table reporting the results from the three models you created above (two linear regressions and one logistic).

```
stargazer(model1, model2, logit_model, title = "Challenge Regression Results", type = "text")
#>
#> Challenge Regression Results
#> -----
#>                               Dependent variable:
#>                               -----
#>                               lifeExp
#>                               OLS
#>                               (1)          (2)
#> -----
#> log(pop)                  0.885***      0.881***      0.285***  

#>                               (0.104)       (0.104)       (0.050)
#>
#> log(gdpPercap)           7.790***      7.780***      2.130***  

#>                               (0.135)       (0.135)       (0.100)
#>
```

#> year	0.178*** (0.010)		0.035*** (0.005)
#>			
#> factor(year)1957		1.260 (0.798)	
#>			
#>			
#> factor(year)1962		2.310*** (0.799)	
#>			
#>			
#> factor(year)1967		3.120*** (0.801)	
#>			
#>			
#> factor(year)1972		3.740*** (0.803)	
#>			
#>			
#> factor(year)1977		4.780*** (0.805)	
#>			
#>			
#> factor(year)1982		6.300*** (0.807)	
#>			
#>			
#> factor(year)1987		7.780*** (0.808)	
#>			
#>			
#> factor(year)1992		8.700*** (0.809)	
#>			
#>			
#> factor(year)1997		8.860*** (0.812)	
#>			
#>			
#> factor(year)2002		8.910*** (0.814)	
#>			
#>			
#> factor(year)2007		8.920*** (0.818)	
#>			
#>			
#> Constant	-370.000*** (19.200)	-23.300*** (1.980)	-90.000*** (9.280)
#>			
#>			
#> -----			
#> Observations	1,704	1,704	1,704
#> R2	0.728	0.731	
#> Adjusted R2	0.728	0.729	
#> Log Likelihood			-572.000
#> Akaike Inf. Crit.			1,151.000

```
#> Residual Std. Error      6.740 (df = 1700)      6.730 (df = 1690)
#> F Statistic      1,520.000*** (df = 3; 1700) 353.000*** (df = 13; 1690)
#> =====
#> Note: *p<0.1; **p<0.05; ***p<0.01
```

Chapter 15

Strings and Regular Expressions

This unit focuses on character (or “string”) data. We’ll explore:

1. **common string operations**, like concatenating, subsetting, and replacing strings.
2. **regular expressions**, a powerful cross-language tool for working with string data.

15.1 Common String Operations

15.1.1 Concatenating strings with `paste()`

Let’s say we wanted to concatenate the following two strings into one larger character string:

```
firstName <- "Johan"  
lastName <- "Gambolputty"
```

Using the usual combine operator `c()` on two or more character strings will not create a single character string, but rather a **vector** of character strings.

```
firstName <- "Johan"  
lastName <- "Gambolputty"  
  
fullName <- c(firstName, lastName)  
print(fullName)  
#> [1] "Johan"           "Gambolputty"
```

```
length(fullName)
#> [1] 2
```

Combining two or more character strings into one larger character string requires using the `paste()` function. This function takes character strings or vectors and collapses their values into a single character string, with each value separated by a character string selected by the user.

```
fullName <- paste(firstName, lastName)
print(fullName)
#> [1] "Johan Gembolputty"

fullName <- paste(firstName, lastName, sep = "+")
print(fullName)
#> [1] "Johan+Gembolputty"

fullName <- paste(firstName, lastName, sep = "___")
print(fullName)
#> [1] "Johan___Gembolputty"
```

15.1.2 Extracting Substrings

R can also extract substrings based on the index position of its characters. Some things to note:

1. Index positions in R start at 1. This is in contrast to Python, where indexation starts at 0.
2. Object subsets using index positions in R contain all the elements in the specified range. If some object called `data` contains five elements, `data[2:4]` will return the elements at the second, third, and fourth positions. By contrast, the same subset in Python would return the objects at the third and fourth positions (or second and third positions, depending upon whether your index starts at 0 or 1).
3. R does not allow index-based character string subsetting using the object name, as this functionality is generally reserved for vector subsetting.

```
firstName <- "Johan"
lastName <- "Gembolputty"
fullName <- paste(firstName, lastName)

# This won't work
fullName[0]
#> character(0)
fullName[1]
#> [1] "Johan Gembolputty"
```

```
fullName[1:4]
#> [1] "Johan Gambolputty" NA
#> [4] NA
```

Instead, you must use the `substr()` function. Note that this function must receive both the `start` and `stop` arguments. So if you want to get all the characters between some index and the end of the string, you must use the `nchar()` function, which will tell you the length of a character string.

```
substr(x = fullName, start = 1, stop = 1)
#> [1] "J"
substr(x = fullName, start = 5, stop = 5)
#> [1] "n"
substr(x = fullName, start = 1, stop = 5)
#> [1] "Johan"
substr(x = fullName, start = 6, stop = nchar(fullName))
#> [1] " Gambolputty"
substr(x = fullName, start = 6, stop = nchar(fullName)-2)
#> [1] " Gambolput"
```

15.1.3 Replace Substrings with `gsub()`

The function `gsub()` replaces substrings in a larger string using a specified pattern.

```
firstName <- "Johan"
lastName <- "Gambolputty"
fullName <- paste(firstName, lastName)

gsub(pattern = "G", replacement = "B", x = fullName)
#> [1] "Johan Bambolputty"
gsub(pattern = "Johan", replacement = "Mike", x = fullName)
#> [1] "Mike Gambolputty"
gsub(pattern = "johan", replacement = "Mike", x = fullName) # Note the importance of cases!
#> [1] "Johan Gambolputty"
```

The same function is used for replacements and stripping:

```
gsub(pattern = " ", replacement = "", x = fullName)
#> [1] "JohanGambolputty"
```

15.2 Regular Expressions

`gsub()` is part of a suite of functions to search and substitute substrings using **regular expressions** (or “regex” for short). For more information on regular expressions, see:

1. regexpal.com
2. [this cheatsheet](#)

[MORE HERE](#)

Chapter 16

Programming in R

This unit covers some more advanced programming in R - namely:

1. Conditional Flow
2. Functions
3. Iteration

Mastering these skills will make you virtually invincible in R!

Note that these concepts are **not specific to R**. While the syntax might vary, the basic idea of flow, functions, and iteration are common across all scripting languages. So if you ever think of picking up Python or something else, it's critical to familiarize yourself with these concepts.

16.1 Conditional Flow

Sometimes you only want to execute code if a certain condition is met. To do that, we use an **if-else statement**. It looks like this:

```
if (condition) {  
    # code executed when condition is TRUE  
} else {  
    # code executed when condition is FALSE  
}
```

`condition` is a statement that must always evaluate to either `TRUE` or `FALSE`. This is similar to `filter()`, except `condition` can only be a single value (i.e. a vector of length 1), whereas `filter()` works for entire vectors (or columns).

Let's look at a simple example:

```
age = 84
if (age > 60) {
  print(paste(age, "is old"))
} else {
  print("But you don't look like a professor!")
}
#> [1] "84 is old"
```

We refer to the first `print` command as the first *branch*.

Let's change the `age` variable to execute the second branch:

```
age = 20
if (age > 60) {
  print(paste(age, "is old"))
} else {
  print("But you don't look like a professor!")
}
#> [1] "But you don't look like a professor!"
```

16.1.1 Multiple Conditions

You can chain conditional statements together:

```
if (this) {
  # do that
} else if (that) {
  # do something else
} else {
  # do something completely different
}
```

16.1.2 Complex Statements

We can generate more complex conditional statements with boolean operators like `&` and `|`:

```
age = 45

if (age > 60) {
  print(paste(age, "is old"))
} else if (age < 60 & age > 40) {
  print("How's the midlife crisis?")
} else {
  print("But you don't look like a professor!")
```

```
}
#> [1] "How's the midlife crisis?"
```

16.1.3 Code Style

Both `if` and `function` should (almost) always be followed by squiggly brackets (`{}`), and the contents should be indented. This makes it easier to see the hierarchy in your code by skimming the left-hand margin.

An opening curly brace should never go on its own line and should always be followed by a new line. A closing curly brace should always go on its own line, unless it's followed by `else`. Always indent the code inside curly braces.

```
# Bad
if (y < 0 && debug)
  message("Y is negative")

if (y == 0) {
  log(x)
}
else {
  y ~ x
}

# Good
if (y < 0 && debug) {
  message("Y is negative")
}

if (y == 0) {
  log(x)
} else {
  y ~ x
}
```

16.1.4 `if` vs. `if_else`

Because `if-else` conditional statements like the ones outlined above must always resolve to a single `TRUE` or `FALSE`, they cannot be used for vector operations. Vector operations are where you make multiple comparisons simultaneously for each value stored inside a vector.

Consider the `gapminder` data and imagine you wanted to create a new column identifying whether or not a country-year observation has a life expectancy of at least 35.

```
gap <- read.csv("Data/gapminder-FiveYearData.csv")
head(gap)
#>      country year    pop continent lifeExp gdpPercap
#> 1 Afghanistan 1952 8425333     Asia    28.8      779
#> 2 Afghanistan 1957 9240934     Asia    30.3      821
#> 3 Afghanistan 1962 10267083    Asia    32.0      853
#> 4 Afghanistan 1967 11537966    Asia    34.0      836
#> 5 Afghanistan 1972 13079460    Asia    36.1      740
#> 6 Afghanistan 1977 14880372    Asia    38.4      786
```

This sounds like a classic if-else operation. For each observation, if `lifeExp` is greater than or equal to 35, then the value in the new column should be 1. Otherwise, it should be 0. But what happens if we try to implement this using an if-else operation like above?

```
gap_if <- gap %>%
  mutate(life.35 = if(lifeExp >= 35){
    1
  } else {
    0
  })
#> Warning in if (lifeExp >= 35) {: the condition has length > 1 and only the
#> first element will be used

head(gap_if)
#>      country year    pop continent lifeExp gdpPercap life.35
#> 1 Afghanistan 1952 8425333     Asia    28.8      779      0
#> 2 Afghanistan 1957 9240934     Asia    30.3      821      0
#> 3 Afghanistan 1962 10267083    Asia    32.0      853      0
#> 4 Afghanistan 1967 11537966    Asia    34.0      836      0
#> 5 Afghanistan 1972 13079460    Asia    36.1      740      0
#> 6 Afghanistan 1977 14880372    Asia    38.4      786      0
```

This did not work correctly. Because `if()` can only handle a single TRUE/FALSE value, it only checked the first row of the data frame. That row contained 28.801, so it generated a vector of length 1704 with each value being 0.

Because we in fact want to make this if-else comparison 1704 times, we should instead use `if_else()`. This **vectorizes** the if-else comparison and makes a separate comparison for each row of the data frame. This allows us to correctly generate this new column.

```
gap_ifelse <- gap %>%
  mutate(life.35 = if_else(lifeExp >= 35, 1, 0))

head(gap_ifelse)
#>      country year    pop continent lifeExp gdpPercap life.35
```

```
#> 1 Afghanistan 1952 8425333 Asia 28.8 779 0
#> 2 Afghanistan 1957 9240934 Asia 30.3 821 0
#> 3 Afghanistan 1962 10267083 Asia 32.0 853 0
#> 4 Afghanistan 1967 11537966 Asia 34.0 836 0
#> 5 Afghanistan 1972 13079460 Asia 36.1 740 1
#> 6 Afghanistan 1977 14880372 Asia 38.4 786 1
```

16.2 Functions

Functions are the basic building blocks of programs. Think of them as “mini-scripts” or “tiny commands.” We’ve already used dozens of functions created by others (e.g. `filter()`, `mean()`.)

This lesson teaches you how to write your own functions, and why you would want to do so. The details are pretty simple, but this is one of those ideas where it’s good to get lots of practice!

16.2.1 Why Write Functions?

Functions allow you to automate common tasks in a more powerful and general way than copy-and-pasting. For example, take a look at the following code:

```
df <- data.frame(
  a = rnorm(10),
  b = rnorm(10),
  c = rnorm(10),
  d = rnorm(10)
)

df$a <- (df$a - min(df$a)) / (max(df$a) - min(df$a))
df$b <- (df$b - min(df$b)) / (max(df$b) - min(df$a))
df$c <- (df$c - min(df$c)) / (max(df$c) - min(df$c))
df$d <- (df$d - min(df$d)) / (max(df$d) - min(df$d))
```

You might be able to puzzle out that this rescales each column to have a range from 0 to 1. But did you spot the mistake? I made an error when copying-and-pasting the code for `df$b`: I forgot to change an `a` to a `b`.

Functions have a number of advantages over this “copy-and-paste” approach:

- **They are easy to reuse.** If you need to change things, you only have to update code in one place, instead of many.
- **They are self-documenting.** Functions name pieces of code the way variables name strings and numbers. Give your function a good name and

you will easily remember the function and its purpose.

- **They are easier to debug.** There are fewer chances to make mistakes because the code only exists in one location (i.e. updating a variable name in one place, but not in another).

16.2.2 Anatomy of a Function

Functions have three key components:

1. A **name**. This should be informative and describe what the function does.
2. The **arguments**, or list of inputs, to the function. They go inside the parentheses in `function()`.
3. The **body**. This is the block of code within {} that immediately follows `function(...)`, and is the code that you develop to perform the action described in the name using the arguments you provide.

```
my_function <- function(x, y){
  # do
  # something
  # here
  return(result)
}
```

In this example, `my_function` is the **name** of the function, `x` and `y` are the **arguments**, and the stuff inside the {} is the **body**.

16.2.3 Writing a Function

Let's re-write the scaling code above as a function. To write a function you need to first analyze the code. How many inputs does it have?

```
df <- data.frame(
  a = rnorm(10),
  b = rnorm(10),
  c = rnorm(10),
  d = rnorm(10)
)

(df$a - min(df$a)) / (max(df$a) - min(df$a))
#> [1] 0.289 0.751 0.000 0.678 0.853 1.000 0.172 0.611 0.612 0.601
```

This code only has one input: `df$a`. To make the inputs more clear, it's a good idea to rewrite the code using temporary variables with general names. Here this code only requires a single numeric vector, which I'll call `x`:

```
x <- df$a
(x - min(x)) / (max(x) - min(x))
#> [1] 0.289 0.751 0.000 0.678 0.853 1.000 0.172 0.611 0.612 0.601
```

There is some duplication in this code. We're computing the range of the data three times, so it makes sense to do it in one step:

```
rng <- range(x)
rng
#> [1] -2.44 1.15

(x - rng[1]) / (rng[2] - rng[1])
#> [1] 0.289 0.751 0.000 0.678 0.853 1.000 0.172 0.611 0.612 0.601
```

Pulling out intermediate calculations into named variables is a good practice because it becomes more clear what the code is doing. Now that I've simplified the code, and checked that it still works, I can turn it into a function:

```
rescale01 <- function(x) {
  rng <- range(x)
  scaled <- (x - rng[1]) / (rng[2] - rng[1])
  return(scaled)
}
```

Note the overall process: I only made the function after I'd figured out how to make it work with a simple input. It's easier to start with working code and turn it into a function; it's harder to create a function and then try to make it work.

At this point it's a good idea to check your function with a few different inputs:

```
rescale01(c(-10, 0, 10))
#> [1] 0.0 0.5 1.0

rescale01(c(1, 2, 3, 5))
#> [1] 0.00 0.25 0.50 1.00
```

16.2.4 Using a Function

Two important points about using (or *calling**) functions:

1. Notice that when we **call** a function, we're passing a value into it that is assigned to the parameter we defined when writing the function. In this case, the parameter **x** is automatically assigned to `c(-10, 0, 10)`.
2. When using functions, by default the returned object is merely printed to the screen. If you want it saved, you need to assign it to an object.

Let's see if we can simplify the original example with our brand new function:

```
df$a <- rescale01(df$a)
df$b <- rescale01(df$b)
df$c <- rescale01(df$c)
df$d <- rescale01(df$d)
```

Compared to the original, this code is easier to understand and we've eliminated one class of copy-and-paste errors. There is still quite a bit of duplication since we're doing the same thing to multiple columns. We'll learn how to eliminate that duplication in the lesson on iteration.

Another advantage of functions is that if our requirements change, we only need to make the change in one place. For example, we might discover that some of our variables include NA values, and `rescale01()` fails:

```
rescale01(c(1, 2, NA, 3, 4, 5))
#> [1] NA NA NA NA NA NA
```

Because we've extracted the code into a function, we only need to make the fix in one place:

```
rescale01 <- function(x) {
  rng <- range(x, na.rm = TRUE)
  (x - rng[1]) / (rng[2] - rng[1])
}
rescale01(c(1, 2, NA, 3, 4, 5))
#> [1] 0.00 0.25   NA 0.50 0.75 1.00
```

16.2.5 Variable Scope

Analyze the following function:

1. Identify the name, arguments, and body
2. What does it do?
3. If `a = 3` and `b = 4`, what should we expect the output to be?

```
pythagorean <- function(a, b){
  hypotenuse <- sqrt(a^2 + b^2)
  return(hypotenuse)
}
```

Now take a look at the following code:

```
pythagorean(a = 3, b = 4)
#> [1] 5

hypotenuse
#> Error in eval(expr, envir, enclos): object 'hypotenuse' not found
```

Why does this generate an error? Why can we not see the results of `hypotenuse`? After all, it was generated by `pythagorean`, right?

When you call a function, a temporary workspace is set up that will be destroyed when the function returns, either by:

1. getting to the end, or
2. an explicit return statement

So think of functions as an alternative reality, where objects are created and destroyed in a function call.

This is why you do not see `hypotenuse` listed in the environment - it has already been destroyed.

Global vs. Local Environments

Things can get confusing when you use the same names for variables both inside and outside a function. Check out this example:

```
pressure = 103.9
adjust <- function(t){
  temperature = t * 1.43 / pressure
  return(temperature)
}
pressure
#> [1] 104
temperature
#> Error in eval(expr, envir, enclos): object 'temperature' not found
```

`t` and `temperature` are **local** variables in `adjust`. Local variables are:

- Defined in the function.
- Not visible in the main program.
- Remember: a function parameter is a variable that is automatically assigned a value when the function is called.

`pressure` is a **global** variable. Global variables are:

- Defined outside any particular function.
- Visible everywhere.

This difference is referred to as **scope**. The **scope** of a variable is the part of a program that can ‘see’ that variable.

16.2.6 Arguments

Functions do not need to take input.

```
print_hello <- function(){
  print("hello")
}
print_hello()
#> [1] "hello"
```

But if a function takes input, arguments can be passed to functions in different ways.

- 1) **Positional arguments** are mandatory and have no default values.

```
send <- function(message, recipient){
  message <- paste(message, recipient)
  return(message)
}
send("Hello", "world")
#> [1] "Hello world"
```

In the case above, it is possible to use argument **names** when calling the functions and, by doing so, it is possible to switch the order of arguments. For instance:

```
send(recipient='World', message='Hello')
#> [1] "Hello World"
```

However, positional arguments (`send('Hello', 'World')`) are greatly perfered over names (`send(recipient='World', message='Hello')`), as it is very easy to accidentally specifying incorrect argument values.

- 2) **Keyword arguments** are not mandatory and have default values. They are often used for optional parameters sent to the function.

```
send <- function(message, recipient, cc=NULL){
  message <- paste(message, recipient, "cc:", cc)
  return(message)
}
send("Hello", "world")
#> [1] "Hello world cc: "
send("Hello", "world", "rochelle")
#> [1] "Hello world cc: rochelle"
```

Here `cc` and `bcc` are **optional**, and evaluate to `NULL` when they are not passed another value.

16.2.7 Challenges

Challenge 1

Write a function that calculates the sum of the squared value of two numbers. For instance, it should generate the following output:

```
my_function(3, 4)
# [1] 25

my_function <- function(a, b) {
  sum <- a^2 + b^2
  return(sum)
}

my_function(3, 4)
#> [1] 25
```

Challenge 2

Write `both_na()`, a function that takes two vectors of the same length and returns the number of positions that have an NA in both vectors.

Challenge 3

Fill in the blanks to create a function that takes a name like “Rochelle Terman” and returns that name in uppercase and reversed, like “TERMAN, ROCHELLE”

```
standard_names <- function(name){
  upper_case = toupper(name) # make upper
  upper_case_vec = strsplit(upper_case, split = ' ')[[1]] # turn into a vector
  first_name = _____ # take first name
  last_name = _____ # take last name
  reversed_name = paste(last_name, first_name, sep = ", ") # reverse and separate by a comma and space
  return(reversed_name)
}

#Solution -- HIDE ME
standard_names <- function(name){
  upper_case = toupper(name) # make upper
  upper_case_vec = strsplit(upper_case, split = ' ')[[1]] # turn into a list
  first_name = upper_case_vec[1] # take first name
  last_name = upper_case_vec[2] # take last name
  reversed_name = paste(last_name, first_name, sep = ", ") # reverse and separate by a comma and space
```

```

    return(reversed_name)
}
standard_names('Rochelle Terman')

```

Challenge 4

Look at the following function:

```

print_date <- function(year, month, day){
  joined = paste(as.character(year), as.character(month), as.character(day), sep = "")
  return(joined)
}

```

What does this short program print?

```
print_date(day=1, month=2, year=2003)
```

Acknowledgements and Resources

- R for Data Science.
- Computing for Social Sciences

16.3 Iteration

In the last unit, we talked about how important it is to reduce duplication in your code by creating functions instead of copying-and-pasting. Avoiding duplication allows for more readable, more flexible, and less error-prone code.

Functions are one method of reducing duplication in your code. Another tool for reducing duplication is **iteration**, which lets you do the same task to multiple inputs.

In this chapter you'll learn about four approaches to iteration:

1. Vectorized functions
2. For-loops
3. `map` and functional programming
4. Scoped verbs in `dplyr`

16.3.1 Vectorized Functions

Most of R's built-in functions are **vectorized**, meaning that the function will operate on all elements of a vector without needing to loop through and act on each element at a time.

That means you should never need to perform explicit iteration when performing simple mathematical computations.

```
x <- 1:4
x * 2
#> [1] 2 4 6 8
```

Notice that the multiplication happened to each element of the vector. Most built-in functions also operate element-wise on vectors:

```
x <- 1:4
log(x)
#> [1] 0.000 0.693 1.099 1.386
```

We can also add two vectors together:

```
x <- 1:4
y <- 6:9
x + y
#> [1] 7 9 11 13
```

Notice that each element of x was added to its corresponding element of y:

x:	1	2	3	4
	+	+	+	+
y:	6	7	8	9
<hr/>				
	7	9	11	13

What happens if you add two vectors of different lengths?

```
1:10 + 1:2
#> [1] 2 4 4 6 6 8 8 10 10 12
```

Here, R will expand the shortest vector to the same length as the longest. This is called **recycling**. This usually (but not always) happens silently, meaning R will not warn you. Beware!

16.3.2 For-loops

You will frequently need to iterate over vectors or data frames, perform an operation on each element, and save the results somewhere.

For example, imagine we have this simple data frame:

```
df <- data.frame(
  a = rnorm(10),
  b = rnorm(10),
  c = rnorm(10),
```

```
d = rnorm(10)
)
```

We want to compute the median of each column. You *could* do with copy-and-paste:

```
median(df$a)
#> [1] -0.246
median(df$b)
#> [1] -0.287
median(df$c)
#> [1] -0.0567
median(df$d)
#> [1] 0.144
```

But that breaks our rule of thumb: never copy and paste more than twice. Instead, we could use a `for` loop:

```
output <- vector("double", ncol(df)) # 1. output
for (i in seq_along(df)) {           # 2. sequence
  output[i] <- median(df[[i]])       # 3. body
}
output
#> [1] -0.2458 -0.2873 -0.0567  0.1443
```

Components of a `for` Loop

Every `for` loop has three components:

1. The `output`: `output <- vector("double", length(x))`.

Before you start a loop, you need to create an empty vector to store the output of the loop. Notice that the object is created **outside** the loop!

Preallocating space for your output is very important for efficiency: if you grow the `for` loop at each iteration using `c()` (for example), your `for` loop will be very slow.

2. The `sequence`: `i in seq_along(df)`.

This determines what to loop over. In this case, the sequence is `seq_along(df)`, which creates a numeric vector for a sequence of numbers beginning at 1 and continuing until it reaches the length of `df` (the length here is the number of columns in `df`).

```
seq_along(df)
#> [1] 1 2 3 4
```

It's useful to think of `i` as a pronoun, like "it". Each iteration of the `for` loop will assign `i` to a new value based on the designed sequence:

```
| Iteration | i = |
|-----|-----|
| 1       | 1   |
| 2       | 2   |
| 3       | 3   |
| 4       | 4   |
=
```

NB: `seq_along` is a safe version of the more familiar `1:length(1)`, with an important difference: if you have a zero-length vector, `seq_along()` does the right thing:

```
y <- vector("double", 0)
seq_along(y)
#> integer(0)
1:length(y)
#> [1] 1 0
```

You probably won't create a zero-length vector deliberately, but it's easy to create one accidentally. If you use `1:length(x)` instead of `seq_along(x)`, you're likely to get a confusing error message.

3. The body: `output[[i]] <- median(df[[i]])`.

This is the code that does the work. It runs repeatedly, each time with a different value for `i`:

```
| Iteration | i = | body
|-----|-----|-----|
| 1       | 1   | output[[1]] <- median(df[[1]])
| 2       | 2   | output[[2]] <- median(df[[2]])
| 3       | 3   | output[[3]] <- median(df[[3]])
| 4       | 4   | output[[4]] <- median(df[[4]])
```

NB: We use `[[` notation to reference each column of `df` using indices of columns, instead of \$ and column names.

16.3.3 Challenges

Challenge 1.

Fill in the blanks to write a `for` loop that calculates the arithmetic mean for every column in `mtcars`.

```
mtcars.means <- vector("double", _____)
for(i in _____){
```

```
      _____[i] <- mean(_____[[i]])
}

mtcars.means <- vector("double", ncol(mtcars))
for(i in seq_along(mtcars)){
  mtcars.means[i] <- mean(mtcars[[i]])
}
mtcars.means
#> [1] 20.091   6.188 230.722 146.688   3.597   3.217 17.849   0.438
#> [9]  0.406   3.688   2.812
```

Challenge 2.

Check out the `iris` dataset:

```
kable(head(iris))
```

Sepal.Length

Sepal.Width

Petal.Length

Petal.Width

Species

5.1

3.5

1.4

0.2

setosa

4.9

3.0

1.4

0.2

setosa

4.7

3.2

1.3

0.2

```

setosa
4.6
3.1
1.5
0.2
setosa
5.0
3.6
1.4
0.2
setosa
5.4
3.9
1.7
0.4
setosa

```

Write a `for` loop that calculates the number of unique values in each column of `iris`. Before you write the `for` loop, identify the three components you need:

1. Output
2. Sequence
3. Body

```

out <- vector("double", ncol(iris))
for(i in seq_along(iris)){
  out[i] <- length(unique(iris[[i]]))
}
out
#> [1] 35 23 43 22 3

```

Challenge 3.

Generate 10 random normals for each of $\mu = -10, 0, 10$, and 100 . Store them in a list.

```

# SOLUTION - HIDE ME
mus <- c(-10, 0, 10, 100)

```

```

out <- vector("list", 4)
for (i in seq_along(mus)){
  out[[i]] <- rnorm(10, mean = mus[i])
}

```

16.3.4 Functional Programming and `map`

Loops are not as important in R as they are in other languages because R is a **functional** programming language. This means that it's possible to wrap up `for` loops in a function, and call that function instead of using the `for` loop directly.

The pattern of looping over a vector, doing something to each element and saving the results is so common that the `purrr` package provides a family of functions to do it for you. They effectively eliminate the need for many common `for` loops.

There is one function for each type of output:

1. `map()` makes a list.
2. `map_lgl()` makes a logical vector.
3. `map_int()` makes an integer vector.
4. `map_dbl()` makes a double vector.
5. `map_chr()` makes a character vector.

Each function takes a vector as input, applies a function to each piece, and then returns a new vector that's the same length (and has the same names) as the input.

NB: Some people will tell you to avoid `for` loops because they are slow. They're wrong! (Well, at least they're rather out of date, as `for` loops haven't been slow for many years). The main benefit of using functions like `map()` is not speed, but clarity: they make your code easier to write and to read.

To see how `map` works, consider (again) this simple data frame:

```

df <- tibble(
  a = rnorm(10),
  b = rnorm(10),
  c = rnorm(10),
  d = rnorm(10)
)

```

What if we wanted to calculate the mean, median, and standard deviation of each column?

```

map_dbl(df, mean)
#>      a      b      c      d

```

```
#> 0.116 0.127 -0.089 0.281
map_dbl(df, median)
#>      a      b      c      d
#> 0.0583 0.0244 -0.0571 0.2604
map_dbl(df, sd)
#>      a      b      c      d
#> 1.161 1.226 1.024 0.798
```

Compared to using a for loop, this approach is much easier to read, and less error-prone.

The data can even be piped!

```
df %>% map_dbl(mean)
#>      a      b      c      d
#> 0.116 0.127 -0.089 0.281
df %>% map_dbl(median)
#>      a      b      c      d
#> 0.0583 0.0244 -0.0571 0.2604
df %>% map_dbl(sd)
#>      a      b      c      d
#> 1.161 1.226 1.024 0.798
```

We can also pass additional arguments. For example, the function `mean` passes an optional argument `trim`. From the help file: “the fraction (0 to 0.5) of observations to be trimmed from each end of `x` before the `mean` is computed.

```
map_dbl(df, mean, trim = 0.5)
#>      a      b      c      d
#> 0.0583 0.0244 -0.0571 0.2604
```

Check out other fun applications of `map` functions here

16.3.5 Challenges

Challenge 1.

Write code that uses one of the `map` functions to:

1. Calculates the arithmetic mean for every column in `mtcars`.

```
map(mtcars, mean)
```

2. Calculates the number of unique values in each column of `iris`.

```
iris %>% map(unique) %>% map_dbl(length)
#> Sepal.Length Sepal.Width Petal.Length Petal.Width      Species
#>          35         23          43          22            3
```

3. Generate 10 random normals for each of $\mu = -10, 0, 10$, and 100 .

```
map(c(-10, 0, 10, 100), ~rnorm(n = 10, mean = .))
#> [[1]]
#> [1] -8.08 -8.70 -9.25 -9.44 -10.55 -8.89 -12.61 -10.16 -9.57 -10.38
#>
#> [[2]]
#> [1] 0.4242 1.0631 1.0487 -0.0381 0.4861 1.6729 -0.3544 0.9463
#> [9] 1.3168 -0.2966
#>
#> [[3]]
#> [1] 9.61 9.21 8.94 9.20 8.24 9.31 9.44 9.46 10.23 10.98
#>
#> [[4]]
#> [1] 99.8 98.6 100.3 99.6 100.6 102.1 100.4 98.3 100.2 101.1
```

16.3.6 Scoped Verbs

The last iteration technique we'll discuss is scoped verbs in `dplyr`.

Frequently, when working with dataframes, we want to apply a function to multiple columns. For example, let's say we want to calculate the mean value of each column in `mtcars`.

If we wanted to calculate the average of a single column, it would be pretty simple using just regular `dplyr` functions:

```
mtcars %>%
  summarize(mpg = mean(mpg))
#>   mpg
#> 1 20.1
```

But if we want to calculate the mean for all of them, we'd have to duplicate this code many times over:

```
mtcars %>%
  summarize(mpg = mean(mpg),
            cyl = mean(cyl),
            disp = mean(disp),
            hp = mean(hp),
            drat = mean(drat),
            wt = mean(wt),
            qsec = mean(qsec),
            vs = mean(vs),
            am = mean(am),
            gear = mean(gear),
            carb = mean(carb))
```

```
#>   mpg cyl disp hp drat wt qsec vs am gear carb
#> 1 20.1 6.19 231 147 3.6 3.22 17.8 0.438 0.406 3.69 2.81
```

This is very repetitive and prone to mistakes!

We just saw one approach to solve this problem: `map`. Another approach is **scoped verbs**.

Scoped verbs allow you to use standard verbs (or functions) in `dplyr` that affect multiple variables at once.

- `_if` allows you to pick variables based on a predicate function like `is.numeric()` or `is.character()`
- `_at` allows you to pick variables using the same syntax as `select()`
- `_all` operates on all variables

These verbs can apply to `summarize`, `filter`, or `mutate`. Let's go over `summarize`:

`summarize_all()`

`summarize_all()` takes a dataframe and a function and applies that function to each column:

```
mtcars %>%
  summarize_all(.funs = mean)
#>   mpg cyl disp hp drat wt qsec vs am gear carb
#> 1 20.1 6.19 231 147 3.6 3.22 17.8 0.438 0.406 3.69 2.81
```

`summarize_at()`

`summarize_at()` allows you to pick columns in the same way as `select()`, that is, based on their names. There is one small difference: you need to wrap the complete selection with the `vars()` helper (this avoids ambiguity).

```
mtcars %>%
  summarize_at(.vars = vars(mpg, wt), .funs = mean)
#>   mpg wt
#> 1 20.1 3.22
```

`summarize_if()`

`summarize_if()` allows you to pick variables to summarize based on some property of the column. For example, what if we want to apply a numeric summary function only to numeric columns:

```
iris %>%
  summarize_if(.predicate = is.numeric, .funs = mean)
#>   Sepal.Length Sepal.Width Petal.Length Petal.Width
#> 1       5.84      3.06      3.76      1.2
```

`mutate` and `filter` work in a similar way. To see more, check out Scoped verbs by the Data Challenge Lab

Acknowledgments

A good portion of this lesson is based on:

- R for Data Science
- Computing for Social Sciences

Chapter 17

Collecting Data from the Web

17.1 Introduction

There's a ton of web data that's useful to social scientists, including:

- social media
- news media
- government publications
- organizational records

There are two ways to get data off the web:

1. **Web APIs** - i.e. application-facing, for computers
2. **Webscraping** - i.e. user-facing websites for humans

Rule of Thumb: Check for API first. If not available, scrape.

17.2 Web APIs

API stands for **Application Programming Interface**. Broadly defined, an API is a set of rules and procedures that facilitate interactions between computers and their applications.

A very common type of API is the **Web API**, which (among other things) allows users to query a remote database over the internet.

Web APIs take on a variety of formats, but the vast majority adhere to a particular style known as **Representational State Transfer** or **REST**. What

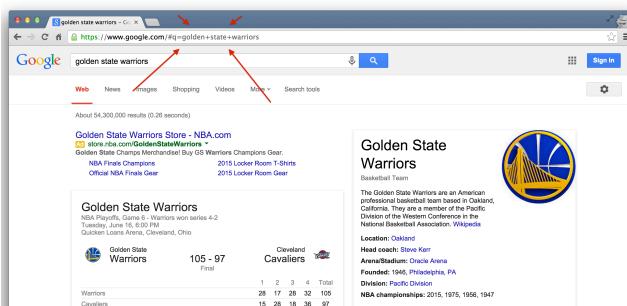
makes these “RESTful” APIs so convenient is that we can use them to query databases using URLs.

RESTful Web APIs are All Around You...

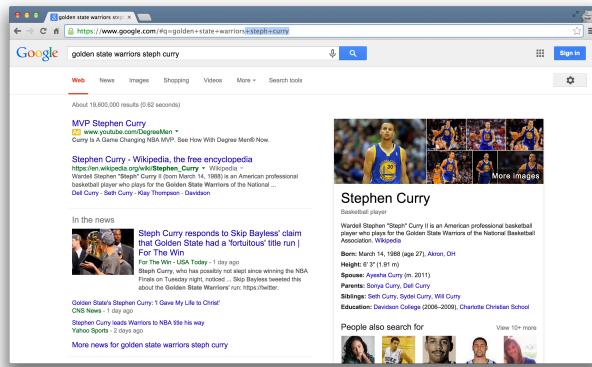
Consider a simple Google search:



Ever wonder what all that extra stuff in the address bar was all about? In this case, the full address is Google’s way of sending a query to its databases requesting information related to the search term “golden state warriors”.



In fact, it looks like Google makes its query by taking the search terms, separating each of them with a “+”, and appending them to the link “[https://www.google.com/#q=”](https://www.google.com/#q=). Therefore, we should be able to actually change our Google search by adding some terms to the URL and following the general format...



Learning how to use RESTful APIs is all about learning how to format these URLs so that you can get the response you want.

17.2.1 Some Basic Terminology

Let's get on the same page with some basic terminology:

- **Uniform Resource Location (URL):** a string of characters that, when interpreted via the Hypertext Transfer Protocol (HTTP), points to a data resource, notably files written in Hypertext Markup Language (HTML) or a subset of a database. This is often referred to as a “call”.
- **HTTP Methods/Verbs:**
 - *GET*: requests a representation of a data resource corresponding to a particular URL. The process of executing the GET method is often referred to as a “GET request” and is the main method used for querying RESTful databases.
 - *HEAD, POST, PUT, DELETE*: other common methods, though mostly never used for database querying.

17.2.2 How Do GET Requests Work?

A Web Browsing Example

As you might suspect from the example above, surfing the web is basically equivalent to sending a bunch of GET requests to different servers and asking for different files written in HTML.

Suppose, for instance, I wanted to look something up on Wikipedia. My first step would be to open my web browser and type in <http://www.wikipedia.org>. Once I hit return, I'd see the page below.



Several different processes occurred, however, between me hitting “return” and the page finally being rendered. In order:

1. The web browser took the entered character string and used the command-line tool “Curl” to write a properly formatted HTTP GET request and submitted it to the server that hosts the Wikipedia homepage.
2. After receiving this request, the server sent an HTTP response, from which Curl extracted the HTML code for the page (partially shown below).
3. The raw HTML code was parsed and then executed by the web browser, rendering the page as seen in the window.

```
#> No encoding supplied: defaulting to UTF-8.
#> [1] "<!DOCTYPE html>\n<html lang=\"mul\" class=\"no-js\">\n<head>\n<meta charset=\"u
```

Web Browsing as a Template for RESTful Database Querying

The process of web browsing described above is a close analogue for the process of database querying via RESTful APIs, with only a few adjustments:

1. While the Curl tool will still be used to send HTML GET requests to the servers hosting our databases of interest, the character string that we supply to Curl must be constructed so that the resulting request can be interpreted and successfully acted upon by the server. In particular, it is likely that the character string must encode **search terms and/or filtering parameters**, as well as one or more **authentication codes**. While the terms are often similar across APIs, most are API-specific.
2. Unlike with web browsing, the content of the server’s response that is extracted by Curl is unlikely to be HTML code. Rather, it will likely be **raw text response that can be parsed into one of a few file formats commonly used for data storage**. The usual suspects include .csv, .xml, and .json files.

3. Whereas the web browser capably parsed and executed the HTML code, **one or more facilities in R, Python, or other programming languages will be necessary for parsing the server response and converting it into a format for local storage** (e.g. matrices, dataframes, databases, lists, etc.).

17.2.3 Finding APIs

More and more APIs pop up every day. Programmable Web offers a running list of APIs. This list provides a list of APIs that may be useful to Political Scientists.

Here are some APIs that may be useful to you:

- NYT Article API: Provides metadata (title, summaries, dates, etc) from all New York Times articles in their archive.
- GeoNames geographical database: Provides lots of geographical information for all countries and other locations. The `geonames` package provides a wrapper for R.
- The Manifesto Project: Provides text and other information on political party manifestos from around the world. It currently covers over 1000 parties from 1945 until today in over 50 countries on five continents. The `manifestoR` package provides a wrapper for R.
- The Census Bureau: Provides datasets from US Census Bureau. The `tidycensus` package allows users to interface with the US Census Bureau's decennial Census and five-year American Community APIs.

17.2.4 Getting API Access

Most APIs require a key or other user credentials before you can query their database.

Getting credentialized with a API requires that you register with the organization. Most APIs are set up for developers, so you'll likely be asked to register an "application". All this really entails is coming up with a name for your app/bot/project, and providing your real name, organization, and email. Note that some more popular APIs (e.g. Twitter, Facebook) will require additional information, such as a web address or mobile number.

Once you've successfully registered, you will be assigned one or more keys, tokens, or other credentials that must be supplied to the server as part of any API call you make. To make sure that users aren't abusing their data access privileges (e.g. by making many rapid queries), each set of keys will be given **rate limits** governing the total number of calls that can be made over certain intervals of time.

For example, the NYT Article API has relatively generous rate limits — 4,000 requests per day and 10 requests per minute. So we need to “sleep” 6 seconds between calls to avoid hitting the per minute rate limit.



17.2.5 Using APIs in R

There are two ways to collect data through APIs in R.

1. Plug-n-play packages

Many common APIs are available through user-written R Packages. These packages offer functions that “wrap” API queries and format the response. These packages are usually much more convenient than writing our own query, so it’s worth searching around for a package that works with the API we need.

2. Writing our own API request

If no wrapper function is available, we have to write our own API request, and format the response ourselves using R. This is trickier, but definitely do-able.

17.3 Collecting Twitter Data with RTweet

Twitter actually has two separate APIs:

1. The **REST API** allows you to read and write Twitter data. For research purposes, this allows you to search the recent history of tweets and look up specific users.
2. The **Streaming API** allows you to access public data flowing through Twitter in real-time. It requires your R session to be running continuously, but allows you to capture a much larger sample of tweets while avoiding rate limits for the REST API.

There are several packages for R for accessing and searching Twitter. In this unit, we'll practice using the `RTweet` library, which allows us to easily collect data from Twitter's REST and stream APIs.

17.3.1 Setting up RTweet

To use `RTweet`, follow these steps:

1. If you don't have a Twitter account, create one here.
2. Install the `RTweet` package from CRAN.
3. Load the package into R.
4. Send a request to Twitter's API by calling any of the package's functions, like `search_tweets` or `get_timeline`.
5. Approve the browser popup (to authorize the `rstats2twitter` app).
6. Now, you're ready to use `RTweet`!

Let's go ahead and load `RTweet` along with some other helpful functions:

```
library(tidyverse)
library(rtweet)
library(lubridate)
library(kableExtra)
```

17.3.2 UChicago Political Science Prof Tweets

Let's explore the `RTweet` package to see what we can learn about the tweeting habits of UChicago Political Science faculty.

The function `get_timeline` will pull the most recent `n` number of tweets from a given handle(s). To pull tweets from multiple handles, write out a vector of the handles in the `user` argument.

Let's pull tweets from five faculty members in the department.

```
profs <- get_timeline(
  user = c("carsonaustr", "profpaulpoast", "psttanpolitics", "rochelleterman", "bobbygulotty"),
  n = 1000
)
kable(head(profs))

user_id
status_id
created_at
screen_name
text
```

```
source
display_text_width
reply_to_status_id
reply_to_user_id
reply_to_screen_name
is_quote
is_retweet
favorite_count
retweet_count
hashtags
symbols
urls_url
urls_t.co
urls_expanded_url
media_url
media_t.co
media_expanded_url
media_type
ext_media_url
ext_media_t.co
ext_media_expanded_url
ext_media_type
mentions_user_id
mentions_screen_name
lang
quoted_status_id
quoted_text
quoted_created_at
quoted_source
quoted_favorite_count
quoted_retweet_count
```

quoted_user_id
quoted_screen_name
quoted_name
quoted_followers_count
quoted_friends_count
quoted_statuses_count
quoted_location
quoted_description
quoted_verified
retweet_status_id
retweet_text
retweet_created_at
retweet_source
retweet_favorite_count
retweet_retweet_count
retweet_user_id
retweet_screen_name
retweet_name
retweet_followers_count
retweet_friends_count
retweet_statuses_count
retweet_location
retweet_description
retweet_verified
place_url
place_name
place_full_name
place_type
country
country_code
geo_coords

coords_coords
bbox_coords
status_url
name
location
description
url
protected
followers_count
friends_count
listed_count
statuses_count
favourites_count
account_created_at
verified
profile_url
profile_expanded_url
account_lang
profile_banner_url
profile_background_url
profile_image_url
805833715
1181260032916250624
1570469313
carsonaut
MPSA deadline extended If you didn't have a chance to submit, you still can! <https://t.co/KfZSPg6o7f>
Twitter Web App
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<https://twitter.com/carsonaustralia/status/1181260032916250624>

Austin Carson

Chicago, IL

Assistant Professor @ University of Chicago, author of *Secret Wars: Covert Conflict in International Politics*. Dad & NBA / Pistons enthusiast

<https://t.co/kApIyoe7RG>

FALSE

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<https://t.co/kApIyoe7RG>

<https://austinmcarson.com/>

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<http://abs.twimg.com/images/themes/theme1/bg.png>

http://pbs.twimg.com/profile_images/1024384740181336064/ROqTG_uN_normal.jpg

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1179794348709498880

1570119866

carsonaustr

Was just told it's sad women don't do strategic studies. Through my tears I used Google to locate smthg called "Journal of Strategic Studies." Current issue co-edited by woman & 4/7 articles have female authors But yes, stop hiding, lady experts! <https://t.co/T2Xkx7CdGU>

Twitter Web App

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Was just told it's sad women don't do strategic studies. Through my tears I used Google to locate smthg called "Journal of Strategic Studies." Current issue co-edited by woman & 4/7 articles have female authors But yes, stop hiding, lady experts! <https://t.co/T2Xkx7CdGU>

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Twitter Web App

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ProfTalmadge

ProFTalmadge

2709

945

1357

Washington, DC

Associate Professor ? ?. Senior Fellow ?. Military ops, defense policy, nuclear deterrence & escalation, authoritarianism.

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Analysis | The Cybersecurity 202: Hacking back may be less risky than we thought (ft work by myself, ?, and ?) <https://t.co/aMC42VruUo>

Twitter for iPhone

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Analysis | The Cybersecurity 202: Hacking back may be less risky than we thought (ft work by myself, ?, and ?) <https://t.co/aMC42VruUo>

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Twitter Web Client

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15706926

sekreps

Sarah Kreps

2447

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1009

Ithaca, NY

Professor of Gov't, Cornell | Former USAF officer | I Outdoors | Europhile | Research=Venn diagram of military, technology, and politics

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<https://twitter.com/carsonaustralia/status/1179595524283998209>

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carsonaustralia

Can cyber operations deter Iran? Will they escalate the crisis into regional war?
My thoughts on both here (no, no). <https://t.co/8xJ0P55QQr>

Twitter for iPhone

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NA

816351261314482177

JackieGSchneid

en

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1179023709484412933

Can cyber operations deter Iran? Will they escalate the crisis into regional war?
My thoughts on both here (no, no). <https://t.co/8xJ0P55QOr>

1569936132

Twitter for iPhone

66

30

816351261314482177

JackieGSchneid

Jacquelyn Schneider

2822

497

1112

Hoover Fellow ?, Non-Resident Fellow ?, specializing in cyber, unmanned weapons, and national security. Views are my own.

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<https://twitter.com/carsonaustralia/status/1179038732231593984>

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carsonaut

Important to think a few steps ahead of White House reaction to impeachment inquiry. If Trump's tweets are any indication, his rearguard actions – even short of craziness like starting a war – may be abrupt and extreme. Targeting intel leaders who show independence is one route

Twitter Web App

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<http://abs.twimg.com/images/themes/theme1/bg.png>

http://pbs.twimg.com/profile_images/1024384740181336064/ROqTG_uN_normal.jpg

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carsonaut

Another possible casualty: US election security. Outgoing DNI Dan Coats appointed a new coordinator for election security and elevated the issue within IC. A loyalist DNI replacement may quietly slow play, starve of resources, or ignore those efforts

Twitter Web App

251

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carsonaut

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<https://twitter.com/carsonaustralia/status/1178999439983288320>

Austin Carson

Chicago, IL

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<https://t.co/kApIyoe7RG>

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<https://austinmcarson.com/>

NA

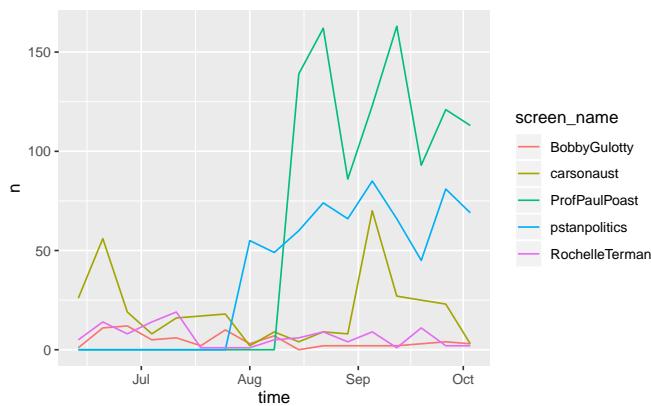
https://pbs.twimg.com/profile_banners/805833715/1533067436

<http://abs.twimg.com/images/themes/theme1/bg.png>

http://pbs.twimg.com/profile_images/1024384740181336064/ROqTG_uN_normal.jpg

Now, let's visualize which professors are tweeting the most, by week.

```
profs %>%
  group_by(screen_name) %>%
  mutate(created_at = as.Date(created_at)) %>%
  filter(created_at >= "2019-06-15") %>%
  ts_plot(by = "week")
```



17.3.3 Hashtags and Text Strings

We can also use `RTweet` to explore certain hashtags or text strings.

Let's take Duke Ellington again – we can use `search_tweets` to pull the most recent n number of tweets that include the hashtag `#DukeEllington` or the string "Duke Ellington".

Hashtag Challenge

Using the documentation for `search_tweets` as a guide, try pulling the 2,000 most recent tweets that include `#DukeEllington` or "Duke Ellington" – be sure to exclude retweets from the query.

1. Why didn't your query return 2,000 results?
2. Identify the user that has used either the hashtag or the string in the greatest number of tweets – where is this user from?

```
duke <- search_tweets(
  q = '#DukeEllington OR "Duke Ellington"',
  n = 2000,
  include_rts = FALSE
)

duke %>%
  group_by(user_id, location) %>%
  summarise(n = n()) %>%
  arrange(desc(n))
#> # A tibble: 973 x 3
#> # Groups:   user_id [973]
#>   user_id          location      n
#>   <chr>            <chr>        <int>
#> 1 2561373848     Florida, USA    94
#> 2 764290456599396353 Rochester, New York 45
#> 3 1022122568004894720   ""
#> 4 1030069194539368448   ""
#> 5 714738130557992960  Chiclana de la Frontera, Spain 29
#> 6 2375819586        Villavicencio, Colombia 22
#> # ... with 967 more rows
```

17.4 Writing API Queries

If no wrapper package is available, we have to write our own API query, and format the response ourselves using R. This is trickier, but definitely doable.

In this unit, we'll practice constructing our own API queries using the New York Time's **Article API**. This API provides metadata (title, date, summary, etc) on all of New York Times articles.

Fortunately, this API is very well documented!

You can even try it out here.

Load the following packages to get started:

```
library(tidyverse)
library(httr)
library(jsonlite)
library(lubridate)
```

17.4.1 Constructing the API GET Request

Likely the most challenging part of using web APIs is learning how to format your GET request URLs. While there are common architectures for such URLs, each API has its own unique quirks. For this reason, carefully reviewing the API documentation is critical.

Most GET request URLs for API querying have three or four components:

1. *Authentication Key/Token*: a user-specific character string appended to a base URL telling the server who is making the query; allows servers to efficiently manage database access
2. *Base URL*: a link stub that will be at the beginning of all calls to a given API; points the server to the location of an entire database
3. *Search Parameters*: a character string appended to a base URL that tells the server what to extract from the database; basically a series of filters used to point to specific parts of a database
4. *Response Format*: a character string indicating how the response should be formatted; usually one of .csv, .json, or .xml

Let's go ahead and store these values as variables:

```
key <- "Onz0BobMTn2IRJ7krcT5RXHknkGLqiaI"
base.url <- "http://api.nytimes.com/svc/search/v2/articlesearch.json"
search_term <- "Beyonce"
```

How did I know the `base.url`? I read the documentation.. Notice that this `base.url` also includes the *response format*(.json), so we don't need to configure that directly.

We're ready to make the request. We can use the `GET` function from the `httr` package (another `tidyverse` package) to make an HTTP GET Request.

```
r <- GET(base.url, query = list(`q` = search_term,
                                `api-key` = key))
```

Now, we have an object called `r`. We can get all the information we need from this object. For instance, we can see that the URL has been correctly encoded by printing the URL. Click on the link to see what happens.

```
r$url
#> [1] "http://api.nytimes.com/svc/search/v2/articlesearch.json?q=Beyonce&api-key=0nz0BobMTn2IRJ"
```

Challenge 1: Adding a date range

What if we only want to search within a particular date range? The NYT Article Api allows us to specify start and end dates.

Alter the `get.request` code above so that the request only searches for articles in the year 2005.

You're gonna need to look at the documentation here to see how to do this.

Challenge 2: Specifying a results page

The above will return the first 10 results. To get the next ten, you need to add a “page” parameter. Change the search parameters above to get the second 10 results.

17.4.2 Parsing the response

We can read the content of the server’s response using the `content()` function.

```
response <- content(r, "text")
substr(response, start = 1, stop = 1000)
#> [1] "{\"status\":\"OK\",\"copyright\":\"Copyright (c) 2019 The New York Times Company. All Rig"
```

What you see here is JSON text, encoded as plain text. JSON stands for “Javascript object notation.” Think of JASON like a nested array built on key/value pairs.

We want to convert the results from JSON format to something easier to work with – notably a data.frame.

The `jsonlite` package provides several easy conversion functions for moving between JSON and vectors, data.frames, and lists. Let’s use the function `fromJSON` to convert this response into something we can work with:

```
# Convert JSON response to a dataframe
response_df <- fromJSON(response, simplifyDataFrame = TRUE, flatten = TRUE)

# Inspect the dataframe
str(response_df, max.level = 2)
#> List of 3
#> $ status : chr "OK"
#> $ copyright: chr "Copyright (c) 2019 The New York Times Company. All Rights Reserved."
#> $ response :List of 2
#>   ..$ docs:'data.frame': 10 obs. of  27 variables:
#>     ..$ meta:List of 3
```

That looks intimidating! But it's really just a big, nested list. Let's see what we got in there.

```
names(response_df)
#> [1] "status"      "copyright"    "response"

# This is boring
response_df$status
#> [1] "OK"

# So is this
response_df$copyright
#> [1] "Copyright (c) 2019 The New York Times Company. All Rights Reserved."

# This is what we want!
names(response_df$response)
#> [1] "docs"        "meta"
```

Within `response_df$response`, we can extract a number of interesting results, including the number of total hits, as well as information on the first ten documents:

```
# What's in 'meta'?
response_df$response$meta
#> $hits
#> [1] 3892
#>
#> $offset
#> [1] 0
#>
#> $time
#> [1] 21

# pull out number of hits
response_df$response$meta$hits
```

```
#> [1] 3892

# Check out docs
names(response_df$response$docs)
#> [1] "web_url"                  "snippet"
#> [3] "lead_paragraph"           "abstract"
#> [5] "print_page"               "source"
#> [7] "multimedia"              "keywords"
#> [9] "pub_date"                 "document_type"
#> [11] "news_desk"                "section_name"
#> [13] "type_of_material"        "_id"
#> [15] "word_count"              "uri"
#> [17] "subsection_name"          "headline.main"
#> [19] "headline.kicker"          "headline.content_kicker"
#> [21] "headline.print_headline" "headline.name"
#> [23] "headline.seo"             "headline.sub"
#> [25] "byline.original"          "byline.person"
#> [27] "byline.organization"

# put it in another variable
docs <- response_df$response$docs
```

17.4.3 Iteration through results pager

That's great. But we only have 10 items. The original response said we had 3,876 hits! Which means we have to make 3876 /10, or 18 requests to get them all. Sounds like a job for iteration!

First, let's write a function that passes a search term and a page number, and returns a dataframe of articles.

```
nytapi <- function(term = NULL, n){
  base.url = "http://api.nytimes.com/svc/search/v2/articlesearch.json"
  key = "0nz0BobMTn2IRJ7krcT5RXHknkGLqiaI"

  # Send GET request
  r <- GET(base.url, query = list(`q` = term,
                                    `api-key` = key,
                                    `page` = n))

  # Parse response to JSON
  response <- content(r, "text")
  response_df <- fromJSON(response, simplifyDataFrame = T, flatten = T)

  return(response_df$response$docs)
```

```

}

docs <- nytimes("Duke Ellington", 2)

```

Now, we're ready to iterate over each page. First, let's review what've done so far:

```

# set key and base
base.url = "http://api.nytimes.com/svc/search/v2/articlesearch.json"
key = "Onz0BobMTn2IRJ7krcT5RXHknkGLqiaI"
search_term = "fleek"

# Send GET request
r <- GET(base.url, query = list(`q` = search_term,
                                `api-key` = key))

# Parse response to JSON
response <- content(r, "text")
response_df <- fromJSON(response, simplifyDataFrame = T, flatten = T)

# extract hits
hits = response_df$response$meta$hits

# get number of pages
pages = ceiling(hits/10)

# iterate over pages, getting all docs
docs_list <- map((1:pages), ~nytimes(term = search_term, n = .))

# flatten to create one bit dataframe
docs_df <- bind_rows(docs_list)

```

17.4.4 Visualizing Results

To figure out how Adam Rippon's popularity is changing over time, all we need to do is add an indicator for the year and month each article was published in.

```

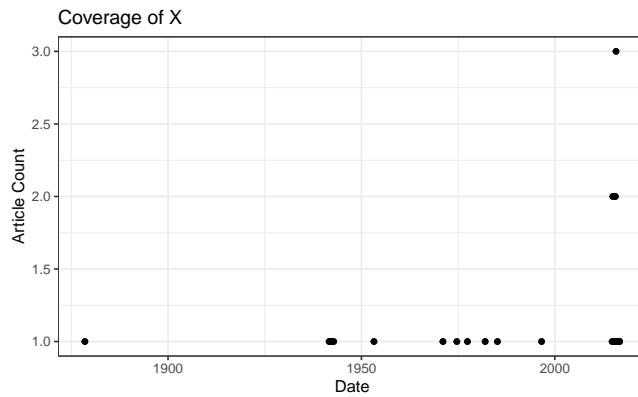
# Format pub_date using lubridate
docs_df$date <- ymd_hms(docs_df$pub_date)

by_month <- docs_df %>% group_by(floor_date(date, "month")) %>%
  summarise(count = n()) %>%
  rename(month = 1)

by_month %>%

```

```
ggplot(aes(x = month, y = count)) +
  geom_point() +
  theme_bw() +
  xlab(label = "Date") +
  ylab(label = "Article Count") +
  ggtitle(label = "Coverage of X")
```



17.4.5 More resources

The documentation for httr includes two useful vignettes:

1. httr quickstart guide - summarizes all the basic httr functions like above
2. Best practices for writing an API package - document outlining the key issues involved in writing API wrappers in R

17.5 Webscraping

If no API is available, we can scrape a website directory. Webscraping has a number of benefits and challenges compared to APIs:

Webscraping Benefits

- Any content that can be viewed on a webpage can be scraped. Period
- No API needed
- No rate-limiting or authentication (usually)

Webscraping Challenges

- Rarely tailored for researchers
- Messy, unstructured, inconsistent
- Entirely site-dependent

Some Disclaimers

- Check a site's terms and conditions before scraping.
 - Be nice - don't hammer the site's server.
 - Sites change their layout all the time. Your scraper will break.

17.5.1 What's a website?

A website is some combination of codebase and database. The “front end” product is HTML + CSS stylesheets + javascript, looking something like this:

Your browser turns that into a nice layout.

Current Senate Members 99th General Assembly
[Leadership](#) [Officers](#) [Senate Seating Chart](#) Democrats: 39 Republicans: 20

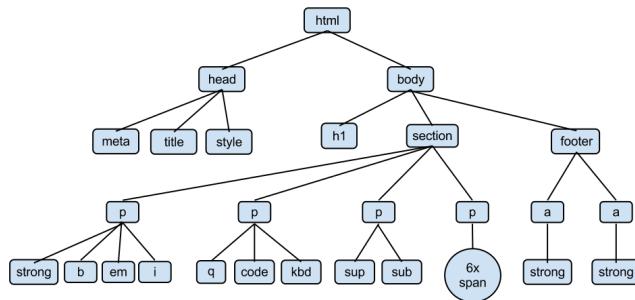
Senator	Bills	Committees	District	Party
Pamela J. Althoff	Bills	Committees	32	R
Neil Anderson	Bills	Committees	36	R
Jason A. Barickman	Bills	Committees	53	R
Scott M. Bennett	Bills	Committees	52	D
Jennifer Bertino-Tarrant	Bills	Committees	49	D
Daniel Biss	Bills	Committees	9	D
Tim Bivins	Bills	Committees	45	R
William E. Brady	Bills	Committees	44	R
Melinda Bush	Bills	Committees	31	D
James F. Clayborne, Jr.	Bills	Committees	57	D
Jacqueline Y. Collins	Bills	Committees	16	D
Michael Connely	Bills	Committees	21	R
John J. Cullerton	Bills	Committees	6	D

17.5.2 HTML

The core of a website is **HTML** (Hyper Text Markup Language.) HTML is composed of a tree of HTML **elements**, such as headers, paragraphs, etc.

```
<!DOCTYPE html>
<html>
  <head>
    <title>Page title</title>
  </head>
  <body>
    <p>Hello world!</p>
  </body>
</html>
```

HTML elements can contain other elements:



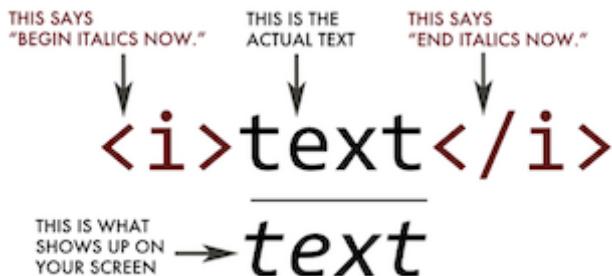
Generally speaking, an HTML element has three components:

1. Tags (starting and ending the element)
2. Attributes (giving information about the element)
3. Text, or Content (the text inside the element)

```
knitr::include_graphics(path = "img/html-element.png")
```



HTML: Tags

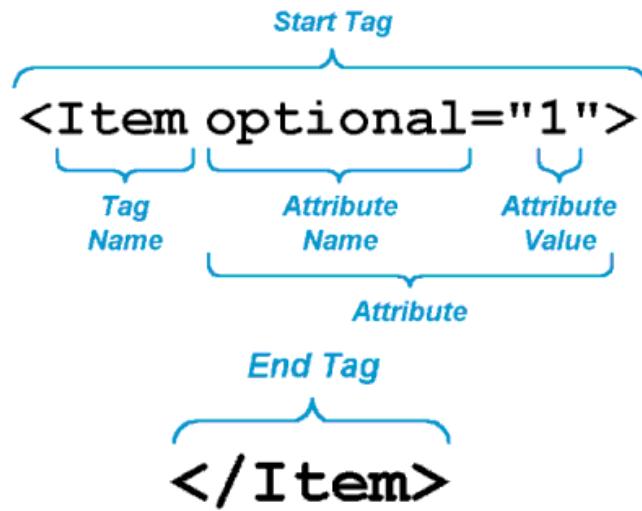


Common HTML tags

Tag	Meaning
<code><head></code>	page header (metadata, etc)
<code><body></code>	holds all of the content
<code><p></code>	regular text (paragraph)
<code><h1>,<h2>,<h3></code>	header text, levels 1, 2, 3
<code>,,</code>	ordered list, unordered list, list item
<code></code>	link to "page.html"
<code><table>,<tr>,<td></code>	table, table row, table item
<code><div>,</code>	general containers

HTML Attributes

- HTML elements can have attributes.
- Attributes provide additional information about an element.
- Attributes are always specified in the start tag.
- Attributes come in name/value pairs like: `name="value"`



17.5.3 CSS

CSS stands for **Cascading Style Sheet**. CSS defines how HTML elements are to be displayed.

HTML came first. But it was only meant to define content, not format it. While HTML contains tags like `` and `<color>`, this is a very inefficient way to develop a website.

To solve this problem, CSS was created specifically to display content on a webpage. Now, one can change the look of an entire website just by changing one file.

Most web designers litter the HTML markup with tons of `classes` and `ids` to provide “hooks” for their CSS.

You can piggyback on these to jump to the parts of the markup that contain the data you need.

CSS Anatomy

- Selectors
 - Element selector: `p`
 - Class selector: `p class="blue"`
 - I.D. selector: `p id="blue"`
- Declarations
 - Selector: `p`
 - Property: `background-color`
 - Value: `yellow`

- Hooks

Basic Anatomy of a CSS Rule



Declaring a CSS Rule for a **Class** Attribute

the XHTML
`Brochure`

the CSS
`.pdf {background: url(images/pdf.gif) no-repeat left 50%}`

use a **period** when writing a rule for a **class**

Declaring a CSS Rule for an **Id** Attribute

the XHTML
`<div id="wrapper">Main Content</div>`

the CSS
`#wrapper {width: 750px; margin: 0 auto;}`

use a **pound sign** when writing a rule for a **id**

17.5.3.1 CSS + HTML

```

<body>
  <table id="content">
    <tr class='name'>
      <td class='firstname'>
        Kurtis
      </td>
      <td class='lastname'>
        McCoy
      </td>
    </tr>
    <tr class='name'>
      <td class='firstname'>
        Leah
      </td>
      <td class='lastname'>
        Guerrero
      </td>
    </tr>
  </table>
</body>

```

Challenge 1

Find the CSS selectors for the following elements in the HTML above.

(Hint: There will be multiple solutions for each)

1. The entire table
2. The row containing “Kurtis McCoy”
3. Just the element containing first names

17.5.4 Finding Elements with Selector Gadget

Selector Gadget is a browser plugin to help you find HTML elements. Install Selector Gadget on your browser by following [these instructions(<https://selectorgadget.com/>)].

Once installed, run Selector Gadget and simply click on the type of information you want to select from the webpage. Once this is selected, you can then click the pieces of information you **don’t** want to keep. Do this until only the pieces you want to keep remain highlighted, then copy the selector from the bottom pane.

Here’s the basic strategy of webscraping:

1. Use Selector Gadget to see how your data is structured
2. Pay attention to HTML tags and CSS selectors
3. Pray that there is some kind of pattern
4. Use R and add-on modules like `Rvest` to extract just that data.

Challenge 2

Go to <http://rochelleterman.github.io/>. Using Selector Gadget,

1. Find the CSS selector capturing all rows in the table.
2. Find the image source URL.
3. Find the HREF attribute of the link.

17.6 Scraping Presidential Statements

To demonstrate webscraping in R, we’re going to collect records on presidential statements here: <https://www.presidency.ucsb.edu/>

Let’s say we’re interested in how presidents speak about “space exploration”. On the website, we punch in this search term, and we get the following 295 results.

Our goal is to scrape these records, and store pertinent information in a dataframe.

Load the following packages to get started:

```
library(tidyverse)
library(rvest)
library(stringr)
library(purrr)
library(knitr)
```

17.6.1 Using Rvest to Read HTML

The package **Rvest** allows us to:

1. Collect the HTML source code of a webpage
2. Read the HTML of the page
3. Select and keep certain elements of the page that are of interest

Let's start with step one. We use the `read_html` function to call the results URL and grab the HTML response. Store this result as an object.

```
space <- read_html("https://www.presidency.ucsb.edu/advanced-search?field-keywords=%22

#Let's take a look at the object we just created
space
#> {xml_document}
#> <html lang="en" dir="ltr" prefix="content: http://purl.org/rss/1.0/modules/content/
#> [1] <head profile="http://www.w3.org/1999/xhtml/vocab">\n<meta charset=" ...
#> [2] <body class="html not-front not-logged-in one-sidebar sidebar-first ...
```

This is pretty messy. We need to use **Rvest** to make this information more useable.

17.6.2 Find Page Elements

Rvest has a number of functions to find information on a page. Like other webscraping tools, **Rvest** lets you find elements by their:

1. HTML tags
2. HTML Attributes
3. CSS Selectors

Let's search first for HTML tags.

The function `html_nodes` searches a parsed HTML object to find all the elements with a particular HTML tag, and returns all of those elements.

What does the example below do?

```
html_nodes(space, "a")
#> {xml_nodeset (227)}
```

```
#> [1] <a href="#main-content" class="element-invisible element-focusable" ...
#> [2] <a href="https://www.presidency.ucsb.edu/">The American Presidency ...
#> [3] <a class="btn btn-default" href="https://www.presidency.ucsb.edu/about ...
#> [4] <a class="btn btn-default" href="/advanced-search"><span class="gly ...
#> [5] <a href="https://www.ucsb.edu/" target="_blank"><img alt="ucsb word ...
#> [6] <a href="/documents" class="dropdown-toggle" data-toggle="dropdown" ...
#> [7] <a href="/documents/presidential-documents-archive-guidebook">Guide ...
#> [8] <a href="/documents/category-attributes">Category Attributes</a>
#> [9] <a href="/statistics">Statistics</a>
#> [10] <a href="/media" title="">Media Archive</a>
#> [11] <a href="/presidents" title="">Presidents</a>
#> [12] <a href="/analyses" title="">Analyses</a>
#> [13] <a href="https://giving.ucsb.edu/Funds/Give?id=185" title="">Support ...
#> [14] <a href="https://www.presidency.ucsb.edu/how-to-search">MORE TIPS</a>
#> [15] <a id="main-content"></a>
#> [16] <a href="/advanced-search?field-keywords=%22space%20exploration%22&...
#> [17] <a href="/advanced-search?field-keywords=%22space%20exploration%22&...
#> [18] <a href="/people/president/dwight-d-eisenhower">Dwight D. Eisenhower ...
#> [19] <a href="/documents/special-message-the-congress-relative-space-sci ...
#> [20] <a href="/people/president/dwight-d-eisenhower">Dwight D. Eisenhower ...
#> ...
```

That's a lot of results! Many elements on a page will have the same HTML tag. For instance, if you search for everything with the `a` tag, you're likely to get a lot of stuff, much of which you don't want.

In our case, we only want the links of Document Titles:

```
knitr:::include_graphics(path = "img/scraping_links.png")
```

RESULTS 1 - 100 of 295 records found

Date	Related	Document Title
Apr 02, 1958	Dwight D. Eisenhower	Special Message to the Congress Relative to Space Science and Exploration eventually provide the means for spaceexploration . The United States of America ... reached this conclusion because spaceexploration holds promise of adding importantly ...
May 14, 1958	Dwight D. Eisenhower	Statement by the President in Support of the Administration Bill Relative to Space Science and Exploration of the clear evidence that spaceexploration holds promise of adding importantly ...
Jul 29, 1958	Dwight D. Eisenhower	Statement by the President Upon Signing the National Aeronautics and Space Act of 1958 fields of aeronautics and spaceexploration . The new Act contains one ... Services. The combination of spaceexploration responsibilities with the ...

What if we wanted to search for HTML tags **only** with certain attributes, like particular CSS classes?

We can do this by modifying our argument in `html_nodes` to look for a more specific CSS tag.

Selector Gadget

In order to easily identify these more specific tags, we can use **Selector Gadget**.

Install Selector Gadget in your browser. Once installed, run Selector Gadget and simply click on the type of information you want to select from the webpage. Once this is selected, you can then click the pieces of information you **don't** want to keep. Do this until only the pieces you want to keep remain highlighted, then copy the selector from the bottom pane.

You can use this new tag in `html_nodes`.

17.6.3 Get Attributes and Text of Elements

Once we identify elements, we want to access information in that element. Often times this means two things:

- 1) Text
- 2) Attributes

Getting the text inside an element is pretty straightforward. We can use the `html_text()` command inside of RVest to get the text of an element:

```
#Scrape individual document page
document1 <- read_html("https://www.presidency.ucsb.edu/documents/special-message-the-"

#identify element with Speaker name
speaker <- html_nodes(document1, ".diet-title a") %>%
  html_text() #select text of element

speaker
#> [1] "Dwight D. Eisenhower"
```

You can access a tag's attributes using `html_attr`. For example, we often want to get a URL from an `a` (link) element. This is the URL the link “points” to. It's contained in the attribute `href`:

```
speaker_link <- html_nodes(document1, ".diet-title a") %>%
  html_attr("href")
speaker_link
#> [1] "/people/president/dwight-d-eisenhower"
```

17.6.4 Let's DO this.

Believe it or not, that's all you need to scrape a website. Let's apply these skills to scrape a sample document from the UCSB website – the first item in our search results.

We'll collect the document's date, speaker, title, and full text.

1. Date

```
document1 <- read_html("https://www.presidency.ucsb.edu/documents/special-message-the-congress-re")

date <- html_nodes(document1, ".date-display-single") %>%
  html_text() %>% # grab element text
  mdy() #format using lubridate
date
#> [1] "1958-04-02"
```

2. Speaker

```
#Speaker
speaker <- html_nodes(document1, ".diet-title a") %>%
  html_text()
speaker
#> [1] "Dwight D. Eisenhower"
```

3. Title

```
#Title
title <- html_nodes(document1, "h1") %>%
  html_text()
title
#> [1] "Special Message to the Congress Relative to Space Science and Exploration."
```

4. Text

```
#Text
text <- html_nodes(document1, "div.field-docs-content") %>%
  html_text()

#this is a long document, so let's just display the first 1000 characters
text %>% substr(1, 1000)
#> [1] "\n      To the Congress of the United States:\nRecent developments in long-range rockets fo
```

17.6.5 Challenge 1: Make a function

Make a function called `scrape_docs` that accepts a URL of an individual document, scrapes the page, and returns a list containing the document's date,

speaker, title, and full text.

This involves:

- Requesting the HTML of the webpage using the full URL and RVest.
- Using RVest to locate all elements on the page we want to save.
- Saving each of these items into a list.

```
scrape_doc <- function(URL){  
  doc <- read_html(URL)  
  
  speaker <- html_nodes(doc, ".diet-title a") %>%  
    html_text()  
  
  date <- html_nodes(doc, ".date-display-single") %>%  
    html_text() %>%  
    mdy()  
  
  title <- html_nodes(doc, "h1") %>%  
    html_text()  
  
  text <- html_nodes(doc, "div.field-docs-content") %>%  
    html_text()  
  
  return(list(speaker = speaker, date = date, title = title, text = text))  
}  
  
# uncomment to test  
# scrape_doc("https://www.presidency.ucsb.edu/documents/letter-t-keith-glennan-adminis")
```

Part III

Assignments and Projects

Chapter 18

Assignments

Part IV

Resources

Chapter 19

Cheat Sheets and Guides

1. RStudio IDE Cheat Sheet
2. R Markdown Cheat Sheet
3. R Markdown Reference Guide Base R Cheat Sheet
4. Data Transformation with `dplyr` Cheat Sheet
5. Data Visualization Cheat Sheet
6. Regular Expressions Cheat Sheet

Bibliography