Data Science for Public Policy

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Introduction to R

Reading

- R for Data Science – Chapters 1, 2, & 4
- What all policy analysts need to know about data science
- What is Data Science @ the Urban Institute?

Six Principles for Data Analysis

1) Accuracy

Deliberate steps *should* be taken to minimize the chance of making an error and maximize the chance of catching errors when errors inevitably occur.

Embrace Your Fallibility: Thoughts on Code Integrity

2) Computational reproducibility

Computational reproducibility *should* be embraced to improve accuracy, promote transparency, and prove the quality of analytic work.

Replication: the recreation of findings across repeated studies, is a cornerstone of science.

Reproducibility: the ability to access data, source code, tools, and documentation and recreate all calculations, visualizations, and artifacts of an analysis.

Computational reproducibility *should* be the minimum standard for computational social sciences and statistical programming.

3) Human interpretability

Code *should* be written so humans can easily understand what's happening—even if it occasionally sacrifices machine performance.

4) Portability

Analyses *should* be designed so strangers can understand each and every step without additional instruction or inquiry from the original analyst.

5) Accessibility

Research and data are non-rivalrous and can be non-excludable. They are public goods that should be widely and easily shared. Decisions about tools, methods, data, and language during the research process should be made in ways that promote the ability of anyone and everyone to access an analysis.

6) Efficiency

Analysts *should* seek to make all parts of the research process more efficient with clear communication, by adopting best practices, and by managing computation.

R

R is a free, open-source software for statistical computing. It is a fully-functioning programming language and it is known for intuitive, crisp graphics and an extensive, growing library of statistical and analytic methods. Above all, R boasts an enthusiastic community of developers, instructors, and users. The copyright and documentation for R is held by a not-for-profit organization called the R Foundation.

R comes from the S programming language and S-PLUS system. In addition to offering better graphics and more extensibility than proprietary languages, R has a pedagogical advantage:

> The ambiguity [of the S language] is real and goes to a key objective: we wanted users to be able to begin in an interactive environment, where they did not consciously think of themselves as programming. Then as their needs became clearer and their sophistication increased, they should be able to slide gradually into programming, when the language and system aspects would become more important.

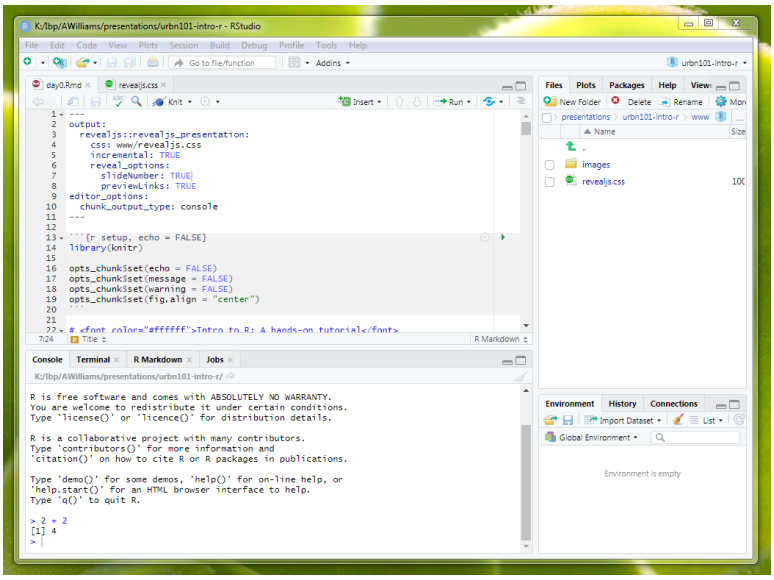
Source: "Stages in the Evolution of S" via Roger Peng

RStudio

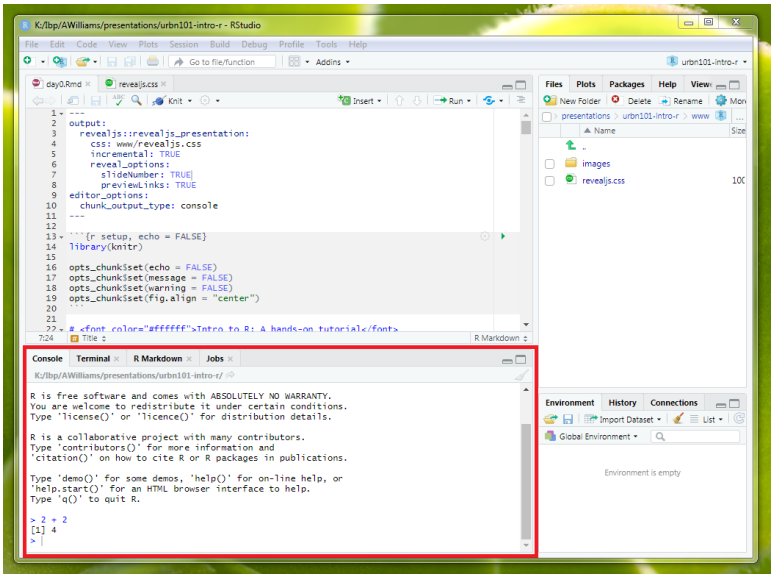
RStudio is a free, open-source integrated development environment (IDE) that runs on top of R. In practice, R users almost exclusively open RStudio and rarely directly open R.

RStudio is developed by a for-profit company called RStudio. RStudio, the company, employs some of the R community's most prolific, open-source developers and creates many open-source tools and resources.

While R code can be written in any text editor, the RStudio IDE is a powerful tool with a console, syntax-highlighting, and debugging tools. The RStudio IDE cheatsheet outlines some of the power of RStudio.



RStudio Console



The RStudio Console contains the R command line and R output from previously submitted R code.

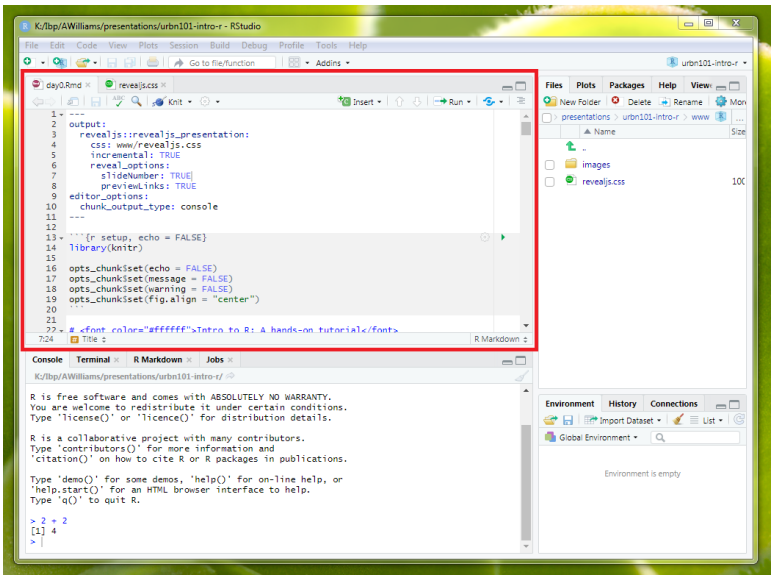
Code can be submitted by typing to the right of the last blue `>` and the hitting enter.

Exercise

R has all of the functionality of a basic calculator. Let's run some simple calculations with addition (`+`), subtraction (`-`), multiplication (`*`), division (`/`), exponentiation (`^`), and grouping (`()`).

. . .

.R Scripts



By default, there isn't a record of code directly typed and submitted into the RStudio Console. So, most R programmers use `.R` scripts to develop R code before submitting code to the console.

`.R` scripts are simple text files with R code. They are similar to `.py` files in Python, `.sas` files in SAS, and `.do` files in Stata.

Exercise

Click the new script button in the top left corner of RStudio to create a new script.

Add some R code to your new script. Place your cursor on a line of R code and hit Command-Enter on Macs or Control-Enter on Windows. Alternatively, highlight the code (it can be multiple lines) and click the run button.

In both cases, the code from your `.R` script should move to the R Console and evaluate.

. . .

Comments

R will interpret all text in a `.R` script as R code unless the code follows `#`, the comment symbol. Comments are essential to writing clear code in any programming language.

```
# Demonstrate the value of a comment and make a simple calculation
2 + 2
```

It should be obvious *what* a line of clear R code accomplishes. It isn't always obvious *why* a clear line of R code is included in a script. Comments should focus on the *why* of R code and not the *what* of R code.

The following comment isn't useful because it just restates the R code, which is clear:

```
# divide every value by 1.11
cost / 1.11
```

The following comment is useful because it adds context to the R code:

```
# convert costs from dollars to Euros using the 2020-01-13 exchange rate
cost / 1.11
```

Exercise

Add comments to your `.R` that clarify the *why*. Since we only know a few operations, the comments may need to focus on your why you picked your favorite numbers.

. . .

Style

Good coding style is like correct punctuation: you can manage without it, butitsuremakesthingseasiertoread. ~ Hadley Wickham

Human interpretability is one of the six principles because clear code can save time and reduce the chance of making errors. After time, eyes can be trained to quickly spot incorrect code if a consistent R style is adopted.

First, note that R is case-sensitive. Capitalization is rare and deviations from the capitalization will throw errors. For example, `mean()` is a function but `Mean()` is not a function.

The tidyverse style guide is a comprehensive style guide that, in general, reflects the style of the plurality of R programmers. For now, just focus on consistency.

Data Structures

Data analysis is not possible without data structures for data. R has several important data structures that shape how information is stored and processed.

Vectors

Vectors are one-dimensional arrays that contain one and only one type of data. Atomic vectors in R are *homogeneous*. There are six types of atomic vectors:

- logical
- integer
- double
- character
- complex (uncommon)
- raw (uncommon)

For now, the simplest way to create a vector is with `c()`, the combine function.

```
# a logical vector
c(TRUE, FALSE, FALSE)
```

```
## [1]  TRUE FALSE FALSE
```

```
# an integer vector
c(1, 2, 3)
```

```
## [1] 1 2 3
```

```
# a double vector
c(1.1, 2.2, 3.3)
```

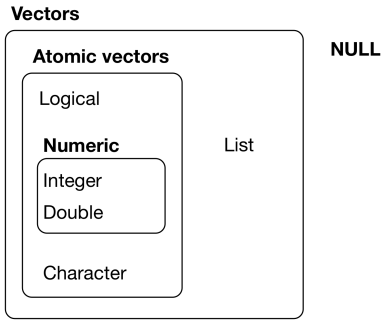
```
## [1] 1.1 2.2 3.3
```

```r
# a character vector
c("District of Columbia", "Virginia", "Maryland")
```

```
## [1] "District of Columbia" "Virginia"             "Maryland"
```

Lists are one- or multi-dimensional arrays that are made up of other lists. Lists are *heterogeneous* - they can contain many lists of different types and dimensions. A vector is a list but a list is not necessarily a vector.

`NULL` is the null object in R. It means a value does not exist.



Source: R4DS

`NA` is a missing value of lenth 1 in R. `NA`s are powerful representations in R with special properties. `NA` is a contagious value in R that will override all calculations.

```r
1 + 2 + 3 + NA
```

```
## [1] NA
```

This forces programmers to be deliberate about missing values. This is a feature, not a bug!

R contains special functions and function arguments for handling `NA`s. For example, we can wrap a vector with missing values in `is.na()` to create a vector of Booleans where `TRUE` represents an element that is an `NA` and `FALSE` represents an element that is not an `NA`.

```r
is.na(c(1, 2, NA))
```

```
## [1] FALSE FALSE  TRUE
```

Note: `NA` and `NULL` have different meanings! `NULL` means no value exists. `NA` means a value could exist but it is unknown.

Matrices

Matrices are multi-dimensional arrays where every element is of the same type. Most data in data science contains at least numeric information and character information. Accordingly, we will not use matrices much in this course.

Data frames

Instead, `data frames`, and their powerful cousins `tibbles`, are the backbone of data science and this course. `Data frames` are two-dimensional arrays where each column is a list (usually a vector). Most times, each column will be of one type while a given row will contain many different types. We usually refer to columns as *variables* and rows as *observations*.

Here are the first six rows of a data frame with information about diamond prices and diamond characteristics:

```
head(ggplot2::diamonds)
```

```
## # A tibble: 6 x 10
##   carat cut       color clarity depth table price     x     y     z
##   <dbl> <ord>     <ord> <ord>   <dbl> <dbl> <int> <dbl> <dbl> <dbl>
## 1  0.23 Ideal     E     SI2      61.5    55   326  3.95  3.98  2.43
## 2  0.21 Premium   E     SI1      59.8    61   326  3.89  3.84  2.31
## 3  0.23 Good      E     VS1      56.9    65   327  4.05  4.07  2.31
## 4  0.29 Premium   I     VS2      62.4    58   334  4.2   4.23  2.63
## 5  0.31 Good      J     SI2      63.3    58   335  4.34  4.35  2.75
## 6  0.24 Very Good J     VVS2     62.8    57   336  3.94  3.96  2.48
```

tibbles

`tibbles` are special data frames that have a few extra features:

- Only the first ten rows of `tibbles` print by default and extra meta data are printed with `tibbles`
- They have some convenient protections against partial subsetting
- They are easier to create from scratch in a `.R` script

From this moment forward, I will use tibble to mean data frame.

Assignment

R can operate on many different vectors and data frames in the same R session. This creates much flexibility. It also means most unique objects in an R session need unique names.

`<-` is the assignment operator. An object created on the right side of an assignment operator is assigned to a name on the left side of an assignment operator. Assignment operators are important for saving the consequences of operations and functions. Without assignment, the result of a calculation is not saved for use in a future calculation. Operations without assignment operators will typically be printed to the console but not saved for future use.

```
# this important calculation is saved to the R environment
important_calculation <- 2 + 2
```

```
# this important calculation is NOT saved to the R environment
2 + 2
```

```
## [1] 4
```

Exercise

Write three arithmetic operations in R and assign them to unique names. Then perform arithmetic operations using the named results. For example:

```
a <- 5 + 5 + 5
b <- 6 - 6 - 6

a + b
```

```
## [1] 9
```

. . .

Functions

`+`, `-`, `*`, and `/` are great, but data science requires a lot more than just basic arithmetic.

R contains many more functions that can perform mathematical operations, control your computer operating system, process text data, and more. In fact, R is built around functions.

Because R was developed by statisticians, R's functions have a lot in common with mathematical functions.

- Functions have inputs and outputs
- Each input has one and only one output (unless is involves a random process)

Functions are recognizable because they end in `()`. For example, the following calculates the mean of a numeric vector two ways:

```
mean(x = c(1, 2, 3))
```

```
## [1] 2
```

```
numeric_vector <- c(1, 2, 3)
mean(x = numeric_vector)
```

```
## [1] 2
```

This free book chapter contains more information about functional programming in R.

?

Documentation for functions can be easily accessed by prefacing the function name with `?` and dropping the `()`.

```
?mean
```

The documentation typically includes a description, a list of the arguments, references, a list of related functions, and examples. The examples are incredibly useful.

Arguments

R functions typically contain many arguments. For example, `mean()` has `x`, `trim`, and `na.rm`. Many arguments have default values and don't need to be included in function calls. Default values can be seen in the documentation. `trim = 0` and `na.rm = FALSE` are the defaults for `mean()`.

Arguments can be passed to functions implicitly by position or explicitly by name.

```
numeric_vector <- c(1, 2, 3, 4, 5, 6, 7, 8, 9, 10)

# by position (correctly)
mean(numeric_vector, 0.2)
```

```
## [1] 5.5
```

```
# by position (incorrectly)
mean(0.2, numeric_vector)
```

```
# by name
mean(x = numeric_vector, trim = 0.2)
```

```
## [1] 5.5
```

Function calls can include arguments by position and by name. The first argument in most functions is `data` or `x`. It is custom to usually include the first argument by position and then all subsequent arguments by name.

```
mean(numeric_vector, trim = 0.2)
```

```
## [1] 5.5
```

R Packages

Base R

Opening RStudio automatically loads "base R", a fundamental collection of code and functions that handles simple operations like math and system management.

For years, R was only base R. New paradigms in R have developed over the last fifteen years that are more intuitive and more flexible than base R. Next week, we'll discuss the "tidyverse", the most popular paradigm for R programming.

All R programming will involve some base R, but much base R has been replaced with new tools that are more concise. Just know that at some point you may end up on a Stack Overflow page that looks like alphabet soup because it's in a paradigm that you have not learned.

One other popular R paradigm is `data.table`. We will not discuss `data.table` in this class.

Extensibility

R is an *extensible* programming language. It was designed to allow for new capabilities and functionality.

R is also *open source*. All of it's source code is publicly available.

These two features have allowed R users to contribute millions of lines of code that can be used by other users without condition or compensation. The main mode of contribution are R packages. Packages are collections of functions and data that expand the power and usefulness of R.

The predecessor of R, the S programming language, was designed to call FORTRAN subroutines. Accordingly, many R packages used to call compiled FORTRAN code. Now, many R packaged call compiled C++ code. This gives users the intuition of R syntax with better performance. Here's a brief history of R and S.

CRAN

Most R packages are stored on the Comprehensive R Archive Network (CRAN). Packages must pass a modest number of tests for stability and design to be added to CRAN.

`install.packages()`

Packages can be directly installed from CRAN using `install.packages()`. Simply include the name of the desired package in quotes as the only argument to the function.

Installation need only happen once per computer per package version. It is customary to never include `install.packages()` in a `.R` script.

Exercise

For practice, let's install the `RXKCD` package so we can view some comics in R.

```
install.packages("RXKCD")
```

. . .

`library()`

After installation, packages need to be loaded once per R session using the `library()` function. While `install.packages()` expects a quoted package name, it is best practice to use unquoted names in `library()`.

It is a good idea to include `library()` statements at the top of scripts for each package used in the script. This way it is obvious at the top of the script which packages are necessary.

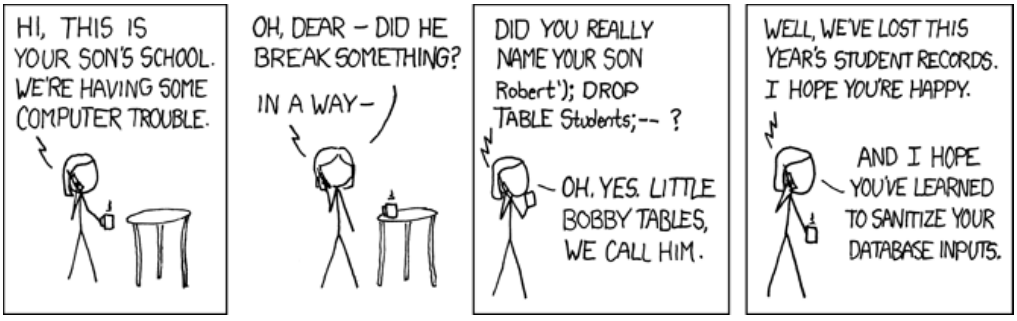
Exercise

For practice let's load the `RXKCD` package.

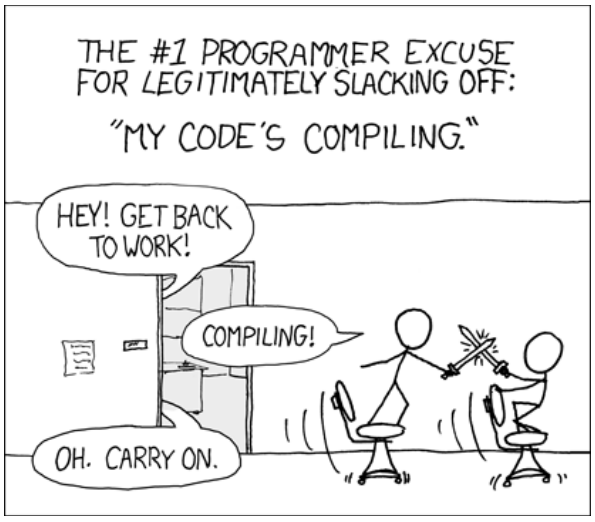
```
library(RXKCD)
```

Finally, let's look at some comics!

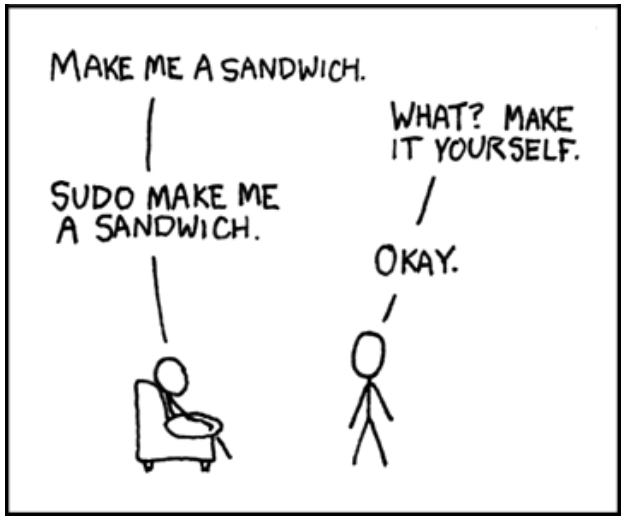
```
meta_data <- getXKCD(which = 327)
```




```
meta_data <- getXKCD(which = 303)
```




```
meta_data <- getXKCD(which = 149)
```



. . .

`::`

Sometimes two packages have functions with the same name. `::` can be used to directly access an exported R object from a package's namespace.

`dplyr::select()`

`MASS::select()`

Organizing an Analysis

R Projects

R Projects, proper noun, are the best way to organize an analysis. They have several advantages:

- They make it possible to concurrently run multiple RStudio sessions.
- They allow for project-specific RStudio settings.
- They integrate well with Git version control.
- They are the "node" of relative file paths. (more on this in a second) This makes code highly portable.

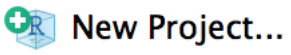
Exercise

Before setting up an R Project, go to Tools > Global Options and uncheck "Restore most recently opened project at startup".

. . .

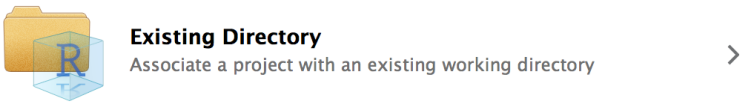
Every new analysis in R should start with an R Project. First, create a directory that holds all data, scripts, and files for the analysis. Storing files and data in a sub-directories is encouraged. For example, data can be stored in a folder called `data/`.

Next, click "New Project. . . " in the top right corner.



这个操作要自己试一下

When prompted, turn your recently created "Existing Directory" into a project.



Upon completion, the name of the R Project should now be displayed in the top right corner of RStudio where it previously displayed "Project: (None)". Once opened, .RProj files do not need to be saved. Double-clicking .Rproj files in the directory is now the best way to open RStudio. This will allow for the concurrent use of multiple R sessions and ensure the portability of file paths. Once an RStudio project is open, scripts can be opened by double-clicking individual files in the computer directory or clicking files in the "Files" tab in the top right of RStudio.

Exercise

Let's walk through this process and create an R project for this class.

...

Filepaths

Windows file paths are usually delimited with \. *nix file paths are usually delimited with /. Never use \ in file paths in R. \ is an escape character in R and will complicate an analysis. Fortunately, RStudio understands / in file paths regardless of operating system.

Never use `setwd()` in R. It is unnecessary, it makes code unreproducible across machines, and it is rude to collaborators. R Projects create a better framework for file paths. Simply treat the directory where the R Project lives as the working directory and directories inside of that directory as sub-directories.

For example, say there's a `.Rproj` called `starwars-analysis.Rproj` in a directory called `starwars-analysis/`. If there is a .csv in that folder called `jedi.csv`, the file can be loaded with `read_csv("jedi.csv")` instead of `read_csv("H:/ibp/analyses/starwars-analysis/diamonds.csv")`. If that file is in a sub-directory of starwars-analysis called data, it can be loaded with `read_csv("data/jedi.csv")`. The same concepts hold for writing data and graphics.

This simplifies code and makes it portable because all relative file paths will be identical on all computers. To share an analysis, simply send the entire directory to a collaborator or share it with GitHub.

Here's an example directory:

```
starwars-analysis/
    starwars-analysis.RProj
    README.md
    data/
        droid.csv
        jedi.csv
        sith.csv
    scripts/
        merge-and-clean.R
        regressions.R
        star-wars-report.Rmd
    output/
        star-wars-report.html
    www/
        styles.css
        images/
            c3p0.png
            r2ds.png
```

Getting help

Googling

When Googling for R or data science help, set the search range to the last year or less to avoid out-of-date solutions and to focus on up-to-date practices. The search window can be set by clicking Tools after a Google search.

Stack Overflow

Stack Overflow contains numerous solutions. If a problem is particularly perplexing, it is simple to submit questions. Exercise caution when submitting questions because the Stack Overflow community has strict norms about questions and loose norms about respecting novices.

RStudio community

RStudio Community is a new forum for R Users. It has a smaller back catalog than Stack Overflow but users are friendlier than on Stack Overflow.

CRAN task views

CRAN task views contains thorough introductions to packages and techniques organized by subject matter. The Econometrics, Reproducible Research, and and Social Sciences task views are good starting places.

Twitter

Twitter is mostly bad. But the #rstats hashtag and #rstats community are mostly good. They are also generally inclusive and civil. In particular, open sources developers like Hadley Wickham (@hadleywickham), Jenny Bryan (@JennyBryan), and Joe Cheng (@jcheng) are active.