

RH: dispRity package.

## **dispRity : a modular R package for measuring disparity.**

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## Abstract

1. Biological data is multivariate in essence: many traits in organisms co-vary with each other in space and time. This causes biologists to either reduce these to a manageable number of variables or, increasingly, to use multivariate toolkits. One such toolkit is based on creating a multidimensional space where the variables are the axes. It is then possible to measure diverse aspects of the distribution of some observation (e.g. species) in this space. For example, if studying morphology, one can create a morphospace for two groups of species, measure the volume occupied by each of these groups and then test whether these two volumes are significantly different or not.

2. There are as many definitions of these multidimensional spaces, metrics and tests as there are questions that can be tackled with such methods. Many of these methods are implemented in specific software or R packages. However, the definition of the space, metric and test is often dependent on the software/package authors points of view or specific questions. This can unfortunately hamper researchers' ability to apply different methods that best suits their specific questions.

3. Here I present the `disprity` package, a flexible R package for performing multidimensional analysis. It allows users to define each step of the analysis (whether it is the space, the metric or the test) through a highly modular architecture where each definition can be passed as a function. It also provides a tidy interface through the `disprity` object, allowing users to easily run reproducible multivariate analysis.

24 4. The `disPRity` package also comes with an extend manual regularly updated  
25 following users' questions or suggestions. Furthermore, the package contains  
26 some simulation tools (e.g to simulate complex multidimensional space or  
27 morphological data). Finally, it also contains a suite of utility functions to  
28 work with `disPRity` objects aimed at helping users to develop their own  
29 multidimensional metrics and/or tests.

30 (Keywords: disparity, ordination, multidimensionality, disparity-through-time,  
31 palaeobiology, ecology)

## INTRODUCTION

Biological data are complex. To understand the ecology and evolution of species we must use multiple variables that inevitably covary with each other through time and space. One solution to this problem is to analyse these data in a multivariate framework (e.g. Price et al., 2015; Díaz et al., 2016). Such analyses aim to capture the complex multidimensionality of biological data, while still providing outputs that are interpretable. These multivariate analyses can be used to investigate changes in morphological diversity through time (e.g. Close et al., 2015), competitive replacement scenarios (e.g. Brusatte et al., 2008), relationships among form and function (e.g. Díaz et al., 2016) and even to describe the entirety of possible shapes for a group of organisms (e.g. Raup, 1966). The biological variables in such analyses are equally diverse, including morphological traits (discrete traits like the presence or absence of a character, e.g. Close et al. 2015; or continuous traits such as lengths, e.g. Price et al. 2015), life history traits (e.g. Díaz et al., 2016), or even ecosystem properties (e.g. Donohue et al., 2013).

In all these analysis, each set of multivariate traits forms a multidimensional space. This space is represented as a matrix where rows are regarded as samples or observations (e.g. specimens, field sites, etc.) and columns are variables or some transformation thereof (e.g. embedding, scaling, ordination, etc.). These multidimensional spaces can be defined in many ways, for example as a pairwise distance matrix (Lloyd 2016 and references therein; e.g. in Close et al. 2015), or as

53 outputs from an ordination, whether it being a principal components analysis (PCA,  
54 Hotelling 1933; e.g. in Zelditch et al. 2012 ), a metric scaling (PCO, PCoA, Torgerson  
55 1958 ; e.g. in Brusatte et al. 2008 ) or a non-metric scaling (MDS, NMDS, Shepard 1962 ;  
56 e.g. in Liow 2004; Donohue et al. 2013). The name we give to the multidimensional  
57 space tends to vary with the kinds of traits used to construct it. For example, when  
58 using morphological traits, the space will be a morphospace, when using ecological  
59 traits it may be referred to as an ecospace, etc.

60 One can then measure how the observations are distributed within this space to  
61 answer related questions (e.g. “does group A occupy more space than group B?”). This  
62 requires the definition of a proxy for space occupancy: the disparity metric (or index;  
63 Hopkins and Gerber, 2017) which can be measured in a multitude of ways. For  
64 example, one could use a metric based on the variance or the range of each axis of  
65 space (Wills, 2001; Ciampaglio et al., 2001), a distance (e.g. Euclidean) measured  
66 between observations (Foote, 1993, 1996), a more direct approximation of the hyper  
67 volume (Cornwell et al., 2006; Donohue et al., 2013), or many more (e.g. Navarro, 2003).

68 Finally, all these different multidimensional spaces and their associated disparity  
69 metrics can be used in an equal variety of statistical tests such as non-parametric  
70 multivariate analyses of variance (NPMANOVA, Anderson 2001; e.g. in Brusatte et al.  
71 2008) multidimensional permutation tests (Manly 1997; e.g. in Díaz et al. 2016) or even,  
72 less rigorously, by looking at the confidence interval overlaps between disparity  
73 measurements. In summary, there are many different ways to perform each step of a

multidimensional analysis, making analyses of complexity ever more complex.

In theory, this multitude of ways to generate and define multidimensional spaces, measure disparity within and analyse these metrics is not an issue, in fact, it allows researchers to choose both the most appropriate method for their question or data, or even to test their question using multiple methods. In practice, however, this is hampered by existing software implementations. Although many software packages exist for multidimensional analysis (e.g. Navarro, 2003; Bouxin, 2005; De Caceres et al., 2007; Oksanen et al., 2007; Harmon et al., 2008; Adams and Otárola-Castillo, 2013; Lloyd, 2015; Adams et al., 2017), package maintainers/software developers choose their preferred definition of multidimensional space and disparity metric to best fit their needs (i.e. data, hypothesis, etc.) making the implementations sometimes hard to adapt to different needs. For example, in the excellent and widely used geomorph package, morphological disparity analysis uses the `morphol.disparity` function that defines the multidimensional space as the ordination of the Procrustes transform of the morphometric data, the disparity metric as the relative sum of the diagonal of the covariance of the ordination scores (Procrustes variance) , and uses permutation tests (Zelditch et al., 2012; Adams and Otárola-Castillo, 2013; Adams et al., 2017). This is ideal for testing volume based hypothesis (e.g. “does groups A and B have the same volume?”), but in other cases may not be appropriate in non-volume based hypothesis (e.g. “do they occupy the same location?”). This can lead to inappropriate analyses by users confined by the existing software implementations.

The aim of the `disPRity` package is avoid such problems by providing a flexible framework for studying multidimensional data. This package is based on a modular architecture where each decision in multidimensional analysis (which data, metric and test) can be specified by the user. It implements many commonly used disparity metrics, as well as providing a simple interface for users to implement their own disparity functions. The package is described here for the use of discrete morphological data disparity analysis but can be generalised to any type of multidimensional data (see the glossary Table 1).

in this manuscript	in dispRity	in palaeobiology	in ecology
multidimensional space	matrix ( $n \times k$ )	morphospace, traitspace, etc.	ecospace, function-space, etc.
elements	rows ( $n$ )	taxa, specimen, etc.	taxa, field sites, environments, etc.
dimensions	columns ( $k$ )	ordination scores, distances, etc.	ordination scores, distances, etc.
subsets	matrix ( $m \times k$ , with $m \leq n$ )	e.g. every element in a stratum or sharing the same ancestor	e.g. elements living in the same environment
disparity	a dimension-level 1 or 2 function <sup>1</sup>	disparity: e.g. the sum of variances (Wills, 2001), the average pairwise distances between taxa (Foote, 1994), etc.	dissimilarity: e.g. ellipsoid volume (Donohue et al., 2013), convex hull volume (Cornwell et al., 2006), etc.

Table 1: Glossary and equivalences between this manuscript, the dispRity package and terms commonly used in palaeobiology or ecology. <sup>1</sup>See Fig. 2.



## DESCRIPTION

In brief, the package takes a `matrix` object (the multidimensional space), calculates a disparity metric from the space and analyse the resulting `disprity` object through hypothesis testing and visualisation. Some additional functions modify the space, for example by dividing it by groups or through time and/or bootstrapping it (see Fig. 1). Note that the input matrix is not restricted to an ordinated matrix but can be any kind of matrix as long as its rows represent elements (e.g. the space can be a distance matrix Close et al., 2015). The matrix is always considered as the final multidimensional space to analyse and no correction is applied to it (e.g. potential corrections should be applied prior to using the `disprity` package).

### *Measuring disparity*

The `disprity` function measures disparity from a `matrix` where the columns correspond to the dimensions and the rows correspond to the elements present in the space. The disparity metric is passed through the `metric` argument and is defined by the user as one or more function(s) that can either transform the matrix into:

- Another matrix (a dimension-level 3 function - e.g. a variance-covariance matrix;  
`stats::cor`)
- A vector (a dimension-level 2 function - e.g. the variance of each dimension;  
`disprity::variances` - see below)

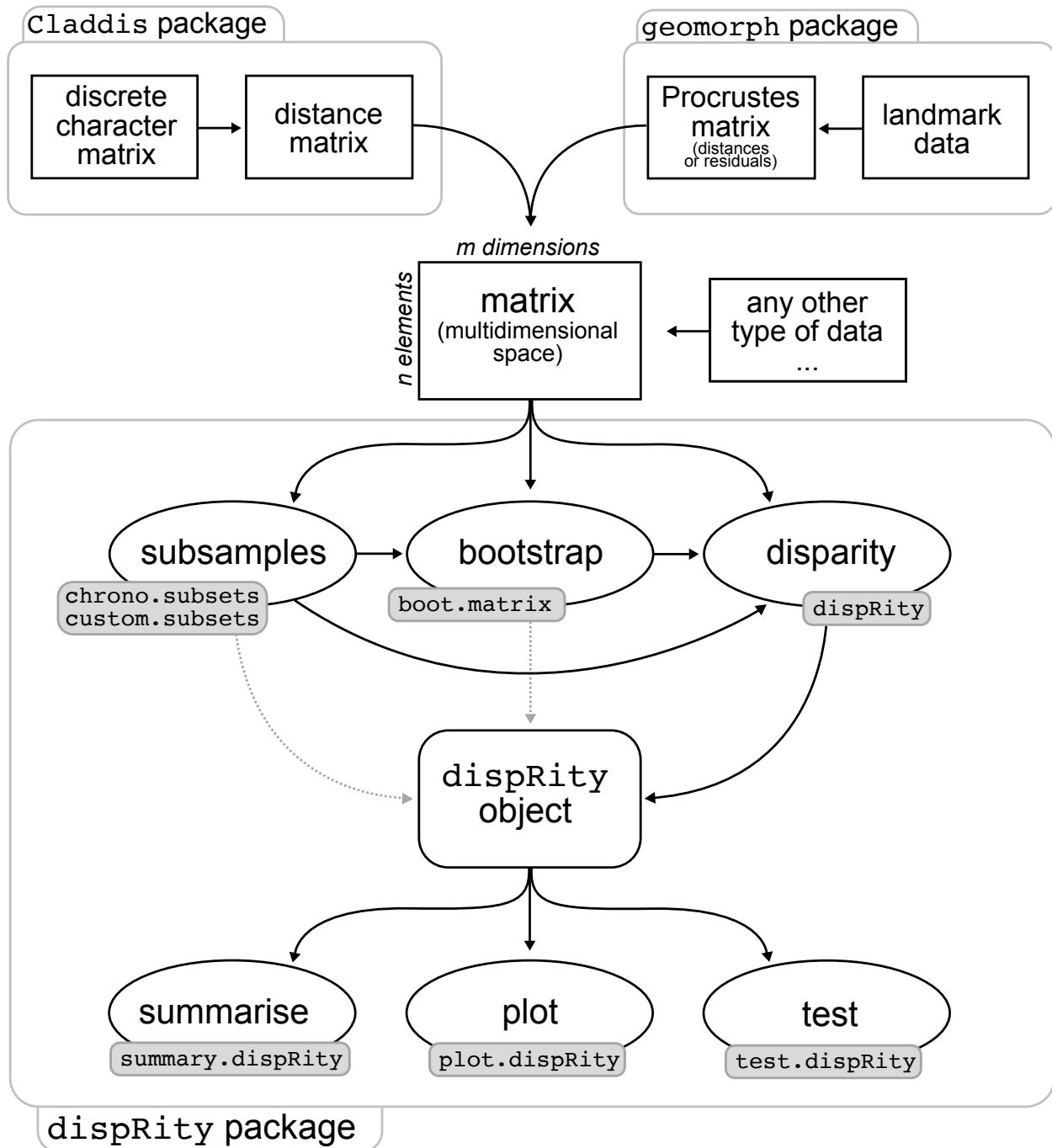


Figure 1: **dispRity** package workflow: rectangles represent matrices; ellipses represent functions; plain black arrows indicate input/output; dashed grey arrows indicate output (though the summary, plot, and test function cannot be applied if no disparity has been calculated).

- A single value (a dimension-level 1 function - e.g. the overall standard deviation;  
stats::sd)

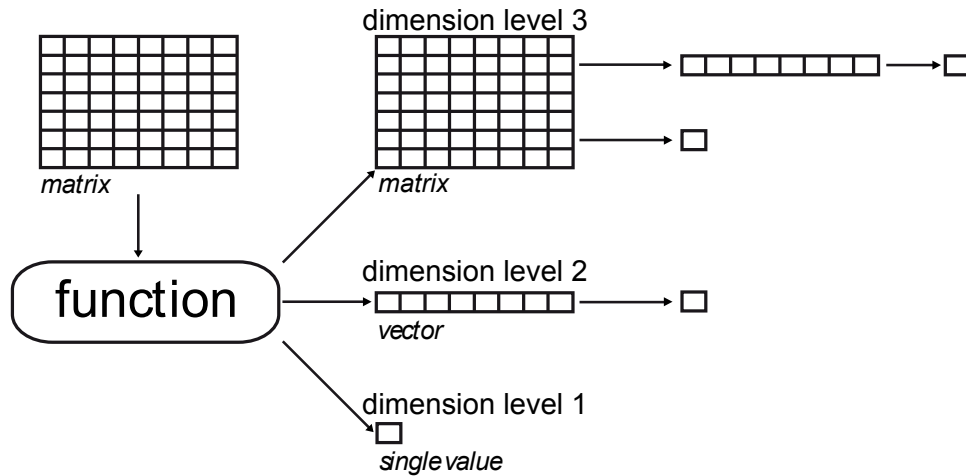


Figure 2: Illustration of the different metric dimension-levels in the dispRity package. In this example, each cell corresponds to a single value (e.g. a  $8 \times 7$  matrix or a vector of eight elements). A dimension-level 3 matrix would be a metric output a matrix (e.g. the function stats::cor to calculate the correlation between each dimension), a dimension-level 2 metric would output a vector (i.e. a distribution, e.g. dispRity::variances which calculates the variance within each dimension) and a dimension-level 1 metric would output a single value (e.g. stats::sd which calculates the standard deviation of the input matrix)

The disparity metrics can be any R function (see Table 2 for metrics implemented in the package). When multiple functions are passed to the metric argument, they are sorted by dimension-level and applied in decreasing order to the data. For example, if

127 the metric is defined as `metric = c(prod, ranges)` (the hypercube volume), the ranges  
128 function (dimension-level 2) is first applied to data and the function `prod` is then  
129 applied to the results (`prod(ranges(data))`). One can also directly pass a function  
130 description to the `metric` argument (e.g. `metric = function(x) mean(dist(x)^2)` for  
131 the average squared pairwise distance). Note that this function also allows to work on  
132 only a subset of dimensions via the `dimensions` argument (e.g. if only the  $n$  first  
133 dimensions must be considered).

name	description	dim	definition	source
ancestral. dist	The distance between an element and its ancestor	2	$\sqrt{\sum_{i=1}^n (k_n - Ancestor_n)^2}$	This package
centroids	The distance between each element and a fixed point <sup>1</sup> of the space	2	$\sqrt{\sum_{i=1}^n (k_n - Centroid_k)^2}$	This package
convhull. surface	The surface of the convex hull	1	NA	geometry::convhulln (Barber et al., 1996; Habel et al., 2015)
convhull. volume	The volume of the convex hull	1	NA	geometry::convhulln (Barber et al., 1996; Habel et al., 2015)
diagonal	The greatest Euclidean distance	1	$\sqrt{\sum_{i=1}^k  max(k_i) - min(k_i) }$	This package
ellipse. volume <sup>2</sup>	The volume of the ellipsoid	1	$\frac{\pi^{k/2}}{\Gamma(\frac{k}{2}+1)} \prod_{i=1}^k (\lambda_i^{0.5})$	This package; based on Donohue et al. (2013)
mode.val	The modal value	1	NA	This package
n.ball. volume	The hyper-spherical ( $n$ -ball) volume	1	$\frac{\pi^{k/2}}{\Gamma(\frac{k}{2}+1)} \prod_{i=1}^k R$	This package
pairwise. dist	The pairwise distances between elements	2	NA	vegan::vegdist (Oksanen et al., 2007)
radius	The radius of each dimensions	2	$ \frac{\sum_{i=1}^n k_i}{n} - f(\mathbf{v}k) $	This package
ranges	The absolute ranges of each dimension	2	$ max(k_i) - min(k_i) $	This package
span.tree. length	The minimal spanning tree length	1	$\sum(\text{branch length})$	vegan::spantree (Oksanen et al., 2007)
variances	The variance of each dimension	2	$\sigma^2 k_i^{13}$	This package

Table 2: Where  $k$  is the number of dimensions,  $n$  the number of elements,  $\Gamma$  is the Gamma

**Table 2 (caption):** Where  $k$  is the number of dimensions,  $n$  the number of

elements,  $\Gamma$  is the Gamma distribution,  $\lambda_i$  is the eigenvalue of each dimensions,  $\sigma^2$  is

their variance and  $Centroid_k$  is their mean,  $Ancestor_n$  is the coordinates of the ancestor

of element  $n$ ,  $f(\mathbf{v}k)$  is function to select one value from the vector  $\mathbf{v}$  of the dimension  $k$

(e.g. it's maximum, minimum, mean, etc.),  $R$  is the radius of the sphere or the product

of the radii of each dimensions ( $\prod_{i=1}^k R_i$  - for a hyper-ellipsoid). <sup>1</sup> by default that point is

the centroid of the elements; <sup>2</sup> this function uses a fast estimation of the eigenvalue that

only works in an ordinated space based on MDS or PCO (*not* PCA).

### *Splitting the multidimensional space into subsets*

Prior to calculating disparity, the space can be subdivided into subsets, typically to be

compared to each other. For example, one may compare the disparity of a specific

subset of the space to another or, how different subsets change sequentially (e.g.

through time). The original space corresponds to the overall space (e.g. a morphospace

contains all the observed morphologies). Subsets correspond to parts of the space with

pooled characteristics.

This splitting can be done using the `custom.subsets` or `chrono.subsets`

functions. The first function takes a matrix defining the space and a list of elements

defining the subsets. The second also takes a matrix and arguments giving the age of

the taxa (a dated phylogeny of the elements present in the morphospace - see below)

and which subsets to create: (1) discrete time subsets (or time-binning) or (2)

continuous time subsets (or time-slicing).

The time-binning method groups elements by specific age range. The time-slicing method works by using a phylogeny and looking at which taxa are present at any specific point in time. This method thus requires the nodes to be part of the space, a dated phylogeny (chronogram) and which model to use when slicing through branches rather than tips and nodes. When a slice occurs not on a tip or a node, six methods are available to select either the descendent or the ancestor's node/tip as an element for this time slice: "acctran", "deltran", "random" and "proximity" as proxy for punctuated evolution models; and "equal.split", "gradual.split" as a proxy for gradual evolution. See Guillerme and Cooper (2018) for full description of the method. Note that there is a trade-off between precision and accuracy when using the time-slicing method: a higher number of slices increases the precision of the disparity analysis but also decreases accuracy.

### *Bootstrapping and rarefying*

Disparity measurement can be influenced by sampling (Butler et al., 2012). To take this source of bias into account, one can bootstrap the multidimensional space or/and to rarefy the data. Additionally, if disparity is defined as a dimension-level 1 metric, it can be useful to measure it on bootstrapped data to obtain a distribution on which to perform statistical analyses.

Bootstrapping can be achieved by using the `boot.matrix` function which pseudo-replicates the space following two algorithms: (1) the "full" algorithm where

the bootstrapping is entirely stochastic ( $n$  elements are replaced by any  $m$  elements drawn from the data); and (2) the “single” algorithm where  $n = 1$  (similar to jackknife).

Similarly, rarefaction can be achieved through the same `boot.matrix` function. In practice, rarefaction limits the number of elements to be drawn for each bootstrap replication: only  $n - x$  elements are selected at each bootstrap replicate (where  $x$  is the number of non-sampled elements).

### *Interpreting results*

The functions above all generate a `dispRity` object that can be summarised or plotted using the S3 method functions `summary.dispRity` and `plot.dispRity`. These results can also be analysed using the `test.dispRity` function for comparing subsets or testing hypotheses.

*Summarising and plotting.*— The `summary.dispRity` and `plot.dispRity` functions allow users to set which central tendency and which quantiles should be represented. The `plot.dispRity` function graphically represents the summarised results using different representations: (1) “continuous” for displaying continuous disparity curves and (2) “box”, “lines”, or “polygons” to display them using boxplots, confidence interval lines or polygons respectively. Additional arguments specific to `dispRity` objects can also be used such as `observed` to display the observed disparity (i.e. non-bootstrapped) or `rarefaction` to only plot the disparity for a certain number of elements (i.e. the rarefaction level). The function can also take any additional graphic arguments (`main`,





diversity together. For example, one can also look the diversity of morphologies (or disparity; Foote, 1991). Using disparity, it is then also possible to assess whether one ecosystem or/and time period display more morphological variation. The following example is based on a classical morphological disparity analysis. Note that more examples are available in the package manual ([https://rawgit.com/TGuillerme/disprity/master/inst/gitbook/\\_book/index.html](https://rawgit.com/TGuillerme/disprity/master/inst/gitbook/_book/index.html)).

*disprity* data.— The package contains a dataset that is a subset from Beck and Lee (2014) and includes:

- BeckLee\_mat50: an ordinated matrix for 50 mammals based on the distance between discrete morphological characters.
- BeckLee\_mat99: the same matrix BeckLee\_mat50 with the reconstruction of their 49 ancestors.
- BeckLee\_tree: a chronogram with the 50 mammal species present in BeckLee\_mat50 and BeckLee\_mat99.
- BeckLee\_ages: the first and last occurrence data for 14 of the mammal species present in BeckLee\_mat50 and BeckLee\_mat99.
- disparity: a pre-analysed disprity object based on the data above.

In this example, the space is defined as a morphospace: the ordination of the distances among discrete morphological characters for 50 mammal species (from Beck

and Lee, 2014). Additionally, we can define disparity as the sum of the variances on each dimension (Foote, 1991; Wills et al., 1994) that will represent an aspect of the the volume of the morphospace.

*Typical disparity among groups analysis.*— One typical question with such analysis would be to test whether two groups of species have a different disparity. For example, using the data described above, we can test whether the crown mammals are more diverse in term of morphology than the stem ones. In other words, whether the approximation of the volume within the morphospace is different in crown or stem mammals. These two groups can be defined using one the package's utility functions, `crown.stem` that separate the crown and stem species given a phylogeny (allowing to ignore the nodes or not):

```
> mammal_groups <- crown.stem(BeckLee_tree, inc.nodes = FALSE)
```

It is then possible to measure the disparity between the two groups as follows:

```
> disparity <- dispRity.per.group(data = BeckLee_mat50,  
    group = mammal_groups, metric = c(sum, variances))
```

Note that this function is a wrapper function that is the equivalent to:

```
> subsets <- custom.subsets(data = BeckLee_mat50, group = mammal_groups)  
> bootstraps <- boot.matrix(subsets)  
> disparity2 <- dispRity(bootstraps, metric = c(sum, variances))
```

Which allows a finer tuning of the optional arguments in each function. The three arguments here are defined as follows: `data = BeckLee_mat50` is our space, `group =`

255 `mammal_groups` indicates which mammals belong to which group and `metric = c(sum,`  
256 `variances)` is our definition of disparity (Foote, 1991; Wills et al., 1994; Ciampaglio  
257 et al., 2001).

258       This function returns a `dispRity` object that summarises the disparity analysis:

259 `> disparity2`

260   -- `dispRity` object --

261 2 customised subsets for 50 elements with 48 dimensions:

262       `crown, stem.`

263 Data was bootstrapped 100 times (`method:"full"`).

264 Disparity was calculated as: `c(sum, variances)`.

265       As indicated, the `dispRity` object contains two customised subsets from a  
266 morphospace made of 50 elements for 48 dimensions. The `dispRity` object also  
267 displays information on the number and method of the bootstrap replicates as well as  
268 the definition of disparity. To visualise the actual disparity values, one can use the  
269 `summary` or/and `plot` options (Table 3 and Fig. 3):

270 `> summary(disparity2)`

271 `> plot(disparity2)`

272       As we can see from the summary table (Table 3) and the plot (Fig. 3), there  
273 seems to be a significant difference in morphospace volume occupied between the two  
274 groups. It is possible to test this hypothesis by using, for example, a non-parametric  
275 Wilcoxon test (`stats::wilcox.test`):

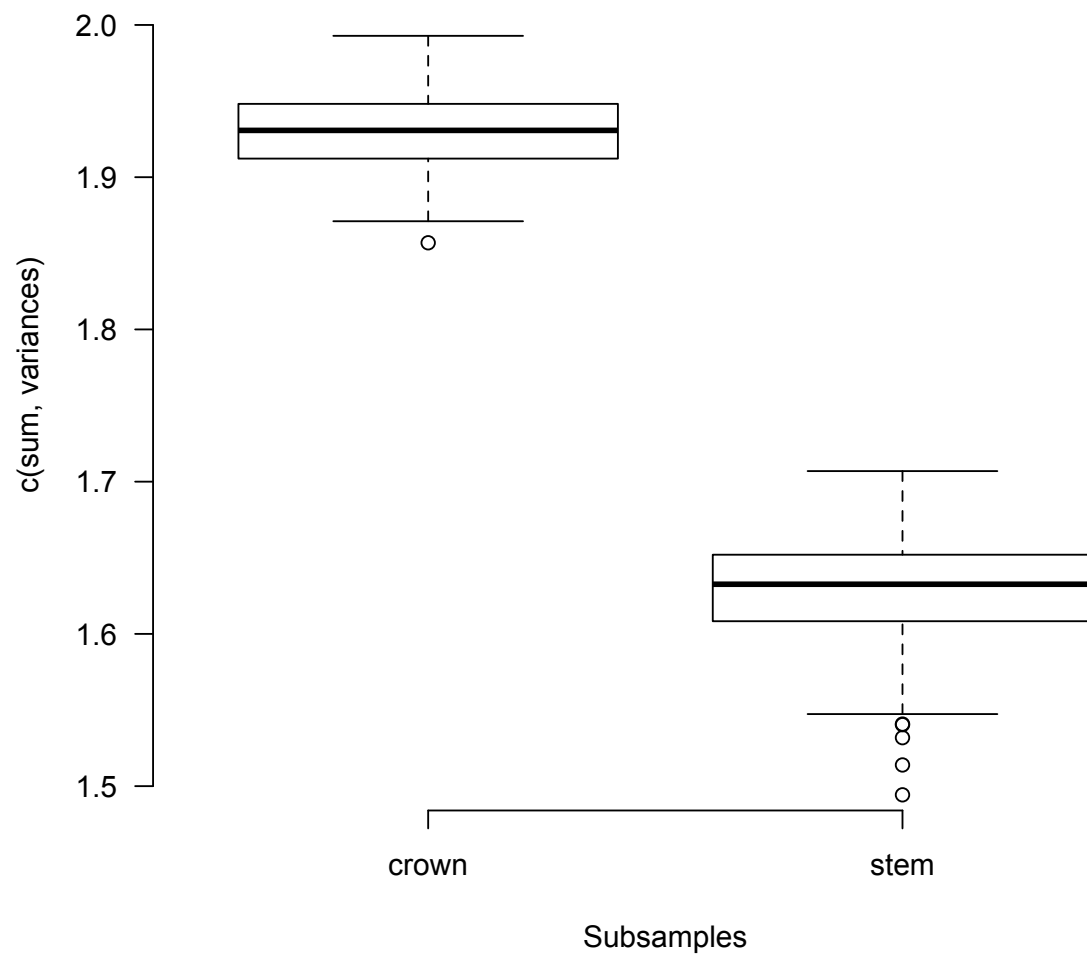


Figure 3: dispRity plot of disparity differences between groups.

	subsets	n	obs	bs.median	2.5%	25%	75%	97.5%
1	crown	30	2.00	1.93	1.87	1.92	1.95	1.98
2	stem	20	1.72	1.63	1.53	1.60	1.66	1.69

Table 3: Summarising a `dispRity` object (disparity per groups).  $n$  is the number of elements per subsets, *obs* the observed disparity (not bootstrapped), *bs.median* is the median bootstrapped disparity (here the median of the sum of variances) and the 2.5, 25, 75 and 97.5% are the confidence intervals.

```

276 > test.dispRity(disparity2, test = wilcox.test)
277 [[1]]
278 statistic: W
279 crown : stem 10000
280 [[2]]
281 p.value
282 crown : stem 2.562144e-34

```

283 As indicated by the  $p$  value, there is a significant difference in disparity between  
284 the groups. Note that by default the function only outputs the test's statistic, parameter  
285 (if parametric) and the  $p$  value. However, the raw test results can also be output using  
286 the option `details = TRUE` in the function above. Additionally, the test is here  
287 performed on the pooled bootstrapped pseudo-replications which can increase the type  
288 I error. It is possible to compare each bootstrap in a pairwise way without pooling the

289 data by using the `concatenate = FALSE` argument. The results will then be a  
290 distribution of statistics and  $p$  values. Relating back to our question: yes, crown  
291 mammals display a higher diversity in morphologies than their stem counterparts (in  
292 this example and dataset).

293 *Typical disparity-through-time analysis.*— A subsequent question to this observation could  
294 be to test whether this difference is due to an overall change in disparity through time  
295 or not. Using the same definition of the multidimensional space and disparity as in the  
296 previous example, we can measure, for example, changes in disparity through time  
297 between the Late Cretaceous (100.5 to 66.0 million years ago - Mya), the Paleocene (66.0  
298 to 56.0 Mya) and the Eocene (56.0 to 33.9 Mya). Note that stratigraphic times can be  
299 generated automatically using the `get.bin.ages` utility function.

```
300 > time_bins <- c(100.5, 66, 56, 33.9)
```

301 It is then possible to measure disparity-through-time using the following  
302 function:

```
303 > disparity3 <- dispRity.through.time(data = BeckLee_mat50,  
304   tree = BeckLee_tree, time = time_bins, metric = c(sum, variances))
```

305 Note that this function is a wrapper function that is the equivalent to:

```
306 > time_subsets <- chrono.subsets(data = BeckLee_mat50, tree = BeckLee_tree,  
307   time = time_bins, method = "discrete")  
308 > bootstraps2 <- boot.matrix(time_subsets)  
309 > disparity4 <- dispRity(bootstraps2, metric = c(sum, variances))
```

310 The arguments `data = BeckLee_mat50` and `metric = c(sum, variances)` are the same  
 311 as in the example above. However, in this type of analysis, we also need to have  
 312 additional arguments: the `time = time_bins` indicates the boundaries of the different  
 313 time bins, the `tree = BeckLee_tree` argument provides information on the age of each  
 314 element and `method = "discrete"` indicates that the data is time-binned. The resulting  
 315 `disprity` object can be summarised and plotted (Table 4 and Fig. 4):  
 316 `> summary(disparity4)`

	subsets	n	obs	bs.median	2.5%	25%	75%	97.5%
1	100.5 - 66	15	1.67	1.55	1.40	1.51	1.58	1.65
2	66 - 56	9	1.88	1.69	1.43	1.63	1.77	1.83
3	56 - 33.9	13	1.96	1.83	1.62	1.77	1.86	1.90

Table 4: Summarising a `disprity` object (disparity through time). *n* is the number of elements per subsets, *obs* the observed disparity (not bootstrapped), *bs.median* is the median bootstrapped disparity (here the median of the sum of variances) and the 2.5, 25, 75 and 97.5% are the confidence intervals.

317 `> plot(disparity4, type = "continuous")`

318 Note that many plot options specific to `disprity` objects are available such as plotting  
 319 disparity in a “continuous” fashion (inferring disparity between the time bins).

320 Similarly to the example above, it is also possible to statistically test this  
 321 hypothesis using, for example, multivariate permutation ANOVA (PERMANOVA;



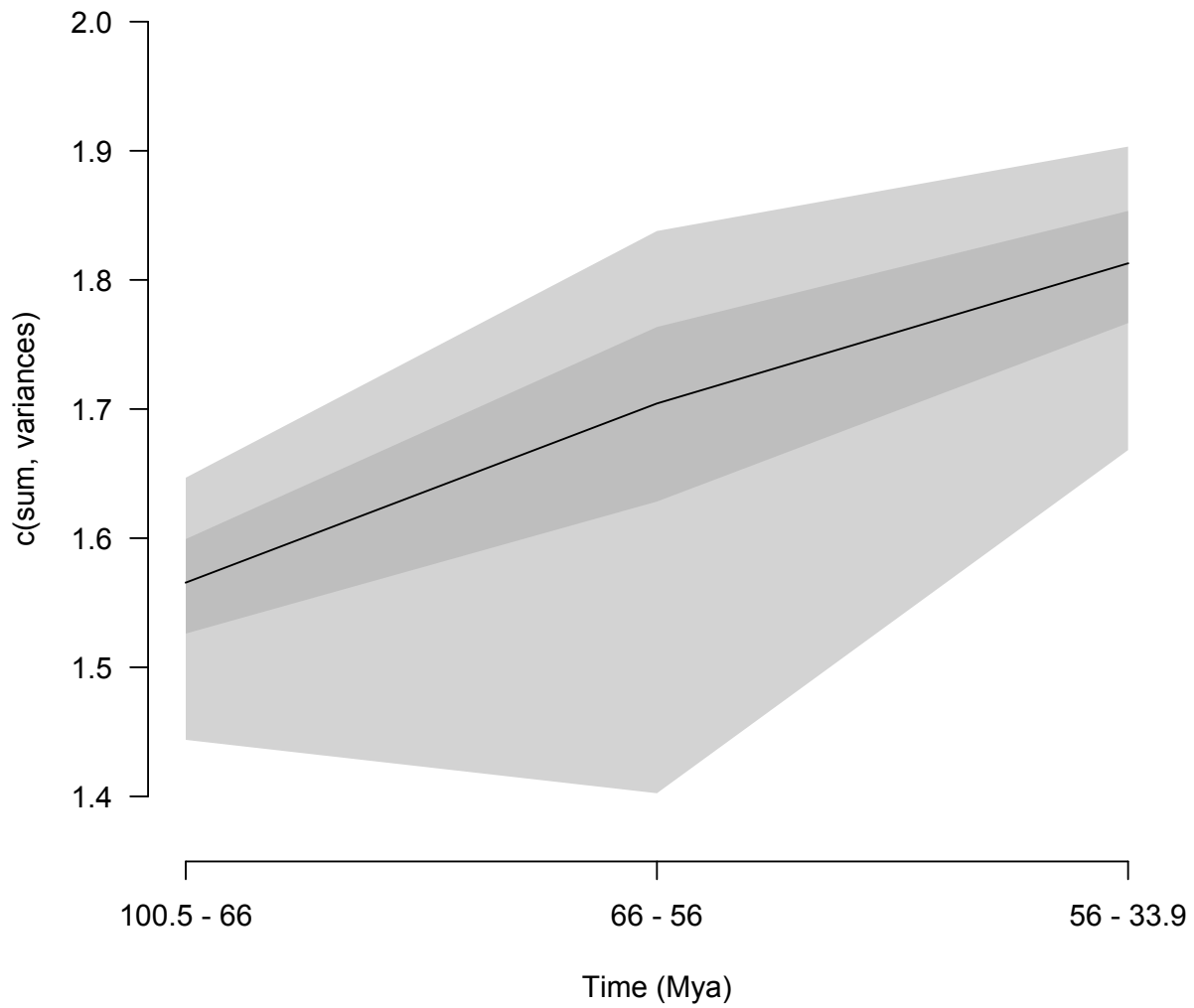


Figure 4: dispRity plot of disparity-through-time. The black line represents the median disparity (median sum of variances), the dark grey and light surfaces represent respectively the 50% and 95% confidence intervals.

Anderson, 2001) through the `adonis.dispRity` function that is a wrapper of the `vegan::adonis` function (Oksanen et al., 2007) for `dispRity` objects:

```
> test.dispRity(disparity4, test = adonis.dispRity)
```

	Df	Sum Sq	Mean Sq	F Model	R2	Pr(>F)
time	2	7.50	3.75	2.06	0.11	<0.01 ***
Residuals	34	61.82	1.81		0.89	
Total	36	69.32			1.00	

Table 5: Permanova output from `adonis.dispRity`:

Call: `vegan::adonis(formula = dist(matrix) ~time, data = disparity2, method = "euclidean")`; Permutation: free; Number of permutations: 999; Terms added sequentially (first to last). Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1.

To answer our specific question above: yes, there is an effect of time on morphological disparity (an increase) in this dataset (Table 5). Note that in this case, the function outputs different warnings on the usage of such test and the eventual data not used in the test. Additionally, the test is not applied to the bootstrapped data and thus might be sensitive to outliers and sampling size.

## ADDITIONAL INFORMATION

*Manuals and vignette*

Supplementary information concerning the package and each function can be found in R, on the project page (<https://TGuillerme/dispRity>) or in the online manual ([https://rawgit.com/TGuillerme/dispRity/master/inst/gitbook/\\_book/index.html](https://rawgit.com/TGuillerme/dispRity/master/inst/gitbook/_book/index.html)). This manual contains substantially more information and detailed examples including a tutorial for a “classic” disparity analysis in palaeobiology as well as an introduction to the use of this package in ecology or other disciplines.

### *Data simulations*

This package also contains functions for simulating random discrete morphological matrices (`sim.morpho`) or random multidimensional spaces (`space.maker`). These functions are based on a similar modular architecture as that used by the `dispRity` functions, allowing users to provide their own distribution parameters for the simulations. For example, `stats::rnorm` can be provided as an argument for drawing normal characters rates with `sim.morpho` or normally distributed spaces with `space.maker`. The discrete morphological data simulations are based on protocols from Guillerme and Cooper (2016), O’Reilly et al. (2016) and Puttick et al. (2017). The space simulations are based on the methods from Díaz et al. (2016). Both functionalities are described in more details in the package manual.

## CONCLUSION

The `dispRity` package is based on a modular architecture allowing researchers to simply define both their multidimensional space and their disparity metric to efficiently

analyse multivariate data. The `disprity` object allows users to pipeline disparity analysis from the data input (the matrix) to publication standard results (tables, plots, hypothesis testing).

## PACKAGE LOCATION

The `disprity` package is available on the CRAN at <https://cran.r-project.org/web/packages/disprity/index.html> or on GitHub at <https://github.com/TGuillerme/disprity> with more associated information. All the versions of the package are archived on ZENODO with associated DOI <https://zenodo.org/record/1186467#.WtfbGsi-kW8>.

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