

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 histori-
36 cal 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. In developing an intu-
47 ition for statistical modeling, it is often is important to be able to explore data
48 visually, to use programmatic statistical tools, such as R ((R Core Team, 2021;
49 RStudio Team, 2015)), to plot and examine distributions, and to simulate data
50 to understand the behavior of models.

51 The phylogenetics software `RevBayes` (Höhna et al., 2014; Höhna et al.,

52 2016) represents an attempt to reconfigure the way phylogenetics software is
53 written. In many software packages developed over the history of phylogenetic
54 estimation, users have been able to select from molecular or morphological evo-
55 lution models implemented by the developers (examples: RAxML (Stamatakis,
56 2014), GARLI (Zwickl, 2006), and IQTree (Minh et al., 2020)). In these types
57 of packages, a researcher might be able to choose analytical settings (e.g., how
58 many bootstrap replicates, how to model character change rate heterogeneity,
59 correcting for ascertainment bias), but to implement a new model or method
60 means either collaborating with a developer or interacting with the source code.
61 RevBayes implements a statistical computing language called Rev. This lan-
62 guage is broadly similar to the well-known computing language R (R Core Team,
63 2021; RStudio Team, 2015). Rev contains a library of probability distributions,
64 as well as mathematical operations, such as Markov Chain Monte Carlo analysis
65 and associated operators. Further phylogenetic functions, such as tree estima-
66 tion and comparative phylogenetic methods using trees are available. Using
67 Rev, infinite combinations of models, priors and data can be assembled into
68 custom analysis workflows. A researcher who has a new idea for a model to
69 analyse their data, then, does not have to wait for a developer to implement
70 their method, but is instead empowered to realize their own workflows. As-
71 sembling a model from all of its constituent pieces means there are no defaults,
72 enabling a radical transparency in phylogenetic analysis. The researcher must,
73 therefore, become an expert in the properties of their data, and how to use
74 statistical models appropriately to analyse those data.

75 While this may be greatly empowering, asking researchers and students to
76 learn a new programming language in order to implement their own analyses
77 means asking them to take on a large cognitive load. It also means that re-
78 searchers are not choosing from a pre-set list of models, but must instead make
79 far more choices about what facets of their data to model. Developing the ability
80 to do this means coming to understand choices in modeling that may be hidden
81 from users of other software packages. In particular for Bayesian analyses, this
82 can mean specifying priors on parameters, which involves knowledge of what dif-
83 ferent probability distributions look like, and the ability to conceptualize how
84 populations of random variables drawn from them will behave. Researchers
85 might also wish to visualize results or intermediate analysis products using the
86 advanced graphical capabilities and phylogenetic package ecosystem of R. To
87 facilitate the development of deeper statistical expertise, we have developed an
88 interface to R and RStudio for RevBayes. Written entirely in R, Revticulate is
89 intended to provide a set of default functions for translating between Rev code
90 and R objects and visualizations. This manuscript will discuss the technical
91 specifications and use of the RevBayes R interface, Revticulate.

92 **3 Materials and Methods**

93 **3.1 Design of Revticulate**

94 **3.1.1 Interaction between R and RevBayes**

95 The Revticulate package is loosely based on the R package Reticulate (Allaire
96 et al., 2018), which allows for the use of the Python programming language
97 (vanRossum, 1995) in an R session. Similar to Reticulate, Revticulate provides
98 a suite of functions for users to interact with an external program in R (in
99 this case, RevBayes). The basic Revticulate function for calling RevBayes is
100 `doRev()`. `doRev()` accepts a Rev language expression in the form of a character
101 string and keeps track of the previous expressions users have submitted. With
102 this technique, Rev language variables persist between calls, and can be exported
103 to R for analysis and visualization.

104 **3.2 Copying of Objects between R and RevBayes**

105 A core functionality of the Revticulate package is its ability to copy RevBayes
106 output into R language format. This functionality is made possible by the func-
107 tion `coerceRev()`. `coerceRev()` uses string parsing and branching statements
108 to determine the structure of a RevBayes output string, and to then convert it
109 into an appropriate R object type. Revticulate supports coercion of several data
110 types, including: numerics, strings, boolean values, NULL, NA/NaN, vectors,
111 numeric matrices, and phylogenetic trees. These values are all converted into
112 their base R equivalent types, with the exception of phylogenetic trees, which
113 become `phylo` objects from the `ape` package. If `coerceRev()` is unable to de-
114 termine a suitable R object type for RevBayes output, it will be returned in its
115 original character format.

116 `coerceRev()` can be used alone, but is more commonly called via `doRev()`.
117 `doRev` includes a boolean 'coerce' parameter, that determines whether or not
118 their output should be coerced automatically. The coercion default for both
119 functions is TRUE, meaning their output will automatically be converted from
120 a string unless specified otherwise. For example, if a user runs `doRev("v(1, 2,`
121 `3)")`, a numeric vector containing the numbers 1, 2, and 3 will be returned and
122 can be saved as a vector. If `coerce=FALSE`, however, the string "[1, 2, 3]"
123 will be returned instead.

124 **3.3 Interfaces to Revticulate**

125 **3.3.1 Using RevBayes interactively**

126 In addition to `doRev()`, other useful tools are available for user interaction with
127 RevBayes. One such tool is the function `repRev()`. `repRev()` creates an in-
128 teractive console session that simulates the RevBayes command line. After this
129 function is called, the prompt `rb>>>` will appear in the user's console. While this

130 prompt is visible, all user code will be interpreted as Rev code, with the excep-
131 tion of some helpful functions to manage the Revticulate history. Attempting
132 to use R language code while this session is active may cause RevBayes to re-
133 turn error messages. By default, output generated during the `repRev()` session
134 is returned in coerced format, but may remain an unformatted string via the
135 `repRev()` argument `coerce=FALSE`. This option may be desirable for users look-
136 ing for a more traditional RevBayes experience. To quit an interactive `repRev()`
137 session, type `quit()`, `q()`, or hit the escape key.

138 While in the `repRev` environment, RevBayes functions can be carried out
139 on any created objects. However, if the desired behavior is to work with these
140 objects in R, they must be exported. For example, if we created a numeric
141 variable in a `repRev()` session like so:

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

142 the value of the variable could be viewed in the `repRev()` session by simply
143 echoing it to the screen like so: `print(a)`. Once the researcher has exited the
144 `repRev()` session, the object can be exported to R using the `doRev()` function.
145 `exported_a <- doRev("a")` will return the variable ‘a’ in string format to R
146 and then coerce it to an appropriate R object type, in this case a numeric value
147 of either integer (if the number is whole) or double (if a decimal). This object
148 can now be used with any R functions available to that data type.

149 3.3.2 knitting RevBayes Documents

150 Revticulate can also be integrated with the R package `knitr` (Xie, 2013). `knitr`
151 allows for dynamic report generation and smooths the process of communi-
152 cating the results of programmatic analyses. `knitr` works with a file format
153 called RMarkdown, which can contain code, text, and image files. `knitr`
154 can generate documents in a variety of formats, including PDF and HTML
155 files. These documents contain ‘chunks’ which contain code. This format al-
156 lows the user to demonstrate code usage in a variety of languages, including
157 R, Python, C++, and many others. To use `knitr` with RevBayes, Revticu-
158 late provides the `kintRev` function, which creates a RevBayes engine called
159 ‘rb’ via `knitr_engines$set()`. To establish this functionality, the user must
160 place `library(Revticulate)` and then `kintRev()` in the initiation chunk of
161 the RMarkdown document that will be knitrtd. Because `knitr` chunks are
162 interpreted in different R sessions, `initRev()` ensures that the same Rev lan-
163 guage history is passed between chunks and defined Rev variables can be used
164 across them.

165 Revticulate can also be used with other R packages that are based on `knitr`
166 and the RMarkdown format. `pkgdown` (Wickham and Hesselberth), for exam-
167 ple, which can be used to generate static websites for R packages, renders the
168 HTML for the website based on `knitr`. `Blogdown` (Xie et al., 2017), which is used
169 for generation of blogs and websites can also render Rev code via RMarkdown.
170 Together, these packages create a powerful interface for generating tutorials and

171 course materials. See Fig. 1 for an example website generated with Revticate
172 and pkgdown.

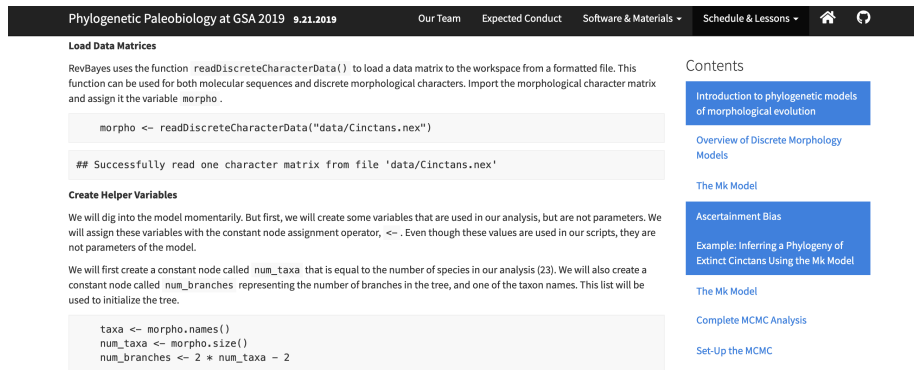


Figure 1: An example of a tutorial website built using Revticate and pkgdown. Content is written using RMarkdown with embedded Rev code, while the HTML for the website is autogenerated via pkgdown.

173 3.3.3 Longer Computations in RevBayes

174 While `doRev()`, `repRev()`, and `knitRev()` provide useful interfaces for users
175 interested in exploratory Rev programming, they do not offer ideal functionality
176 for longer RevBayes computations. This is because they rely on the base R sys-
177 tem2() function for interacting with RevBayes, and returning RevBayes output
178 in this manner requires a mandatory timeout on some operating systems.

179 While this timeout limitation could be a big hinderance to users (MCMC
180 simulations, for example, can take hours to weeks), Revticate provides several
181 functions to circumvent this issue. The first two functions are complementary
182 to each other: `loadRevHistory()` and `saveRev()`. `loadRevHistory()` copies the
183 Rev code from a specified .rev file into the current Revticate history, without
184 executing this code in RevBayes. Additionally, `loadRevHistory()` has second
185 argument, `Overwrite`, that allows the user to specify whether the history they
186 read in should be appended to current Revticate history or should replace it.
187 By default, it is appended.

188 In contrast to `loadRevHistory()`, `saveRev()` allows the researcher to write
189 the current Revticate history to a .Rev script. The user can then execute the
190 file directly in RevBayes for longer computations, or use `loadRevHistory()`
191 for additional editing later on. `saveRev()` has two additional parameters that
192 users should be aware of: `use_wd` and `use_quit`. `use_wd` tells the program
193 to set the default working directory of the saved script to the users current
194 working directory. `use_quit` appends 'q()' to last line of the saved file, which
195 tells RevBayes to terminate after running all of the previous code. The default
196 value of both of these parameters is TRUE.

197 The final function for managing longer RevBayes computations is `callRevFromTerminal()`.
198 This function takes one argument, the file path to a `.rev` file. It then executes
199 this file in an RStudio terminal window. By combining this functionality with
200 `saveRev()`, users can write and troubleshoot Rev code via `doRev()` and related
201 functions, save their work, and immediately execute it in an RStudio terminal.
202 Output from RevBayes monitors can then be read back into R, and explored
203 and visualized with the many phylogenetics packages available in R. These tools
204 together provide a robust and powerful workflow for developing, executing, and
205 interpreting RevBayes code in RStudio.

206 4 Usage Example

207 4.1 Installation of Revticulate

208 Revticulate can be installed in two ways. The first is via CRAN, using the
209 default `install.packages` function in R:

```
210 install.packages("Revticulate").
```

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

```
213 remotes::install_github("revbayes/Revticulate")
```

214 The GitHub repository for Revticulate contains cutting-edge features and may
215 contain bugfixes, but the CRAN is known to be stable for everyday use.

216 Upon first installation, Revticulate will run a package check. This check
217 searches for an `.Renviron` file that contains a RevBayes path. If the package
218 doesn't find this file, or finds it without the path, the package prompts the user
219 to use `usethis::edit_r_environ()`. This opens the `.Renviron` file, and the user
220 will enter `rb=absolute path to RevBayes`. This can be edited at any time if
221 there are multiple installs on the system, or if you recompile RevBayes and want
222 to use a new version.

223 4.2 Use of RevBayes in Console

224 To simulate command line RevBayes usage in R, the function `repRev()` is
225 available. Calling `repRev()` begins a loop that simulates an interactive ses-
226 sion with RevBayes in the R console. Because `repRev()` accesses the same
227 `.Revhistory` file as the other Revticulate functions, Rev variables defined prior
228 to the `repRev()` session can be referenced during the session, and variables
229 defined during the session can be referenced after it is closed.

230 This function enables researchers to pass variables from Rev to R in an
231 interactive session. For example, in the RevBayes Tutorial “Estimating a time-
232 calibrated phylogeny of fossil and extant taxa using RevBayes” (Barido-Sottani
233 et al., 2020), both extinction and speciation values for a birth-death model are
234 drawn from exponential distributions. However, researchers might be interested
235 in understanding both what these distributions look like, and how the quantities
236 of speciation and extinction relate to one another. For example, if a researcher

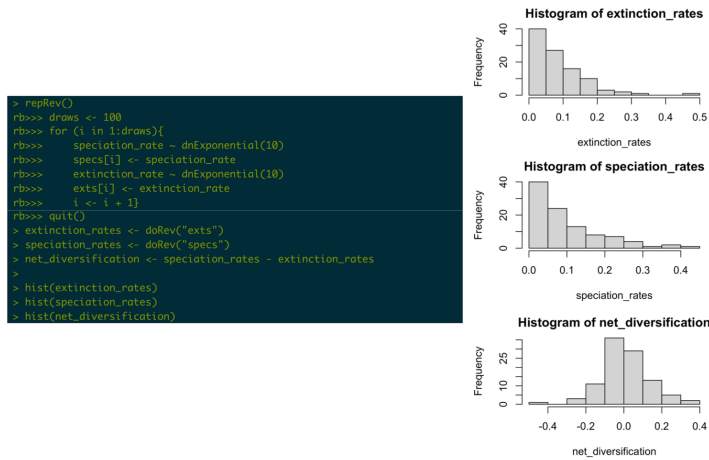


Figure 2: An example using `repRev()` to use RevBayes in an R console. In this case, we use RevBayes to simulate two vectors of values, then export them to R for analysis. Lines beginning with `rb>>>` are run in RevBayes; lines beginning in `>` are run in R.

237 is parameterizing a birth-death model, they may wish to know what their priors
 238 imply about the number of speciation events per extinction events. We can
 239 export the vectors to R for visualization. We can even manipulate these vectors,
 240 in this case calculating a net diversification rate, to visualize what these values
 241 will imply about net diversification. In this case, diversification is near zero,
 242 implying that the number of lineages on the tree is not particularly growing or
 243 shrinking (Fig. 2).

244 4.3 Use of RevBayes in knitr

245 In addition to command line simulation, another possible use of the 'RevTiculate'
 246 package is integration with the package 'knitr'. RevBayes lacks inherent code
 247 visualization capabilities, but knitr provides a smooth and convenient format for
 248 generating markdown documents. A RevBayes engine for knitr can be created
 249 with the function `kintRev()`, and can then be used by changing the language
 250 name in the knitr chunk headers to 'rb'. To enable the use of RevBayes in knitr,
 251 the following should be added to the setup chunk:

```

252
253 ‘‘‘{r setup, include=FALSE}
254 knitr::opts_chunk$set(echo = TRUE, eval=FALSE)
255 library(RevTiculate)
256 kintRev()
257 ’’’

```


258 When knitting a document, knitr chunks are individually interpreted in
259 separate R sessions. Because of this behavior, the functions `knitRev()` and
260 `initRev()` should be placed in the initial knitr setup chunk to ensure each Rev
261 language chunk accesses the same `.Revhistory` file. This practice allows Rev
262 variables defined in one chunk to be referenced in other chunks, a feature not
263 present in many other knitr engines. This inter-chunk accession allows for Rev
264 language chunk output to be accessed in R language chunks via Revtulate
265 functions, allowing for clean and seamless inter-language document creation. In
266 the example below, the variable `myTree` is created using Rev language, and is
267 coerced into a `phylo` object with the function `doRev()`. The code `““{rb}` indi-
268 cates to knitr that this code should be interpreted via the Rev language kernel.
269 The code `““{r}` indicates to knitr that this code should be interpreted via the
270 standard R language kernel.

```
271  
272 ““{rb}  
273 tips <- 2^4  
274 myTree <- simTree(tips)  
275 ””
```

276 Note that Rev and R cannot be used in the same code chunk. This is due to
277 the structure of knitr, in which there may only be one language per code chunk.
278 If you wish to use a variable generated in a Rev chunk, the variable must be
279 imported in a subsequent R chunk.

```
280  
281 ““{r}  
282 thisTree <- doRev("myTree")  
283 phytools::plot(thisTree)  
284 ““
```

285 4.4 Interaction of Revtulate with other R packages

286 Revtulate coerces objects to standard R objects. For example, phylogenetic
287 trees are standard objects, as implemented in `ape` (Paradis et al., 2004). They
288 can be processed with `ape`, `phangorn` (Schliep, 2011), `phytools` (Revell, 2012) and
289 `RevGadgets` (Tribble et al., 2021). For example, below we provide an example
290 of automating the process of processing an MCMC file, computing a maximum
291 clade credibility tree, plotting it, and saving as a publication-quality image.
292 Continuing with the example in the tutorial “Estimating a time- calibrated
293 phylogeny of fossil and extant taxa using RevBayes” (Barido-Sottani et al.,
294 2020), we can plot an FBD tree with a geological time scale (Fig. 3). In so
295 doing, we can automate the process of summarizing trees, annotating trees and
296 exporting publication-quality figures.

297 We can also automate convergence assessment using the R package conve-
298 nience (Fabreti et al., 2021). In the below example (Fig. 5), included with

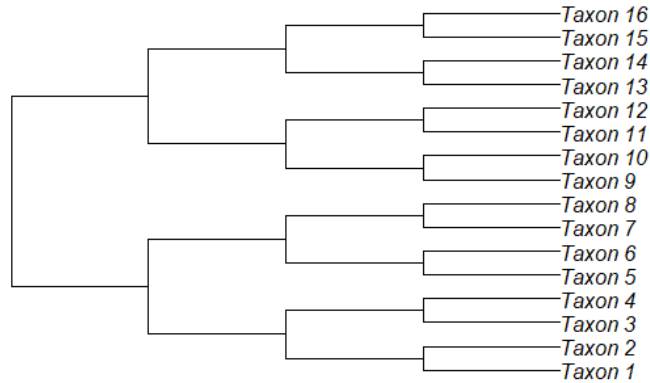


Figure 3: A tree simulated in R, using RevBayes’ `simTree` function. This tree is then imported into R using the `doRev()` function and plotted via `phytools` (Revell, 2012). Trees are one of a number of default phylogenetic objects that can be passed between RevBayes and R.

299 the package, we run a short phylogenetic estimation for a small morphological
 300 dataset from bears using the Mk model (Lewis, 2001). In this case, we are
 301 using the function `callRevFromTerminal()` to complete a longer MCMC. This
 302 function can be called either from the console or the knitr display. It takes a
 303 pre-made Rev script as input and will terminate upon the finish of the analysis.
 304 At this point, the R package convenience (Fabreti et al., 2021) runs the auto-
 305 mated convergence check using the output directory. These two examples show
 306 how Revticulate can facilitate end-to-end reproducibility of RevBayes analyses.

307 4.4.1 `pkgdown`, `blogdown`, and automating tutorial service

308 A considerable strength of the R environment is the ability to prepare and
 309 manage documents using knitr (preparation of reports), `pkgdown` (generation
 310 of websites for R packages), and `blogdown` (generation of weblogs without asso-
 311 ciated packages). This set of tools makes generating and updating tutorials and
 312 associated instructional materials rapid and reproducible. Revticulate contains
 313 a knitr kernel for the Rev language, enabling real-time execution of code in
 314 RMarkdown documents. This allows instructors and developers to show both
 315 syntax and expected outputs in a document. `pkgdown` websites have an ar-
 316 ticles menu for the service of vignettes, but this can also be used to manage
 317 tutorials for a class or workshop. Likewise, `blogdown` enables course and work-
 318 shop content to be served as a continuous list of blog articles rendered from

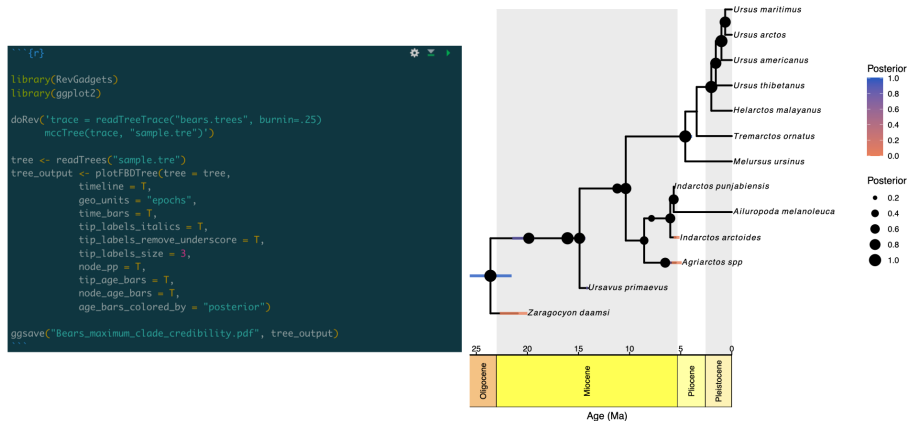


Figure 4: A graphic showing tree summarization in RevBayes via RevTiculate, followed by annotation in RevGadgets (Tribble et al., 2021) and exported via ggplot2 (Wickham and Hesselberth). Researchers can use RevTiculate to make single analytical documents covering summarization and export of results.

319 R Markdown format. Either of these packages make the process of providing
 320 educational content in Rev very simple. Markdown documents form the basis
 321 of pkgdown and blogdown websites, enabling developers and instructors to
 322 serve websites for free via services such as GitHub. An example of a work-
 323 shop website generated using RevTiculate and pkgdown can be seen at https://dwbpast.github.io/PaleoSoc_phylo_short_course_2019/index.html and in Fig.
 324 1.
 325

326 5 Author Contributions

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

329 References

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 333 Walker Pett, and Tracy A Heath. Estimating a time-calibrated phylogeny of
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A

```
{r}
library(convenience)
callRevFromTerminal("mcmc_mk.Rev")
checkConvergence(path = "vignettes/output/")
```

B

```
> source("~/Users/april/projects/Revticulate/vignettes/mcmc_mk.Rev")
Processing file "~/Users/april/projects/Revticulate/vignettes/mcmc_mk.Rev"
Successfully read one character matrix from file "bears.nex"

Running MCMC simulation
This simulation runs 2 independent replicates.
The simulator uses 5 different moves in a random move schedule with 58.4 moves
per iteration
```

Iter	ETA	Posterior	Likelihood	Prior	elapsed
0		-687.017	-674.484	-12.5326	00:00:00
100	-- --	-434.805	-422.428	-12.3777	00:00:00
200	-- --	-424.761	-417.304	-7.45669	00:00:01
300	00:01:39	-438.004	-424.12	-13.8846	00:00:01
	00:01:05				

C

```
LOWEST SPLIT ESS
RUN 1 -> Agriarctos_spp Alluarctos_lufengensis Alluropoda_melanoleuca Ballusia_e
lmenis Indarctos_arctoides Indarctos_punjabiensis Indarctos_vireti Kretzoiarctos_beatr
ix Ursavus_brevirhinus Ursavus_primeoivus Zaragocyon_daamsi 9.51
RUN 2 -> Agriarctos_spp Alluarctos_lufengensis Alluropoda_melanoleuca Ballusia_e
lmenis Indarctos_arctoides Indarctos_punjabiensis Indarctos_vireti Kretzoiarctos_beatr
ix Ursavus_brevirhinus Ursavus_primeoivus Zaragocyon_daamsi 3.8
```

Figure 5: An example using `callRevFromTerminal()` (Panel A) to use RevBayes to compute a complete MCMC from a Rev script. This output is then processed with the package `convenience` (Fabreti et al., 2021) to assess convergence in the MCMC sample (Panel B), and the outputs of the automated convergence checks are printed to the knitr interface (Panel C). Using `Revticulate`, a researcher could make a single, reproducible notebook going through all steps of an analysis.

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 336 gration with zenodo, September 2021. URL [https://doi.org/10.5281/zenodo.](https://doi.org/10.5281/zenodo.5520581)
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 342 and Dan Tenenbaum. `remotes`: R package installation from remote reposi-
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 346 sentation in phylogenetics. *Systematic Biology*, 63(5):753–771, 2014. doi:
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