

1 Revticulate: An R framework for interaction with
2 RevBayes

3 Caleb P. Charpentier and April M. Wright¹

4 ¹Department of Biological Sciences, Southeastern Louisiana
5 University, Hammond, LA, USA

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7 **Running Head: Revticulate**

8 **Keywords**

9 phylogeny, Bayesian phylogenetics, R packages, RevBayes

10 **1 Abstract**

11 1: Phylogenetic methods are increasingly complex. Researchers need to make
12 many choices about how to model different aspects of the data appropriately. It
13 is increasingly common to deploy hierarchical Bayesian models in which different
14 data types may be described by different processes. This necessitates tools to
15 help users understand model assumptions more clearly.

16 2: We describe the package `Revticulate`, which provides an R-based inter-
17 face to the software `RevBayes`. `RevBayes` is a Bayesian phylogenetics program
18 that implements an R-like computing language, but does not interface with R
19 itself. `Revticulate` was designed to allow communication between an R session,
20 and all of its associated capabilities, such as plotting and simulation, and a
21 `RevBayes` session.

22 3: `Revticulate` can be used to copy objects from `RevBayes` into R. We provide
23 several usage examples demonstrating how objects, such as such as random
24 variables drawn from probability distributions and phylogenetic trees, can be
25 generated in `RevBayes`. We then show how these objects can be used with R's
26 phylogenetic ecosystem to plot a phylogenetic tree, or with base R functions to
27 simulate the behavior of a particular probability.

28 4: `Revticulate` is a broadly useful software. `Revticulate` can be used alongside
29 popular document preparation packages, such as `Knitr` and `pkgdown` to generate
30 attractive reports, tutorials, and websites. This means that researchers who are
31 looking to communicate their work in `RevBayes` can do that very easily using
32 `Revticulate`, enabling rapid generation of reproducible research outputs.

33 **2 Introduction**

34 Estimating phylogenetic trees has emerged as one of the predominant challenges
35 in comparative biology. Phylogenetic trees provide researchers with the historical
36 context in which traits and organisms evolved. There is abundant evidence
37 that trying to understand trait evolution without a phylogenetic tree is deeply
38 misleading (Felsenstein, 1985; Uyeda et al., 2018). Phylogenetic trees are often
39 estimated from molecular data (nucleotide sequences, amino acids). However,
40 inclusion of paleontological data are crucially important in comparative analyses
41 (Rabosky, 2010; Slater et al., 2012), and many studies of biogeography are con-
42 ducted in a phylogenetic context. As such, morphological data, biogeographical
43 information, and stratigraphic data are being used in a wider variety of studies,
44 and across more disciplines. A researcher conducting a modern phylogenetic
45 study may be using multiple data types, described by different mathematical
46 models, and involving layers of statistical assumptions.

47 Many phylogenetic methods are now quite complex, and many phylogenetic
48 models are hierarchical, and in which submodels may have complex dependen-
49 cies on one another. For example, the Fossilized Birth-Death model (Stadler,
50 2010; Heath et al., 2014) and models of deep-time biogeography (Landis et al.,
51 2018) involve hierarchical Bayesian models with multiple subcomponents de-

52 scribing any molecular and morphological data used to estimate the tree, stratig-
53 raphy, and geographic locality data. These complex, hierarchical models rely
54 on researchers being able to understand not only the biology of their clade of
55 interest, but also to have deep understandings of statistical concepts in order to
56 be able to set reasonable priors on important model parameters. In developing
57 this type of intuition, it is often is important to be able to explore data visually,
58 to use programmatic statistical tools (such as R (RStudio Team, 2015)) to plot
59 and examine distributions, and to simulate data to understand the behavior of
60 models.

61 The phylogenetics software RevBayes (Höhna et al., 2014; Höhna et al.,
62 2016) represents an attempt to reconfigure the way phylogenetics software is
63 written. In many software packages developed over the history of phylogenetic
64 estimation, users have been able to select from molecular or morphological evo-
65 lution models implemented by the developers (examples: RAxML (Stamatakis,
66 2014), GARLI (Zwickl, 2006), and IQTree (Minh et al., 2020)). In these types
67 of packages, a researcher might be able to choose analytical settings (e.g., how
68 many bootstrap replicates, how to model character change rate heterogeneity,
69 correcting for ascertainment bias), but to implement a new model or method
70 means either collaborating with a developer or interacting with the source code.
71 RevBayes implements a statistical computing language called Rev. This lan-
72 guage is broadly similar to the well-known computing language R (RStudio
73 Team, 2015). Rev contains a library of probability distributions, as well as
74 mathematical operations, such as Markov Chain Monte Carlo analysis and as-
75 sociated operators. Further phylogenetic functions, such as tree estimation and
76 comparative phylogenetic methods using trees are available. Using Rev, infinite
77 combinations of models, priors and data can be assembled into custom analy-
78 sis workflows. A researcher who has a new idea for a model to analyse their
79 data, then, does not have to wait for a developer to implement their method,
80 but is instead empowered to realize their own workflows. Assembling a model
81 from all of its constituent pieces means there are no defaults, enabling a radical
82 transparency in phylogenetic analysis. The researcher must, therefore, become
83 an expert in the properties of their data, and how to use statistical models
84 appropriately to analyse those data.

85 While this may be greatly empowering, asking researchers and students to
86 learn a new programming language in order to implement their own analyses
87 means asking them to take on a large cognitive load. It also means that re-
88 searchers are not choosing from a pre-set list of models, but must instead make
89 far more choices about what facets of their data to model. Developing the ability
90 to do this means coming to understand choices in modeling that may be hidden
91 from users of other software packages. In particular for Bayesian analyses, this
92 can mean specifying priors on parameters, which involves knowledge of what dif-
93 ferent probability distributions look like, and the ability to conceptualize how
94 populations of random variables drawn from them will behave. Researchers
95 might also wish to visualize results or intermediate analysis products using the
96 advanced graphical capabilities and phylogenetic package ecosystem of R. To
97 facilitate the development of deeper statistical expertise, we have developed an

98 interface to R and RStudio for RevBayes. Written entirely in R, Revticulate is
99 intended to provide a set of default functions for translating between Rev code
100 and R objects and visualizations. This manuscript will discuss the technical
101 specifications and use of the RevBayes R interface, Revticulate.

102 3 Materials and Methods

103 3.1 Design of Revticulate

104 3.1.1 Interaction between R and RevBayes

105 The Revticulate package is loosely based on the R package Reticulate (Allaire
106 et al., 2018), which allows the use of the Python computing language in an R
107 session. The Revticulate package accesses RevBayes by passing Rev code in
108 a temporary file to the RevBayes executable. On Windows, this executable is
109 named `rb.exe`. On Mac and Linux systems, it is simply called `rb`. Rev code
110 can be run from a command-line interface by passing a Rev file path, containing
111 the Rev script for the analysis the researcher would like to run, as an argument
112 to RevBayes. This causes RevBayes to use its function `source()` to process the
113 Rev code in this file. Any output resulting from the file being processed (e.g.,
114 results of calculations, error messages) is then printed to the command line.

115 Revticulate accepts user input from R or RStudio via the function `callRev()`.
116 `callRev()` is a core function in the package, which formats the user code for
117 use in RevBayes. `callRev()` then writes the code to a file, which is read with
118 RevBayes' `source()` function. The path to these files is supplied as a command
119 line argument to RevBayes via the base R function `system2()`, and the output
120 from RevBayes is returned in character string format to R. A number of built-in
121 data types (vectors, integers, trees) are then formatted for easy and pleasant
122 viewing. The Rev script is then deleted to avoid filling storage on the user's
123 machine.

124 For Revticulate to function properly, the path to RevBayes must be provided
125 with the function `initRev()`. This function creates environmental variables
126 for locating the RevBayes executable, for locating the temporary files used to
127 manage RevBayes interactions, and for locating the file used to store the Rev
128 code history ('.Revhistory'). `initRev()` takes two arguments: 'searchPath' and
129 'infoDir'. 'searchPath' is the absolute path to RevBayes's location. It can be
130 the path to the RevBayes executable itself, or the path to a parent directory
131 containing the RevBayes executable. If multiple versions of RevBayes can be
132 located below the parent directory, the first version `initRev()` locates will be
133 used. 'infoDir' is the path to the directory where the 'RevInfo' folder should be
134 located. The RevInfo folder is used to manage Rev language history and the
135 temporary files used to interact with RevBayes. For example, if a user had a
136 previous RevBayes session they wanted to import and interact with in R, this
137 can be provided as the 'infoDir' argument to the `initRev()` function. If no
138 path is provided, the RevInfo folder will be created in the parent directory of
139 the current R session's working directory. If a 'RevInfo' folder already exists

Rev Object Type	R Object Type	Example
Numeric vector	Numeric vector	[1, 2, 3]
Character String	Character	"Taxon"
Tree	Phylo (Paradis et al., 2004)	((A, B), (C, D))
Character Matrix	String	<i>Ctenocystis utahensis</i> : 0 1 1 ? ? ?

140 in the 'infoDir' path, the history of the last Revticulate session to refer to
141 this path will be used. Because of this feature, users can save histories from
142 multiple Revticulate sessions, and can access any desired previous history by
143 calling 'initRev' with that history as the 'infoDir' argument.

144 3.2 Copying of Objects between R and RevBayes

145 A core functionality of the `Revticulate` package is its ability to copy objects
146 from `RevBayes` into the current R session in an appropriate R format. 'Copy'
147 is used instead of 'pass' here, as the totality of an object's contents are not
148 always passed into the R environment. For example, additional attributes of
149 Rev objects that are not directly translatable to R objects may not be copied.
150 `Revticulate` works by interacting with `RevBayes` via the command line, and
151 because of this behavior it only retrieves information from output printed to the
152 console.

153 The most general way for users to submit code to `RevBayes` is with the
154 `doRev()` function. `doRev()` accesses `RevBayes` with `callRev()`, while also
155 keeping track of user input from previous `doRev()` calls. This feature allows
156 `RevBayes` history to be tracked and Rev variables to be referenced in further
157 `doRev()` calls, simulating a continuous `RevBayes` session. By default, `doRev()`
158 returns `RevBayes` output to R in character format. For example, if a user creates
159 a Rev vector with `doRev("v(1, 2, 3)")`, the string "[1, 2, 3]" will be re-
160 turned. However, the `coerceRev()` function allows many Rev object types to be
161 coerced into R equivalents. This function works by parsing functional elements
162 from `RevBayes` output strings to determine what R objects or primitive types
163 have similar behaviors and functionalities. For example, the string "[1, 2, 3
164]" would be coerced to into a numeric vector. The equivalent number of opening
165 and closing brackets allows `coerceRev()` to recognize the string as a vector, and
166 because all of the elements in the vector are numbers, they will be coerced into
167 R numeric objects with the base R function `as.numeric()`. Therefore, to call
168 the function as such: `coerceRev("[1, 2, 3]")` would cause the Rev vector
169 to be translated to an R vector. The same behavior can be produced using the
170 `coerce` argument to `doRev`: `doRev("v(1, 2, 3)", coerce = TRUE)`. A variety
171 of other objects, including phylogenetic trees, can be identified and coerced
172 into R equivalents through a series of conditional statements in `coerceRev()`.
173 If `Revticulate` cannot recognize an R equivalent for the `RevBayes` output, the
174 original output string will be returned in an unformatted text string.

175 3.3 Interfaces to Revticulate

176 3.3.1 Using RevBayes interactively

177 In addition to `doRev()`, other useful tools are available for user interaction
178 with RevBayes. One such tool is the function `repRev()`. `repRev()` creates an
179 interactive console session that simulates the RevBayes command line. After
180 this function is called, the prompt `rb>>>` will appear in the user's console. While
181 this prompt is visible, all user code will be interpreted as Rev code, with the
182 exception of some helpful Revticulate functions used to manage the `‘.Revhistory’`
183 file. Attempting to use R language code while this session is active may cause
184 RevBayes to return error messages. By default, output generated during the
185 `repRev()` session is returned in string format, but may be coerced into R code
186 with `coerceRev()` via the `repRev()` argument `coerce`. To quit an interactive
187 `repRev()` session, type `quit()`, `q()`, or hit the escape key.

188 Objects created in a `repRev()` session may also be exported for use in R.
189 While in the `RepRev` environment, RevBayes functions can be carried out on any
190 created objects. However, if the desired behavior is to work with these objects
191 in R, they must be exported. For example, if we created a numeric variable in
192 a `repRev()` session like so:

$$a \sim dnLognormal(10, .1)$$

193 the value of the variable could be viewed in the `repRev()` session by simply
194 echoing it to the screen like so `print(a)`. Once the researcher has exited the
195 `repRev()` session, the object can be exported to R using the `getRevObj` function.
196 `exported_a <- getRevObj("a", coerce = TRUE)` will locate the variable `‘a’`
197 in the `RevHistory` and coerce it to an appropriate R object type, in this case a
198 numeric value of either integer (if the number is whole) or double (if a decimal).
199 This object can now be used with any R functions available to that data type.

200 3.3.2 Knitting RevBayes Documents

201 Revticulate can also be integrated with the R package `knitr` (Xie, 2013). `knitr`
202 allows for dynamic report generation and smooths the process of communi-
203 cating the results of programmatic analyses. `knitr` works with a file format
204 called RMarkdown, which can contain code, text, and image files. `knitr` can
205 generate documents in a variety of formats, including PDF and HTML files.
206 These documents contain `‘chunks’` which contain code. This format allows
207 the user to demonstrate code usage in a variety of languages, including R,
208 Python, C++, and many others. To use `knitr` with RevBayes, Revticulate
209 provides the `knitRev` function, which creates a RevBayes engine called `‘rb’`
210 via `knit_engines$set()`. To establish this functionality, the user must place
211 `initRev()` and then `knitRev()` in the initiation chunk of the RMarkdown doc-
212 ument that will be knitted. Because `‘knitr’` chunks are interpreted in different
213 R sessions, `initRev()` ensures that the same Rev language history is passed
214 between chunks and defined Rev variables can be used across them.

215 Revticate can also be used with other R packages that are based on knitr
 216 and the RMarkdown format. pkgdown (Wickham and Hesselberth), for exam-
 217 ple, which can be used to generate static websites for R packages, renders the
 218 HTML for the website based on knitr. Blogdown (Xie et al., 2017), which is used
 219 for generation of blogs and websites can also render Rev code via RMarkdown.
 220 Together, these packages create a powerful interface for generating tutorials and
 221 course materials. See Fig. 1 for an example website generated with Revticate
 222 and pkgdown.

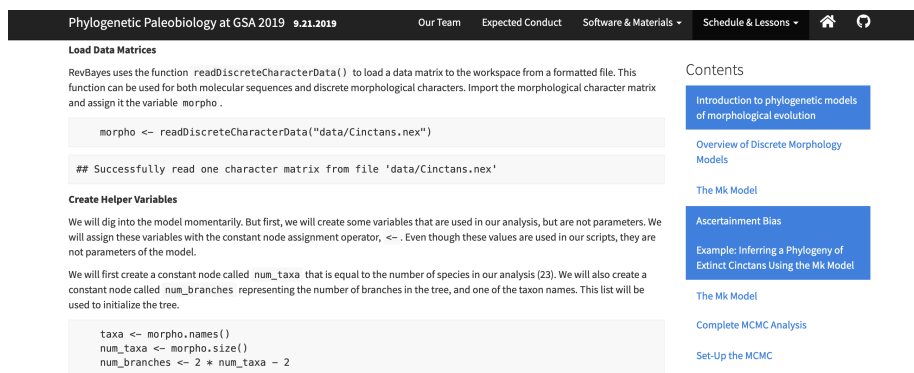


Figure 1: An example of a tutorial website built using Revticate and pkgdown. Content is written using RMarkdown with embedded Rev code, while the HTML for the website is autogenerated via pkgdown.

223 3.4 Limitations

224 Rev and R are still two separate languages, and as such seamless passing of ob-
 225 jects and commands between the two is not possible. Thus, translating custom
 226 functions from Rev to R will still require the researcher to manually change
 227 functions if they would like to use them in both Rev and R. Additionally, since
 228 `system2` is used to pass commands from R to Rev, long computations may run
 229 into time-out warnings. Thus, it is best practice to save long computations to
 230 a plain text file and run them directly in RevBayes.

231 4 Usage Example

232 4.1 Installation of Revticate

233 Revticate can be installed in two ways. The first is via CRAN, using the
 234 default `install.packages` function in R:

```
235 install.packages("Revticate").
```

236 The second is via the `remotes` package (Hester et al., 2020), a lightweight package
 237 enabling installation from GitHub repositories.

```

> repRev()
rb>>>u ~ dnUniform( 0, 1E6 )

rb>>>u
910364.2
rb>>>q()
> u <- getRevObj(name = "u", coerce = TRUE)
> u
[1] 433613.7
> u <- getRevObj(name = "u", coerce = TRUE)
> u
[1] 679174.6
>

```

Figure 2: A `repRev()` session in an RStudio session. In this `repRev()` session, a value, `u`, is drawn from a Uniform distribution. Then, it is converted to an R object using the function `getRevObj`. The value in this figure is used to simulate the distribution in Fig. 3.

```

238   remotes::install_github("revbayes/Revticulate")
239   The GitHub repository for Revticulate contains cutting-edge features and may
240   contain bugfixes, but the CRAN is known to be stable for everyday use.

```

241 4.2 Use of RevBayes in Console

To simulate command line RevBayes usage in R, the function `repRev()` is available. Calling `repRev()` begins a loop that simulates an interactive session with RevBayes in the R console. Because `repRev()` accesses the same `.Revhistory` file as the other Revticulate functions, Rev variables defined prior to the `repRev()` session can be referenced during the session, and variables defined during the session can be referenced after it is closed. For example, a value can be drawn from Uniform distribution in a `repRev()` session with the Rev language line

$$u \sim dnUniform(0, 1E6)$$

242 This command creates a stochastic variable `u` which returns a random value in
 243 a Uniform distribution between 0 and 1. Fig. 1 demonstrates how this looks in
 244 an RStudio window.

245 To use this value with R code, first close the `repRev()` session with `quit()`, `q()`,
 246 or the `esc` key. Then run the R code `u <- getRevObj(name = "u", coerce`
 247 `= TRUE)`. This command will assign an R variable `u`, to be drawn from the Uni-
 248 form(0, 1E6) distribution. As demonstrated in Fig. 1, each time `getRevObj`
 249 is called, a new draw is performed, allowing the user to continually pull new
 250 values from Rev into an R session. Because RevBayes output is returned to
 251 R in character format by default, the argument `coerce = TRUE` is required to
 252 transform the value of 'u' into a more usable numeric format. 'u' can then be

253 used to generate a gamma distribution in R, that can be plotted as a histogram
254 like so:

```
255 > draws <- rgamma(1000, shape = u, rate = u)  
256 > hist(draws, xlab = "Value")
```

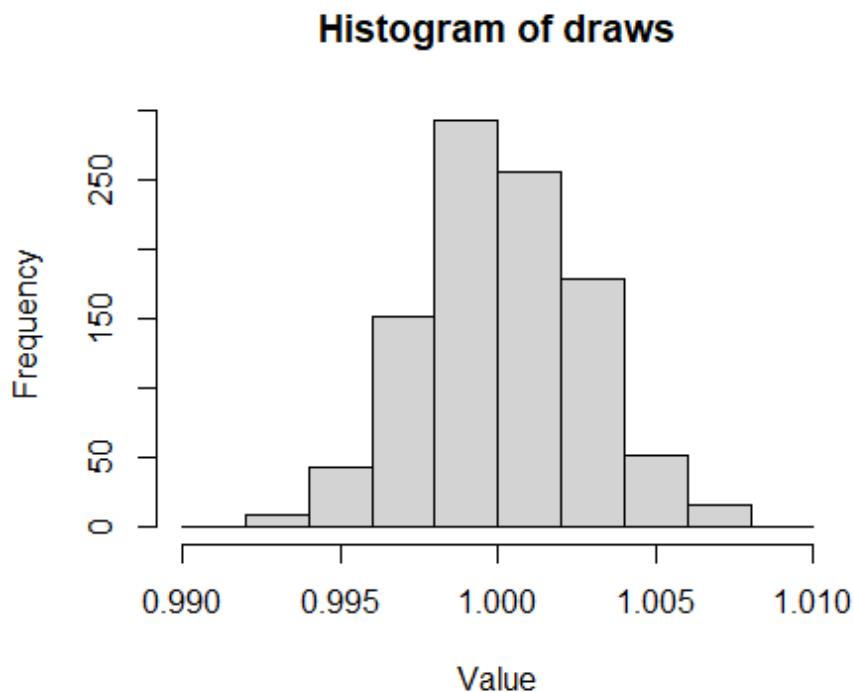


Figure 3: A distribution made by drawing values from the a Gamma distribution with shape and rate u , in which u is a value simulated from a Uniform distribution in RevBayes and passed to R via the `getRevObj` function in Revticulate. Value u was drawn from a distribution in Fig. 1.

257 To empty the Rev language history, use the function `clearRev()`. This
258 function can be called during or out of a `repRev()` session.

259 4.3 Use of RevBayes in KnitR

260 In addition to command line simulation, another possible use of the 'Revticu-
261 late' package is integration with the package 'knitr'. RevBayes lacks inherent
262 code visualization capabilities, but knitr provides a smooth and convenient for-
263 mat for generating markdown documents. A RevBayes engine for knitr can

264 be created with the function `knitRev()`, and can then be used by changing
265 the language name in the knitr chunk headers to 'rb'. When knitting a docu-
266 ment, knitr chunks are individually interpreted in separate R sessions. Because
267 of this behavior, the functions `knitRev()` and `initRev()` should be placed in
268 the knitr setup chunk to ensure each Rev language chunk accesses the same
269 `.Revhistory` file. This practice allows Rev variables defined in one chunk to be
270 referenced in other chunks, a feature not present in many other knitr engines.
271 This inter-chunk accession allows for Rev language chunk output to be accessed
272 in R language chunks via `Revticulate` functions, allowing for clean and seamless
273 inter-language document creation. In the example below, the variable `myTree`
274 is created using Rev language, and is coerced into a `phylo` object with the func-
275 tion `getRevObj()`. The code `““{rb}` indicates to knitr that this code should
276 be interpreted via the Rev language kernel. The code `““{r}` indicates to knitr
277 that this code should be interpreted via the standard R language kernel.

```
278  
279 ““{rb  
280 tips <- 2^4  
281 myTree <- simTree(tips)  
282 ““
```

283 Note that Rev and R cannot be used in the same code chunk. This is due
284 to the structure of Knitr, in which there may only be one language per code
285 chunk.

```
286  
287 ““{r  
288 thisTree <- getRevObj("myTree", coerce = TRUE)  
289 phytools::plot(thisTree)  
290 ““
```

291 4.3.1 `pkgdown`, `blogdown`, and automating tutorial service

292 A considerable strength of the R environment is the ability to prepare and man-
293 age documents using Knitr (preparation of reports), `pkgdown` (generation of
294 websites for R packages), and `blogdown` (generation of weblogs without associ-
295 ated packages). This set of tools makes generating and updating tutorials and
296 associated instructional materials rapid and reproducible. `Revticulate` contains
297 a Knitr kernel for the Rev language, enabling real-time execution of code in
298 RMarkdown documents. This allows instructors and developers to show both
299 syntax and expected outputs in a document. `pkgdown` websites have an ar-
300 ticles menu for the service of vignettes, but this can also be used to manage
301 tutorials for a class or workshop. Likewise, `blogdown` enables course and work-
302 shop content to be served as a continuous list of blog articles rendered from
303 R Markdown format. Either of these packages make the process of providing

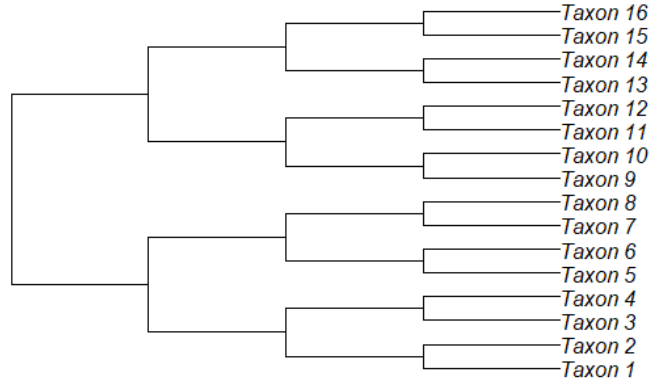


Figure 4: A tree simulated in R, using RevBayes' `simTree` function. This tree is then imported into R using the `getRevObj()` function and plotted via `phytools` (Revell, 2012). Trees are one of a number of default phylogenetic objects that can be passed between RevBayes and R.

304 educational content in Rev very simple. Markdown documents form the ba-
 305 sis of pkgdown and blogdown websites, enabling developers and instructors to
 306 serve websites for free via services such as GitHub. An example of a work-
 307 shop website generated using Revticulate and pkgdown can be seen at https://dwbapst.github.io/PaleoSoc_phylo_short_course_2019/index.html and in Fig.
 308 1.
 309

310 5 Conclusion

311 Phylogenetic methods have become ever more complex in recent decades, and
 312 along with this boon of techniques has become an expanding pool of technolo-
 313 gies to implement them. One of these technologies, RevBayes, provides a very
 314 powerful and flexible interface for custom statistical analysis. However, its us-
 315 age requires the user to learn a new, R-like programming language, a daunt-
 316 ing task for many biologists with limited programming backgrounds. Common
 317 phylogenetic methods also involve developing advanced statistical intuition by
 318 researchers who may have little or no formal training in statistics. To assist
 319 researchers in developing this intuition, and to increase the interoperability of
 320 RevBayes with other common phylogenetics tools, we have developed the R
 321 package Revticulate, which serves as an R-language interface for RevBayes.
 322 Written entirely in R to allow for operation of RevBayes in R and RStudio,

323 Revticulate implements a number of flexible functions to help both researchers
324 and educators make use of RevBayes.

325 **6 Author Contributions**

326 Revticulate was written mostly by CPC with assistance from AMW. AMW and
327 CPC prepared the manuscript together.

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