Ten simple rules for selecting an R package

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Abstract

R is an increasingly preferred software environment for data analytics and statistical computing among scientists and practitioners. Packages markedly extend R's utility and ameliorate inefficient solutions. We outline ten simple rules for finding relevant packages and determining which package is best for your desired use.

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- RStudio   8
- ROpenSci   9
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Introduction   13

R is a programming language and environment for statistical computing and graphics   14
that was developed by statisticians and is maintained by an international group of core   15
contributors [2]. Unlike several popular proprietary languages such as MATLAB or SAS,   16

R is freely available, open source, and easily extensible; the user can access, alter, extend, and share code for various applications. Accordingly, a vibrant community of R users has emerged, many of whom develop R packages to complement and extend the functionality of base R. There are numerous analogies in computing between programming and culinary arts: recipe structures, coding cookbooks, and the like. To conceptualize packages, imagine you are the chef, R is the kitchen, and packages are the special gadgets which allow you to cook and bake new recipes. R packages are coding delectables that enable you to perform practical tasks and solve problems with interesting techniques.

Are there R packages for wrangling and cleaning data frames, designing interactive applications for data visualization, or performing dimensionality reduction? Yes! How do you *find* an R package that will help you train regression and classification models, assess the beta diversity of a population, or analyze gene expression microarray data? This answer is not as simple; there are tens of thousands of R packages. As a natural consequence of the open-source nature of R, there is considerable variation in the quality of R packages and nontrivial differences among those that provide similar tools. The advanced R user—having developed an intuition for their workflow—may be relatively confident when searching for and selecting packages. By contrast, an obstacle that characterizes learning R at the outset is the struggle to (1) find a package to accomplish a particular task or solve a problem of interest and (2) choose the best package to perform that task. Even so, some obscure and complicated recipes make it difficult for an experienced chef to select the best tools.

In both coding and life, we endeavor to make choices that optimize outcomes. Just as one may go about shopping for shoes, deciding which graduate program to pursue, or conducting a literature review, there is a science behind selection. We inform our decisions by assessing, comparing, and filtering options based on indicators of quality such as utility, association, and reputation. Likewise, choosing an R package requires attending to similar details. We outline ten simple rules for finding and selecting R packages, so that you will spend less time searching for the right tools and more time coding delightful recipes.

Rule 1: Consider your purpose

Usually, there are several ways to accomplish the same task or arrive at the same solution while programming, albeit some ways are more elegant and efficient than others. To optimize your workflow, consider your purpose by first identifying your task and goal, and then defining the scope of the task and steps to achieve it. For some tasks, coding your own recipe with existing tools is practical, while other tasks benefit from new tools.

If the scope of your task is simple or reasonable, given your knowledge and skills, using an R package may not be appropriate. That is, some instances do not warrant additional functions, datasets, or documentation. There can be advantages of coding in base R to complete your task or solve your problem. In particular, when you code from scratch, you know precisely what you are running; thus, your script may be easier to decipher and maintain over time. Conversely, packages require you to rely on shared code with features or underlying processes of which you may not be aware.

Packages are favorable in the same sense as kitchen tools: when a task has a broad or complex scope beyond what you can (or desire) to attempt from scratch. While there are ways to cook up an algorithm using for loops and conditionals in base R, a relevant package may accomplish the same goal in a more reproducible, efficient manner, with less code and fewer bugs. The more reasonable it is for a given task to be abstracted away from its context, the more plausible it is that someone has generalized its themes, developed efficient algorithms, and organized them in an intuitive way to share with

other R users. Extensive tasks justify sophisticated frameworks with several functions that form a cohesive package. Many processes that involve data—although varying in application—are ubiquitous. Data manipulation is one such common task that has been streamlined by packages such as `dplyr` and `tidyr` [3,4] (see Table 1). Nevertheless, there are indeed packages for seemingly singular tasks, which you may favor over coding from scratch. Some R packages are small and have a specific use conducive to tasks that require highly specialized functions. For example, there is a package for converting English letters to numbers as on a telephone keypad [5].

Which existing functionalities in base R could be improved in context of your problem? Which new functionalities would you like to add to base R to expand what you can do? If you define your purpose by making observations about and considering limitations of your current toolbox before you start searching for new tools, you will be more likely to recognize what you do and do not need. Develop a list of domain-specific keywords that relate what you are trying to do to how one may go about doing it in order to narrow your search. Identify the type of inputs you have and envision working with them; contemplate the desired outputs and corresponding format. For instance, suppose you are using Bioconductor packages in analyses and have data you want to visualize; you must consider that the inputs will be of a certain class—namely, S4 objects—which impose restrictions when creating graphics [6]. The data visualization package you use should address such limitations.

Rule 2: Spend time searching; find and collect options

Those who have used R packages may know that, although leveraging existing tools can be advantageous, the initial challenge of finding a suitable package for a given task can obstruct potential benefits. Relatedly, new R users who are unfamiliar with the structure and syntax of the language may be hindered by the process of finding packages because they do not know where to search, what to look for, or how to sift through options. R packages are mentioned in a variety of places online, in print, and elsewhere. You can discover new packages any time you learn R-related topics, collaborate with other R users, or browse the internet.

Learn

Packages are essential to venturing beyond base R and, thus, quickly become an integral aspect of advancing your R skills. When learning how to program in R, you are typically introduced to some of the most common packages, which tend to have more general purposes (**Table 1**). In addition, reputable online tutorials, courses, and books are helpful resources for acquiring knowledge about packages that are versatile and reliable—many of which are short, accessible, and either affordable or offered at no cost to the learner. We recommend online R programming courses such as those through Coursera and Codeacademy for interactive learning and R book series including the RStudio books and Springer titles for further reading.

Collaborate

An inclusive and collaborative community is an overlooked, yet integral, aspect of a software's success [7]. A defining feature of R is the enthusiasm of its users and developers alike. The R community has a widespread internet presence across various platforms; however, members are markedly active on Twitter, a place where R users seek help, share ideas, and stay informed on `#rstats` happenings, including releases of new packages [8]. Beyond social media, featured pages and R blogs serve as another informal, up-to-date, and more detailed avenue for communicating and promoting R-related information (**Table ?**). Notably, Joseph Rickert, Ambassador at Large for

RStudio, writes monthly posts on the R Views blog highlighting exceptional new R ₁₁₆
packages. Rickert also features special articles about recently released packages and lists ₁₁₇
of top packages within certain categories, including Computational Methods, Data, ₁₁₈
Machine Learning, Medicine, Science, Statistics, Time Series, Utilities, Visualization. ₁₁₉

A developer of an R package may intend for it to be private (exclusively for personal ₁₂₀
or professional use) or public (at no cost and available for use by anyone) [9]. If your ₁₂₁
task is specific to a line of research, consult colleagues to see if they have relevant ₁₂₂
(private) code they would be willing to share. Alternatively, literature in your field may ₁₂₃
either introduce R packages developed to solve a unique data science problem or ₁₂₄
mention packages used during the research process. The former may be published in the ₁₂₅
Journal of Statistical Software, *The R Journal*, or *BMC Bioinformatics*, for example, ₁₂₆
and search queries that include `"R package"` with domain keywords will narrow results. ₁₂₇
The latter requires identifying authors who used R in their analyses; useful packages ₁₂₈
may be mentioned in the Methods and/or References sections. You can search for ₁₂₉
packages directly by name in Google Scholar: the `Cited by` link displays the number of ₁₃₀
times a package has been cited and connects to a page with those publications. Lastly, ₁₃₁
you can attend conferences to learn about recent R package developments and ₁₃₂
applications. There are two major annual R conferences: rstudio::conf for industry and ₁₃₃
useR! (not exclusively) for academia. Conferences in your field may foster connections ₁₃₄
with fellow scientists who use R for similar tasks and help you collect information about ₁₃₅
packages related to your expertise. Talks and presentations at conferences are often ₁₃₆
recorded and made available online for playback. ₁₃₇

Browse ₁₃₈

The solution-seeking tactics we employ for many tasks nowadays may lead you to ₁₃₉
think that finding R packages relies heavily on internet search queries. Indeed, search ₁₄₀
engines such as Google return ample pages related to anything `"...in R"`. However, ₁₄₁
this approach can lead to frustration and confusion when attempting to find a package ₁₄₂
tailored to your purpose (see Rule 1). Instead, we recommend initially searching for ₁₄₃
packages in repositories such as the Comprehensive R Archive Network (CRAN), ₁₄₄
GitHub, or Bioconductor, all of which will be further discussed in Rule 3. In particular, ₁₄₅
CRAN Task Views are concentrated topics from certain disciplines and methodologies ₁₄₆
related to statistical computing that categorize R packages by the tasks they perform ₁₄₇
(e.g., Econometrics, Genetics, Optimization, Spatial). In the HTML version, you can ₁₄₈
browse alphabetized subcategories within each Task View and read concise descriptions ₁₄₉
to find tools with specific functions. Alternatively, you can access Task Views directly ₁₅₀
from the R console with `ctv::CRAN.views()`. To date, there are 41 Task Views that ₁₅₁
collectively contain thousands of packages which are curated and regularly tested. ₁₅₂
Moreover, CRAN Task Views provide tools that enable you to automatically install all ₁₅₃
packages within a targeted area of interest. Ultimately, by providing task-based ₁₅₄
organization, easy simultaneous installation of related packages, meta-information, ₁₅₅
ensured maintenance, and quality control, CRAN Task Views address several major ₁₅₆
user-end issues that have arisen due to the sheer quantity of available packages [10]. ₁₅₇
Relatedly, CRANberries is a hub of information about new, updated, and removed ₁₅₈
packages from the CRAN network. Another place to find well-maintained tools is ₁₅₉
through rOpenSci packages. These filterable and searchable R packages are organized ₁₆₀
by name, maintainer, description, and status (i.e., activity, association, review). ₁₆₁

Rule 3: Check how it's shared ₁₆₂

Packages can be shared through a variety of platforms; a single package is often ₁₆₃
available in multiple places. While repositories are the primary way in which developers ₁₆₄
share packages for both public and private use, there are alternatives. In lieu of making ₁₆₅

packages accessible to everyone via internet repositories, some developers share their ₁₆₆ code in zipped files or directly with collaborators. As far as R packages are concerned, a ₁₆₇ repository is essentially a warehouse for tools before they enter your kitchen; in ₁₆₈ computing terms, a repository is analogous to a cloud because it is a central location in ₁₆₉ which data is stored and managed. There is growing concern about whether there are ₁₇₀ too many R packages and a simultaneous call for quality control [11]. Some repositories ₁₇₁ impose vetting mechanisms that tame unwieldy aspects of the R ecosystem by regularly ₁₇₂ checking underlying code and managing corresponding webs of dependencies. The ₁₇₃ traditional repositories for R packages are CRAN, Bioconductor, and GitHub; however, ₁₇₄ there are lesser-known remote repositories that have unique properties. ₁₇₅

Much of what we know about statistical methods and algorithms is wrapped up in R ₁₇₆ packages—written and documented in various ways by R users. The CRAN package ₁₇₇ repository is the most established and primary source from which you can install R ₁₇₈ packages. You can simply use the `install.packages()` function to install a package ₁₇₉ from CRAN; source and/or binary code are automatically saved to your computer in a ₁₈₀ designated package library [12]. When you want to use a particular package, you load it ₁₈₁ to your R session via the `library()` function from base R. Due to its longevity and ₁₈₂ historical role, Rickert asserts that "CRAN is the greatest open-source repository for ₁₈₃ statistical computing knowledge in the world" [9]. Evidently, much of what we know ₁₈₄ about statistics is housed in CRAN where people share such information. The R ₁₈₅ Foundation manages CRAN and imposes strict regulatory practices for the selection ₁₈₆ and maintenance of the packages they host. A package must pass a series of stability ₁₈₇ tests in accordance with the CRAN Repository Policy before obtaining publication ₁₈₈ privileges [13]. As such, CRAN only considers packages that make a substantial ₁₈₉ contribution to statistical computing and graphics. CRAN maintainers actively monitor ₁₉₀ source and contributed packages to ensure they are compatible with the latest version of ₁₉₁ R and modify or remove packages that do not uphold publication quality. ₁₉₂

The Bioconductor project was motivated by a need for transparent, reproducible, ₁₉₃ and efficient software in computational biology and bioinformatics and supports the ₁₉₄ integration of computational rigor and reproducibility in research on biological processes ₁₉₅ [14]. The R environment and its package system is fundamental to the implementation ₁₉₆ of Bioconductor's interoperable and object-oriented (S4) infrastructure. Bioconductor ₁₉₇ software is in the form of coordinated, peer-reviewed R packages. Bioconductor boasts a ₁₉₈ modularized design, wherein data structures, functions, and the packages that contain ₁₉₉ them have distinct roles that are accompanied by thorough documentation. ₂₀₀ Accessibility is a pillar of the Bioconductor project, thus all forms of documentation, ₂₀₁ including courses, vignettes, and interactive documents, are curated for individuals with ₂₀₂ expertise in adjacent disciplines and minimal experience with R (see Rule 4) [14]. ₂₀₃ Similar to CRAN, Bioconductor has strict criteria for package submissions: a package ₂₀₄ must be relevant to high-throughput genomic analysis, interoperable with other ₂₀₅ Bioconductor packages, well-documented, supported in the long-term, exclusive to ₂₀₆ Bioconductor, and comply with additional package guidelines [15]. Bioconductor ₂₀₇ packages facilitate the analysis and comprehension of biological data and help users ₂₀₈ solve problems that arise when working with high-throughput genomic data such as ₂₀₉ those related to microarrays, sequencing, flow cytometry, mass spectrometry, and image ₂₁₀ analysis. As a subset of the R community, Bioconductor has a supportive and ₂₁₁ innovative community that hosts annual meetings and conferences. ₂₁₂

The rapid uptick in package development and subsequent inter-repository ₂₁₃ dependencies has sparked an ongoing debate on whether regulated repositories such as ₂₁₄ CRAN and Bioconductor are preferable to other distribution platforms, namely public ₂₁₅ version control systems like GitHub [9,16][17]. While there are practical downsides to ₂₁₆ their restrictive practices, the benefits of exclusive repositories are evident. Nevertheless, ₂₁₇

there are considerable advantages to hosting a package on GitHub [9,16]. GitHub is a ₂₁₈ popular online user interface and multi-purpose development platform that is also ₂₁₉ effective in distributing R packages. An increasing number of packages are hosted on ₂₂₀ GitHub during the development stages; if developers choose not to distribute their ₂₂₁ package through GitHub, the stable release versions of such packages are often ₂₂₂ published on CRAN or Bioconductor [18]. GitHub provides R users with open access to ₂₂₃ package code, a timeline of help resources (see Rule 4), a direct line of communication ₂₂₄ to developers, and permits discovery of up-and-coming packages (see Rule 2). You can ₂₂₅ install the latest version of packages from GitHub via `devtools::install_github();` ₂₂₆ however, the decentralized nature of GitHub is not conducive to a tool that ₂₂₇ automatically locates and installs corresponding dependencies [19]. For developers, ₂₂₈ GitHub provides a convenient means by which anyone can share and contribute public ₂₂₉ or private code without barriers to entry. Authors collaborate within a ₂₃₀ version-controlled system to develop and distribute packages, including those with ₂₃₁ dependencies that are not on CRAN or Bioconductor. Further, the `drat` (Drat R ₂₃₂ Archive Template) package enables developers to design individual repositories and ₂₃₃ suites of coordinated repositories for packages that are stored in and/or distributed ₂₃₄ through GitHub [20]. Both R users and package developers benefit from interactive ₂₃₅ feedback channels through GitHub Issues and the Star rating system. ₂₃₆

Most novice R users will rarely encounter packages that are not shared through the ₂₃₇ abovementioned platforms. The non-profit organization, rOpenSci, runs a repository as ₂₃₈ part of their commitment to promote open science practices through technical and ₂₃₉ social infrastructure for the R community [21]. The repository only includes packages ₂₄₀ that have passed their open review process, which is compliant with GitHub ₂₄₁ infrastructure. Further, GitLab is git-based version control and collaborative cloud for ₂₄₂ package production and deployment. It is an alternative to GitHub for production of ₂₄₃ large-scale packages that require continuous integration and continuous deployment for ₂₄₄ testing data and code to ensure a stable end-product. There are platforms strictly for ₂₄₅ the development, rather than distribution, of R packages such as R-Forge and ₂₄₆ Omegahat, which are beyond the scope of this paper [22]. ₂₄₇

Rule 4: Explore the availability and quality of help ₂₄₈

There has been a call for the development of centralized resources in statistical ₂₄₉ computing to enable a common understanding of software quality and reliability: ₂₅₀ software information specified in publications, domain-specific semantic dictionaries, ₂₅₁ and a single metadata resource for statistical software [11]. No such resources have been ₂₅₂ consolidated to serve these purposes and, given the decentralized nature of today's ₂₅₃ information society, it is questionable whether they will emerge. Current sources of ₂₅₄ information related to R packages are dispersed and plentiful. On one hand, this allows ₂₅₅ users to explore diverse solutions and discover new tools; on the other, not knowing ₂₅₆ where to find help can lead to inefficient and ineffectual roundabouts. Clearly, not all ₂₅₇ package resources share the same level of quality and the fact that there are many ₂₅₈ resources in aggregate does not imply that every package is associated with the same ₂₅₉ availability of resources. While all R packages warrant some minimal standard of ₂₆₀ documentation, beginners and users of complex packages might desire more. ₂₆₁

You can access information about R packages along with an index of help pages from ₂₆₂ the console via `help(package = "...")`. Package information will vary; ideally, ₂₆₃ packages should have thorough documentation, but at minimum, every R package should ₂₆₄ include a `DESCRIPTION` file with metadata. The `DESCRIPTION` is a succinct record of the ₂₆₅ package's purpose, dependencies, version, date, license, associations, authors, and other ₂₆₆ technical details. The help pages feature information about the structure of functions ₂₆₇

within the package and contain executable examples to demonstrate the relationship 268
between various inputs and outputs. If the `DESCRIPTION` and help pages alone leave you 269
wanting, the package likely does not have further (quality) documentation and therefore 270
should not be your first choice, if comparable options exist. In short, if the developer 271
cannot initially communicate how their tool works, then you may not want to use it in 272
your kitchen (read: if the instruction manual is useless, do not use the blender). 273

Fortunately, plenty of R packages include additional documentation beyond mere 274
descriptions. The documentation that accompanies functions within packages is critical; 275
the fact that anyone can read the documentation anytime and use it to guide their own 276
work facilitates extensibility. RDocumentation is a searchable website, package 277
(`install.packages("RDocumentation")`), and JSON API for obtaining integrated 278
documentation for packages that are on CRAN, Bioconductor, and GitHub. This is a 279
subsidiary reason why packages shared on these platforms tend to be superior (see Rule 280
3). RDocumentation may include: an overview, installation instructions, examples of 281
usage, functions, guides, and vignettes. Most software documentation is rather technical 282
and extraneous to new users whereas a vignette is a practical type of documentation in 283
the form of a tutorial. A vignette is a detailed, long-form document that describes the 284
problems an R package can solve, then illustrates applications through clear examples of 285
code with coordination of functions and explanations of outcomes. Packages can have 286
multiple vignettes; you can view or edit a specific vignette or obtain a list of all 287
vignettes for a package of interest via the `vignette()` function. 288

Some packages are branded quite well and include a comprehensive set of resources. 289
Implicitly, this indicates that the authors are at least serious about their package 290
development, which may lead you to infer that they know what they (and their package) 291
are doing. Exemplary documentation can signify an exceptional package. For instance, 292
some packages have websites and/or books. One popular method that developers use to 293
publish books about their package is through `bookdown`, a relatively new extension of R 294
Markdown that is structured in such a way that integrates code, text, links, graphics, 295
videos, and other content in a format that can be published as a free, open, interactive, 296
and downloadable online book [23]. The `bookdown` package itself has an online book 297
that details usage of the package [24]. `Rccp` is another package with notable 298
documentation and first-rate help resources; the developers maintain both a main and 299
additional website with a wealth of organized information about the package and 300
resources, including examples, associations, publications, articles, blogs, code, books, 301
talks, a mailing list, and links to other resources with `Rccp` tags. Aside from the 302
documentation and resources from the developer, further information about some R 303
packages is available in video tutorials, webinars, and code demonstrations (i.e., 304
"demos"). As of RStudio v1.3, you can access tutorials powered by the `learnr` package 305
from the Tutorial pane in the IDE [25]. Finally, keep in mind that RStudio creates 306
cheatsheets of concise usage information for popular packages through code and 307
graphics organized by purpose. Cheatsheets can be accessed directly via the RStudio 308
Menu (Help > Cheatsheets) or from the RStudio website on which you can subscribe to 309
cheatsheet updates and find translated versions. 310

While using a package, anticipate complications beyond the scope of documentation. 311
In this case, you will use resources that involve *asking* for help—should the occasion 312
arise, you want to be assured that you will find a satisfactory answer. In the past, the 313
antiquated R-help mailing list was the only way to seek assistance; since, the R 314
community has formed, with inclusion and creative problem-solving as hallmarks of its 315
online presence [26]. The modern R-help mailing list to which you can subscribe and 316
send questions is moderated by the R Core Development Team and includes additional 317
facets for major announcements about the development of R and availability of new code 318
(R-announce) and new or enhanced contributed packages (R-packages) [27]. Certain 319

packages have independent listservs; `statnet` is an example of a suite of packages that has its own community listserv. If a package has a development repository on GitHub, check the Issues to verify that the maintainer is responsive to posts and fixes bugs in a timely manner. In addition, you can search discussion forums such as Stack Overflow, Cross Validated, and Talk Stats to assess the activity associated with the package in question. Analyses of the popularity of comparable data analysis software in email and discussion traffic suggest that R is rapidly becoming more prevalent and is the leading language by these metrics [28,29]. When you encounter a problem, it is good practice to first update the package to see if the problem is due to a bug in a previous version—if the problem persists, seek help by finding or posting a reproducible example [30]. Overall, avoid using a package if the quality and quantity of related resources is lacking.

Rule 5: Verify the credibility of the author(s)

Just as research is a library of shared insight, open source software is a collection of shared tools. We care about who writes the articles we read; we should also care, arguably more, about who creates the tools we use. Although R is grounded in statistical computing and graphics, there is variation R users' backgrounds and skills, and the same is true for R developers. Associations and reputation are often a proxy for quality; in this way, the process of evaluating and comparing R packages is no different than other decisions. In fact, as you become more immersed in the R community, you will find that name recognition is a crucial factor that determines why you trust certain tools and hesitate to use others [31].

You can assess the credibility of R package developers through direct and indirect signals. Who made the package? Consider whether expertise in a certain domain is vital to the design and creation of the tool. Research the authors' associations in academia, industry, and/or laboratories and gauge the extent to which they have a primary role in R development. Further, you can learn more about their experience, active contributions to the R community, and history related to package development by exploring their profiles on GitHub, Google Scholar, Research Gate, Twitter, or personal or package websites. If an author has such a history, peruse their portfolio of packages to see if any are highly regarded or recognizable. Frequent commits and effective resolutions of GitHub Issues can reveal the authors' priorities and commitment. If the package was developed by multiple authors, research each of them to evaluate the robustness of the team. By extension, these indicators of developer involvement and reputation will help you discern whether a package is worthy of your trust and time.

Rule 6: Investigate the package development

You do not need to be a software engineer to identify strong package development. Scientific software developers sometimes neglect best practices; indeed, these shortcomings are evident in the tools they create [32]. There are concrete ways to measure a tool's robustness beyond whether it works for those who did not create it. R packages often depend on other R packages; you should check the reputations of such *dependencies* when selecting a package—quality packages will rely on a solid web of quality packages. What's more, like other types of software, well-maintained R packages have multiple versions corresponding to iterative releases to indicate that the package is compatible with dependencies and loyally updated (e.g., bug fixes, general improvements, new functionality) [1,12]. You can explore the version history of a package to see if it is up-to-date. As a user, there are two additional development protocols that you can further investigate to assess the underlying stability and utility

of a package: unit tests and version control. [367]

A responsible developer with a consistent and reproducible workflow will implement [368] formal testing on their code to examine expected behavior via an automated process [369] called unit testing [12,33]. Although inconvenient at the outset, the developer—and by [370] extension, the package user—will benefit from unit testing, which results in fewer bugs, [371] a well-designed code structure, an efficient workflow, and robust code that is not [372] sensitive to major changes in the future [12]. To alleviate the burdens of unit testing, [373] `testthat` is a popular, integrative R package that helps developers create reliable [374] functions, minimize error, and visualize progress through automatic code testing [34]. [375] Developers are also interested in quantifying the amount of code in their package that [376] has been tested. Test coverage, a measurement of the proportion of code that has [377] undergone unit testing, is an objective metric for package developers, contributors, and [378] users to evaluate code quality. Many developers use the `covr` package to generate [379] reports and determine the magnitude of coverage on the function, script, and package [380] levels [35]. Relatedly, developers who host their packages on GitHub, post status badges [381] in the overview (`README`) section of the repository webpage. GitHub badges are a [382] common self-imposed method to signal use of best practices and motivate developers to [383] produce a product that is high in quality and transparency [36]. You may see, for [384] example, license, dependency, or style badges, all of which are good indicators of [385] package caliber; however, particular to this Rule, you should look for code coverage [386] (`codecov`) badges which reveal the percentage of test coverage. [387]

As we mentioned in Rule 3, version control has an essential role in package [388] development and computational literacy more broadly [12,37]. Version control is like a [389] time capsule for your workflow because it monitors and tracks changes to files as a [390] project evolves, and stores them as previous versions to be recovered if necessary. In [391] other words, "version control is as fundamental to programming as accurate notes about [392] lab procedures are to experimental science" [37] p6. Git is a decentralized open-source [393] version control system that is useful regardless of whether a project is independent or [394] collaborative [38]. GitHub works in conjunction with Git to provide a powerful [395] structured system to organize and manage components of a project for others and your [396] future self. A growing number of scientists have research programs based in GitHub, [397] which has become a revolutionary tool for productive team science and distributed [398] development efforts [1,39]. As you may expect, Git coupled with GitHub is the version [399] control duo of choice among serious R package developers [12]. Thus, if the package you [400] are interested in using is among the thousands hosted on GitHub, this is evidence that [401] the developer is at least committed to a logical, open, and reproducible workflow, [402] suggestive of more time spent designing their tool. [403]

Rule 7: Read, research literature, seek evidence of [404] peer review [405]

Peer review is an important aspect of scientific research, not least because it establishes [406] scholarly credibility. You can research information about an R package in different [407] forms of literature and determine the extent to which it has been validated by the [408] scientific community. Some journals publish articles about R packages themselves while [409] others feature work that used a particular package (see Rule 2). These packages are [410] technically sound and have made a substantial contribution to their fields and/or a [411] common data science problem. In response to the rising number of researchers creating [412] tools and software to work with their data, GitHub has granted developers the ability to [413] obtain a Digital Object Identifier (DOI) for any GitHub repository archive so that code [414] can be cited in academic literature [40]. If a package has such a DOI, you can explore [415]

the network of research associated with that package. Many R packages are associated with content in books and series from scientific publishers such as Springer. More directly, rOpenSci, is a unique example of an ecosystem of open-source tools with peer reviewed R packages (see Rule 3) [21].

Rule 8: Quantify how established the package is

Consulting data to inform comparisons is never a bad idea; numerical data associated with R packages will give you an impression of how regarded the tool is and whether it has stood the test of time. Since there are tens of thousands of R packages, you may be wondering how they stack up in terms of popularity. On GitHub, a large number of Stars, Forks, and Watchers associated with a package implies a substantial following and widespread usage [31]. Likewise, the number of Google Scholar citations is a metric of a package's impact on scientific research and utility in research contexts (see Rule 2). RDocumentation (see Rule 4) is rich with stats on R packages. RDocumentation hosts a live Leaderboard with trends including the number of indexed packages and indexed functions, most downloaded packages, most active maintainers, newest packages, and newest updates. What's more, each package is assigned a percentile rank—featured on its RDocumentation page—that quantifies the number of times a package has been downloaded in a given month. A ranking algorithm computes the direct, user-requested monthly downloads by accounting for reverse dependencies (indirect downloads) so packages that are commonly depended upon, and hence frequently downloaded, do not skew the calculation [41]. You can research stats on corresponding dependencies for a more holistic picture. To further determine if a package is well-established in the R community, refer to the number of versions and updates (more is better) as well as the date of the most recent versions and updates (newer is better).

Rule 9: Put the package to the test

If you are unable to decide whether to use a package based on prior Rules, test it out. Similarly, if you have narrowed your options, work with each to highlight differences. Exploring the package and engaging in trial and error using your skills in context of your goal will illuminate technical details and solidify any doubts. Note, in the case that the package you want to try has been shared as a zipped file, you can use a GitHub mirror of CRAN via `devtools::install_github("username/reponame")` as an alternative to downloading a large or potentially corrupted zipped file.

At this point, what you have learned about the package should be quite helpful. If the development and documentation are sound, the package should come with a test script or working example that you can run after installation [32]. Vignettes include many common data science problems with solutions; you can run the code examples, tweak them, and compare the outputs. In general, it is essential to know the behavior of different functions within a package, how they interact, and how outputs respond to changes in inputs. Suppose you are testing a package with sparse documentation such that function descriptions often include "..." and the argument descriptions seem incomplete. This will be problematic if making a reasonable change to an argument results in an incomprehensible error for which you cannot find help. When this happens, you may not want to use the package for your task.

Sometimes packages do not interact well with other packages; a recipe prepared with an odd combination of tools will not turn out. If you are interested in working with a certain package but are already using other packages in your workflow, you will need to verify that they work together. More precisely, you should check the *interoperability* of

all the packages you want to use. A given package may be highly specialized and ⁣⁣463
incompatible with certain packages in general, or simply have a few tolerable quirks for ⁣⁣464
which you can develop workarounds. There are some packages that are masterful at ⁣⁣465
doing what they are made to do, yet incongruous with other packages. Such packages ⁣⁣466
might, for example, use S3 or S4 objects, which are two main approaches developers use ⁣⁣467
to implement object-oriented programming in R. Many packages for spatial analysis as ⁣⁣468
well as those from Bioconductor tend to use S4 objects to represent data [14]. On the ⁣⁣469
other hand, the `tidyverse`, a unified suite of packages with an grammatical structure ⁣⁣470
employed within a "pipeline", expects data frame objects [42]. Thus, when you are ⁣⁣471
working in the `tidyverse`, you cannot incorporate S3 and S4 objects into the ⁣⁣472
framework unless their corresponding functions are the final step in the pipeline. The ⁣⁣473
`broom` package, and the bioinformatics analog, `biobroom`, aim to alleviate these ⁣⁣474
disruptions by converting untidy objects into tidy data, thereby making it easier to ⁣⁣475
integrate statistical functions into the structure of the `tidyverse` workflow [43,44]. ⁣⁣476
Furthermore, the `caret` package facilitates interoperability for machine learning ⁣⁣477
packages by providing a uniform interface for modeling with various algorithms from ⁣⁣478
different packages that would otherwise have independent syntax [45]. ⁣⁣479

Rule 10: Develop your own package ⁣⁣480

Alternative solutions can be sought when a package to solve your data science problem ⁣⁣481
is nonexistent. An R package is the fundamental unit of shareable code; rather than ⁣⁣482
exclusively being a user of packages, you can create them—more easily than you may ⁣⁣483
think [12]. The reasons why you might want to create a package are abundant, ⁣⁣484
including necessity, innovation, standardization, automation, specialty, containment, ⁣⁣485
organization, sharing, collaboration, and extensibility. The essence of an R package is a ⁣⁣486
self-contained piece of statistical knowledge that can be used in combination with other ⁣⁣487
self-contained pieces of statistical knowledge of different shapes and sizes; the uniquely ⁣⁣488
structured functions within a package help us implement that knowledge and weave it ⁣⁣489
into novel scientific work. ⁣⁣490
    Whatever your motivation, packages are simply tools; you can create a package out ⁣⁣491
of any collection of specialty functions. Packages need not be formal nor entirely ⁣⁣492
cohesive. For instance, personal R packages such as `Hmisc` and `broman`, are comprised ⁣⁣493
of miscellaneous functions which the creator has developed and frequently uses [46,47]. ⁣⁣494
Functions are necessary for efficiency and warranted when you repetitiously copy and ⁣⁣495
paste your code while making slight modifications after each iteration [30]. The concept ⁣⁣496
of personal R packages demonstrates a unique purpose for packages beyond the ⁣⁣497
conventional. R packages are not solely reserved for specific tasks with comprehensive ⁣⁣498
methods; rather, package development can help you learn how to apply proper coding ⁣⁣499
techniques to writing functions and documentation with reproducibility and ⁣⁣500
collaboration in mind [48]. ⁣⁣501
    Although you may not anticipate that anyone else will use your tools, following best ⁣⁣502
practices for package development will yield more favorable outcomes. As a consumer of ⁣⁣503
shared packages, you know the inherent benefits of robust software development relative ⁣⁣504
to the quality of code, data, documentation, versions, and tests [32]. Similarly, creating ⁣⁣505
a valuable package for personal use requires consideration for your future self and ⁣⁣506
anticipation of distributing your code, should the need arise. Use version control and ⁣⁣507
take advantage of existing resources. Indeed, there are R packages that aid in package ⁣⁣508
development (e.g., `devtools`, `usethis`, `testthat`, `roxygen2`, `rlang`, `drat`) ⁣⁣509
[19,49][50][51][52][20]. In the case of collaboration, the R project within RStudio IDE, is ⁣⁣510
compatible with distributed development—a feature that couples well with version ⁣⁣511
control. There is no lack of effective organizational frameworks to reference in the ⁣⁣512

open-source R community; in fact, repositories for many exemplary packages are 513
available on GitHub. We recommend consulting resources authored by expert R 514
developers including *R Packages* by Hadley Wickham and the official manual, *Writing* 515
R Extensions, from CRAN [12,53]. 516

Conclusion 517

Computational reproducibility is surfacing as a central axiom in academia, as 518
researchers identify the need for means by which they can implement transparent 519
systems [54,55]. It follows that former approaches and traditional methods tend to be at 520
odds with productivity and collaboration; some variability in scientific outcomes can be 521
attributed to differences in workflow thus the absence of automation is deemed 522
irresponsible [56]. The open source R language has become the dominant quantitative 523
programming environment in academic statistics, enabling researchers to share 524
workflows and re-execute scripts within and across subsets of the scientific community 525
[56]. R is increasingly used by researchers in computational biology and bioinformatics, 526
one of many disciplines that is generating extensive heterogenous and complex data that 527
demand standard tools and rigorous methods to support reproducibility [14,57]. More 528
broadly, as the R ecosystem—in which the life of modern data analysis thrives—rapidly 529
evolves alongside the burgeoning R community, R is exhibiting sustained growth when 530
compared to similar languages, particularly in academia, healthcare, and government 531
[28]. 532

R packages are a defining feature of the language insofar as many are robust and 533
user-friendly. Some of the most prominent R packages are a result of the developer 534
abstracting common elements of a data science problem into a workflow that can be 535
shared and accompanied by thorough descriptions of the process and purpose. In this 536
way, R packages have effectively transformed how we interact with data in the modern 537
day in, perhaps, a more impactful manner than several revered contributions to 538
theoretical statistics [56]. Packages greatly enhance the user experience and enable you 539
to be more efficient and effective at learning from data, regardless of prior experience. 540
Nonetheless, the sheer quantity and potential complexity of available R packages can 541
undermine their collective benefits. Finding and choosing packages, particularly for 542
beginners, can be daunting and difficult. R users often struggle to sift through the tools 543
at their disposal and wonder how to distinguish appropriate usage. These ten simple 544
rules for navigating the shared code in the R community are intended to serve as a 545
valuable page in your computing cookbook—one that will evolve into intuition and yet 546
remain a reliable reference. May searching for and selecting proper tools no longer spoil 547
your appetite and dissuade you from discovering, trying, creating, and sharing new 548
recipes. 549

Table 1 (general packages) 550

```
library(kableExtra)
library(knitr)

# general packages data
gen_pkgs <- data.frame(
  Package = c("readr[note]",
              "dplyr[note]",
              "tidyr",
```

```
                  "broom[note]",
                  "purrr[note]",
                  "caret",
                  "keras",

                  "ggplot2[note]",
                  "kableExtra",
                  "rmarkdown"),

   Description = c("read rectangular data (e.g., csv, tsv, and fwf)",
                     "grammar of data manipulation",
                     "create tidy data",

                     "tidy model output",
                     "functional programming tools",
                     "train classification and regression models",
                     "R interface to a neural network library",

                     "data visualization",
                     "tables",
                     "reports"),

   Year = c("readr",
            "dplyr",
            "tidyr",

            "broom",
            "purrr",
            "caret",
            "keras",

            "ggplot2",
            "kableExtra",
            "rmarkdown"),

   Author = c("readr Wickham et al.",
              "dplyr Wickham et al.",
              "tidyr Wickham et al.",

              "broom Robinson et al.",
              "purrr Henry et al.",
              "caret Kuhn et al.",
              "keras Falbel et al.",

              "ggplot2 Wickham et al.",
              "kableExtra Zhu et al.",
              "rmarkdown Allaire et al."),

   Documentation = c("readr",
                     "dplyr",
                     "tidyr",
```

```r
                "broom",
                "purrr",
                "https://topepo.github.io/caret/index.html",
                "keras",

                "ggplot2",
                "kableExtra",
                "rmarkdown")
)
```

```r
# general packages table
kable(gen_pkgs, format = "latex", booktabs = TRUE) %>%
  # scale
  kable_styling(latex_options = "scale_down") %>%
  # separate rows by category
  pack_rows("Data Manipulation", 1, 3) %>%
  pack_rows("Statistical Modeling", 4, 7) %>%
  pack_rows("Data Visualization", 8, 10) %>%
  # column wrap
  column_spec(1, width = "10em") %>%
  column_spec(2, width = "20em") %>%
  # bold column names
  row_spec(0, bold = T) %>%
  add_footnote(c("See the tidyverse",
                 "See the tidyverse",
                 "See the biobroom analog in Bioconductor",
                 "See the tidyverse",
                 "See the tidyverse"),
               notation = "symbol")
```

Package	Description	Year	Author	Documentation
Data Manipulation				
readr[*]	read rectangular data (e.g., csv, tsv, and fwf)	readr	readr Wickham et al.	readr
dplyr[†]	grammar of data manipulation	dplyr	dplyr Wickham et al.	dplyr
tidyr	create tidy data	tidyr	tidyr Wickham et al.	tidyr
Statistical Modeling				
broom[‡]	tidy model output	broom	broom Robinson et al.	broom
purrr[§]	functional programming tools	purrr	purrr Henry et al.	purrr
caret	train classification and regression models	caret	caret Kuhn et al.	https://topepo.github.io/caret/index.html
keras	R interface to a neural network library	keras	keras Falbel et al.	keras
Data Visualization				
ggplot2[¶]	data visualization	ggplot2	ggplot2 Wickham et al.	ggplot2
kableExtra	tables	kableExtra	kableExtra Zhu et al.	kableExtra
rmarkdown	reports	rmarkdown	rmarkdown Allaire et al.	rmarkdown

[*] See the tidyverse
[†] See the tidyverse
[‡] See the biobroom analog in Bioconductor
[§] See the tidyverse
[¶] See the tidyverse

```r
## trying to separate color; striped by group
#  row_spec(1:3 - 1, extra_latex_after = "\\rowcolor{gray!6}")
#  row_spec(0:3, extra_latex_after = "\\rowcolor{orange!6}") %>%
#  row_spec(4:6, extra_latex_after = "\\rowcolor{gray!6}") %>%
#  row_spec(7:11, extra_latex_after = "\\rowcolor{gray!6}")

## QUESTIONS
# Code font for package names in " "? \texttt{}?
```

```
# How do you repeat same symbol on multiple items with one footnote?
# How do you separate colors and stripe by group?
# Add title
# Add caption
# Cite packages in bib and add references in table?
# Embed url link to package documentation? Do we want to link cheatsheets?
# How do you add link/reference to Table 1 in text in the template?
# How do you hide code for table in knitted pdf...include=FALSE errors?
# Title for column 2: description/purpose/usage?
# Length of description/purpose/usage for each package?
```

Supporting information 551

Do we need to include any supporting information? 552

Acknowledgements 553

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