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R-miss-tastic: a unified platform for missing values methods and workflows

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August 13, 2019

Abstract

Missing values are unavoidable when working with data. Their occurrence is exacerbated as more data from different sources become available. However, most statistical models and visualization methods require complete data, and improper handling of missing data results in information loss, or biased analyses. Since the seminal work of Rubin (1976), there has been a burgeoning literature on missing values with heterogeneous aims and motivations. This has resulted in the development of various methods, formalizations, and tools (including a large number of R packages). However, for practitioners, it is challenging to decide which method is most suited for their problem, partially because handling missing data is still not a topic systematically covered in statistics or data science curricula.

To help address this challenge, we have launched a unified platform: “R-miss-tastic”, which aims to provide an overview of standard missing values problems, methods, how to handle them in analyses, and relevant implementations of methodologies. The objective is not only to collect, but also comprehensively organize materials, to create standard analysis workflows, and to unify the community. These overviews are suited for beginners, students, more advanced analysts and researchers.

Keywords: missing data; state of the art; bibliography; reproducibility; teaching material

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1 Context and motivation

Missing data are unavoidable as long as collecting or acquiring data is involved. They occur for many reasons including: individuals choose not to answer survey questions, measurement devices fail, or data have not been recorded. Their presence becomes even more important as data are now obtained at increasing velocity and volume, and from heterogeneous sources not originally designed to be analyzed together. As pointed out by Zhu et al. (2019), “[o]ne of the ironies of working with Big Data is that missing data play an ever more significant role, and often present serious difficulties for analysis.”. Despite this, the approach most commonly implemented by default in software is to toss out cases with missing values. At best, this is inefficient because it wastes information from the partially observed cases. At worst, it results in biased estimates, particularly when the distributions of the missing values are systematically different from those of the observed values (e.g., Enders, 2010, chap. 2).

However, handling missing data in a more efficient and relevant way (than focusing the analysis on solely the complete cases) has attracted a lot of attention in the literature in the last two decades. In particular, a number of reference books have been published (Schafer and Graham, 2002; Little and Rubin, 2002; van Buuren, 2012; Carpenter and Kenward, 2012) and the topic is an active field of research (Josse and Reiter, 2018). The diversity of the problems of missing data means there is great variety in the methods proposed and studied. They include model-based approaches, integrating likelihoods or posterior distributions over missing values, filling in missing values in a realistic way with single, or multiple imputations, or weighting approaches, appealing to ideas from the design-based literature in survey sampling. The multiplicity of the available solutions makes sense because there is no single solution or tool to manage missing data: the appropriate methodology to handle them depends on many features, such as the objective of the analysis, type of data, the type of missing data and their pattern. Some of these methods are available in various and heterogeneous software solutions. As R is one of the main softwares for statisticians and data scientists and as its development has started almost three decades ago (Ihaka, 1998), R is one of the language that offers the largest number of implemented approaches. This is also due to its ease to incorporate new methods and its modular packaging system. Currently, there are over 270 R packages on CRAN that mention missing data or imputation in their DESCRIPTION files. These packages serve many different applications, data types or types of analysis. More precisely, exploratory and visualization tools for missing data are available in packages like **nanianr**, **VIM**, and **MissingDataGUI** (Tierney, Cook, McBain, and Fay, Tierney et al.; Tierney and Cook, 2018; Kowarik and Templ, 2016; Cheng et al., 2015).

Imputation methods are included in packages like **mice**, **Amelia**, and **mi** (van Buuren and Groothuis-Oudshoorn, 2011; Honaker et al., 2011; Gelman and Hill, 2011). Other packages focus on dealing with complex, heterogeneous (categorical, quantitative, ordinal variables) data or with large dimension multi-level data, such as **missMDA**, and **MixedDataImpute** (Josse and Husson, 2016; Murray and Reiter, 2015).

The rich variety of methods and tools for working with missing data means there are many solutions for a variety of applications. Despite the number of options, missing data are often not handled appropriately by practitioners. This may be for a few reasons. First, the plethora of options can be a double-edged sword - the sheer number of options making it challenging to navigate and find the best one. Second, the topic of missing data is often itself missing from many statistics and data science syllabuses, despite its relative omnipresence in data. So then, faced with missing data, practitioners are left powerless: quite possibly never having been taught about missing data, they do not have an idea of how to approach the problem, navigate the methods, software, or choose the appropriate method or workflow for their problem.



Figure 1: R-miss-tastic logo.

To help promote better management and understanding of missing data, we have released R-miss-tastic, an open platform for missing values. The platform takes the form of a reference website <https://rmisstastic.netlify.com/>, which collects and organizes material on missing data (Figure 1). It has been conceived by an infrastructure steering committee (ISC) working group, which first provided a CRAN Task View¹ on missing data² that lists and organizes existing R packages on the topic. The “R-miss-tastic” platform

¹<https://CRAN.R-project.org/package=ctv>

²<https://cran.r-project.org/web/views/MissingData.html>

extends and builds on the CRAN Task View by collecting and organizing articles, tutorials, documentation, and workflows for analyses with missing data. The intent of the platform is to foster a welcoming community, within and beyond the R community, and to provide teachers and professors a reference website they can use for their own classes or refer to students. The platform provides new tutorials and examples of analyses with missing data that span the lifecycle of an analysis. Going from data preparation, to exploratory data analyses, establishing statistical models, analysis diagnostics, through to communication of the results obtained from incomplete data. The platform is easily extendable and well documented, so it can easily incorporate future research in missing values. “R-miss-tastic” has been designed to be accessible for a wide audience with different levels of prior knowledge, needs, and questions. This includes for example, students looking for course material to complement their studies, statisticians searching for solutions or existing work to help with analysis, researchers wishing to understand or contribute information for specific research questions, or find collaborators.

The rest of the article is organized as follows: Section 2 describes the different sections of the platform, the choices that have been made, and the targeted audience. The section is organized as the platform itself, starting by describing materials for less advanced users then materials for researchers and finally resources for practical implementation. Section 3 provides an overview of the planed future development for the platform.

2 Structure and content of the platform

The R-miss-tastic platform is released at <https://rmisstastic.netlify.com/>. It has been developed using the R package **blogdown** Xie et al. (2017) which wraps hugo³. Live examples have been included using the tool <https://rdr.io/snippets/> provided by the website “R Package Documentation”. The sources of the platform have been made public on GitHub⁴, which provides a transparent workflow, and facilitates community contributions.

We now discuss the structure of the R-miss-tastic platform, the aim and content of each subsection, and highlight key features of the platform.

³<https://gohugo.io/>

⁴repository `R-miss-tastic/website`

2.1 Lectures

Before starting to use any of the existing implementations for handling missing values in a statistical analysis, it is essential to understand why missing values are problematic. There are many lenses to view missing data through: the source of the missing values, their potential meaning, the relevance of the features they occur in – and the implications for different types of analyses. For someone unfamiliar with missing data, it is a challenge to know where to begin the journey of understanding them, and the methods to address them.

This challenge is being addressed with “R-miss-tastic”, which makes the material to get started easily accessible.

Teaching and workshop material takes many forms – from slides, course notes, lab workshops, and video tutorials. The material is high quality, and has been generously contributed by numerous renowned researchers who research the problem of missing values, many of whom are professors having designed introductory and advanced classes for statistical analysis with missing data. This makes the material on the “R-miss-tastic” platform well suited for both beginners and more experienced users.

These teaching and workshop materials are described as “lectures”, and are organized into five sections:

1. General lectures: introduction to statistical analyses with missing values, theory and concepts are covered, such as missing values mechanism, likelihood methods, imputation.
2. Multiple imputation: introduction to popular methods of multiple imputation (joint modeling and fully conditional), how to correctly perform multiple imputation and limits of imputation methods
3. Principal component methods: introduction to methods exploiting low-rank type structures in the data for imputation and estimation
4. Specific data or applications types: lectures covering in detail various sub-problems such as missing values in time series, or surveys.
5. Implementation in R: a non-exhaustive list of detailed vignettes describing functionalities of R packages that implement some of the statistical analysis methods covered in the other lectures.

Figure 2 is a screenshot of two views of the lectures page: Figure 2A shows a collapsed view presenting the different topics, Figure 2B shows an example of the expanded view of

R-miss-tastic

A resource website on missing values - Methods and references for managing missing data

Below you will find a selection of high-quality lectures, tutorials and labs on different aspects of missing values.

If you wish to contribute some of your own material to this platform, please feel free to contact us via the [Contact form](#).

[General lectures](#)

[Multiple imputation](#)

[Missing values and principal component methods](#)

[Specific data or application types](#)

[Implementation in R](#)

[Collapse All](#)

+

+

+

+

+

[Collapse All](#)

[General tutorials](#)

+

Statistical Methods for Analysis With Missing Data
(Mark Davidson, course at NC State University, spring 2017)

Handling missing values

(Julie Josse, course at École Polytechnique, fall 2018 and Julie Josse & Rick Tievey, tutorial at useR! 2018, 2016)

Analysis of missing values

(Jae-Kwang Kim, course at Iowa State University, fall 2015)

This course focuses on the theory and methods for missing data analysis. Topics include maximum likelihood estimation under missing data, EM algorithm, Monte Carlo computation techniques, imputation, Bayesian approach, propensity scores, semi-parametric approach, and non-ignorable missing data.

- [Introduction](#)
- [Likelihood-based approach](#)
- [Computation](#)
- [Imputation](#)
- [Multiple imputation](#)
- [Propensity Score approach](#)
- [Nonignorable missing data](#)

Statistical Methods for Analysis with Missing Data
(Mauricio Sadinle, course at University of Washington, winter 2018)

[Multiple imputation](#)

+

[Missing values and principal component methods](#)

+

[Specific data or application types](#)

+

[Implementation in R](#)

+

(a) Collapsed view

(b) Extract

Figure 2: Lectures overview.

one topic (General tutorials), with a detailed description of one of the lecture (obtained by clicking on its title), “Analysis of missing values” by Jae-Kwang Kim. Each lecture can contain several documents (as is the case for this one) and is briefly described by a header presenting its purpose.

Lectures that we found very complete and recommend are:

- *Statistical Methods for Analysis with Missing Data* by Mauricio Sadinle (in “General tutorials”)
- *Missing Values in Clinical Research – Multiple Imputation* by Nicole Erler (in “Multiple imputation”)
- *Handling missing values in PCA and MCA* by François Husson. (in “Missing values and principal component methods”)

2.2 Bibliography

Complementary to the lectures section, this part of the platform serves as a broad overview on the scientific literature discussing missing values taxonomies and mechanisms and sta-

R-miss-tastic

A resource website on missing values - Methods and references for managing missing data

On this platform we attempt to give you an overview of main references on missing values. We do not claim to gather all available references on the subject but rather to offer a peak into different fields of active research on handling missing values, allowing for an introductory reading as well as a starting point for further bibliographical research.

[See here for a full \(and uncommented\) list of references.](#)

Inspired by [CRAN Task View on Missing Data](#) and a [review](#) of Imbert & Villa-Vialaneix on handling missing values (2018, written in French) we organized our selection of relevant references on missing values by different topics.

[Short introduction to missing values](#)

[General references and reviews](#)

[Weighting methods](#)

[Hot-deck and kNN approaches](#)

[Likelihood-based approaches](#)

[Single imputation](#)

[Multiple imputation](#)

[Machine Learning](#)

[Missing values mechanisms](#)

(a) Contextualized version

R-miss-tastic

A resource website on missing values - Methods and references for managing missing data

[A commented version of this bibliography can be found here.](#)

Publication type	Year	Author
All	All	Search by author name..
Citation	Year	Publication type
Collapse All		
Abayomi, K., A. Gelman, and M. Levy. <i>Diagnostics for multivariate imputations</i> . In: <i>Journal of the Royal Statistical Society, Series C (Applied Statistics)</i> 57.3 (2008), pp. 273-291.	2008	Article
DOI		
Albert, P. S. and D. A. Follmann. <i>Modeling repeated count data subject to informative dropout</i> . In: <i>Biometrics</i> 56.3 (2000), pp. 667-677.	2000	Article
DOI		
Allison, P. D. <i>Missing Data, Quantitative Applications in the Social Sciences</i> . Thousand Oaks, CA, USA: Sage Publications, 2001. ISBN: 9780761916727.	2001	Book
DOI		
Andridge, R. and R. J. A. Little. <i>A review of hot deck imputation for survey non-response</i> . In: <i>International Statistical Review</i> 78.1 (2010), pp. 40-64.	2010	Article
DOI		
Audigier, V., F. Husson, and J. Josse. <i>A principal component method to impute missing values for mixed data</i> . In: <i>Advances in Data Analysis and Classification</i> 10.1 (2016), pp. 5-26.	2016	Article
DOI		
Audigier, V., F. Husson, and J. Josse. <i>MIMCA: multiple imputation for categorical variables with multiple correspondence analysis</i> . In: <i>Statistics and Computing</i> 27.2 (2016), pp. 1-18. eprint: 1505.08116.	2016	Article
DOI		
Collapse All		

(b) Unordered version

Figure 3: Bibliography overview.

tistical methods to handle them. This overview covers both classical references with books, articles, etc. such as (Schafer and Graham, 2002; Little and Rubin, 2002; van Buuren, 2012; Carpenter and Kenward, 2012) and more recent developments such as (Josse et al., 2019; Gondara and Wang, 2018). The entire (non-exhaustive) bibliography can be browsed in two ways: 1) a complete list, filtering by publication type and year, with a search option for the authors or 2), as a contextualized version. For 2), we classified the references into several domains of research or application, briefly discussing important aspects of each domain. This double representation is shown in Figure 3 and allows an extensive search in the existing literature, while providing some guidance for those focused on a specific topic. All references are also collected in a unique BibTeX file made available on the GitHub repository⁵. Note that a link is provided for most references, although some are not open access.

⁵in `resources/rmisstastic_biblio.bib`

2.3 R packages

As mentioned in the introduction, prior to the platform development, the project started with the release of the *MissingData* CRAN Task View, which currently lists approximately 150 R packages. The CRAN Task View is continuously updated, adding new R packages, and removing obsolete ones. Packages are organized by topic: *exploration of missing data, likelihood based approaches, single imputation, multiple imputation, weighting methods, specific types of data, specific application fields*. We selected only those that were sufficiently mature and stable, and that were already published on CRAN or Bioconductor. This choice was made to ensure all listed packages can easily be installed and used by practitioners.

Despite the Task View classifying packages into different sub-domains, it may still be a challenge for practitioners and researchers inexperienced with missing values to choose the right package for the right application. To address this challenge, we provide a partial, less condensed overview on existing R packages on the platform, choosing the most popular and versatile. This overview is a blend of the Task View, and the individual package description pages and vignettes. For each selected package (7 at the date of writing of this article, namely **imputeTS**, **mice**, **missForest**, **missMDA**, **naniar**, **simputation** and **VIM**), we provided a category (in the style of the categorization in the Task View), a short description of use-cases, its description (as on CRAN), the usual CRAN statistics (number of monthly downloads, last update), the handled data formats (e.g., `data.frame`, `matrix`, `vector`), a list of implemented algorithms (e.g., k-means, PCA, decision tree), and the list of available datasets, some references (such as articles and books) and a small chunk of code, ready for a direct execution on the platform via the *R package Documentation*⁶. Figure 4 shows the condensed view of the package page and the expanded description sheet of a given package (here **naniar**).

We believe shortlisting R packages is especially useful for practitioners new to the field, as it demonstrates data analysis that handles missing values in the data. We are aware that this selection is subjective, and welcome external suggestions for other packages to add to this shortlist.

2.4 Data sets

Especially in methodology research, an important aspect is the comparison of different methods to assess the respective strengths and weaknesses. There are several data sets that are recurrent in the missing values literature but, they have not been listed together

⁶<https://rdrr.io/snippets/>

R-miss-tastic

A resource website on missing values - Methods and references for managing missing data

R Packages

This page provides introductions to popular missing data packages with small examples on how to use them. Thus the page gives more extensive information than the [CRAN Task View on Missing Data](#), which is recommended to get a first overall overview about the CRAN missing data landscape.

You can also contribute on your own to this page and provide a short introduction to a missing data package. Take a look at [this short description](#) on how to do this. We are very happy about all contributions.

Sort by name

Sort by Category

• missMDA

Category: Single and multiple Imputation, Multivariate Data Analysis
Imputation of incomplete continuous or categorical datasets; Missing values are imputed with a principal component analysis (PCA), a multiple correspondence analysis (MCA) model or a multiple factor analysis (MFA) model; Perform multiple imputation with and in PCA or MCA.

downloads 4000/month

CRAN 2019-01-23

More...

• imputeTS

Category: Time-Series Imputation, Visualisations for Missing Data
Imputation (replacement) of missing values in univariate time series. Offers several imputation functions and missing data plots. Available imputation algorithms include: 'Mean', 'LOCF', 'Interpolation', 'Moving Average', 'Seasonal Decomposition', 'Kalman Smoothing on Structural Time Series models', 'Kalman Smoothing on ARIMA models'.

downloads 12K/month

CRAN 2019-07-01

More...

• mice

Category: Multiple Imputation
Multiple imputation using Fully Conditional Specification (FCS) implemented by the MICE algorithm as described in Van Buuren and Groothuis-Oudshoorn (2011). Each variable has its own imputation model. Built-in imputation models are provided for continuous data (predictive mean matching, normal), binary data (logistic regression), unordered categorical data (polynomial logistic regression) and ordered categorical data (proportional odds). MICE can also impute continuous two-level data (normal model, pan, second-level variables). Passive imputation can be used to maintain consistency between variables. Various diagnostic plots are available to inspect the quality of the imputations.

downloads 41K/month

CRAN 2019-07-10

More...

Package:

naniar

Category:

Data Structures, Summaries, and Visualisations for Missing Data

Use-Cases:

Visualization of missing values, descriptive statistics, ...

Popularity:

downloads 5305/month

Description:

Missing values are ubiquitous in data and need to be carefully explored and handled in the initial stages of analysis. In this vignette we describe the tools in the package naniar for exploring missing data structures with minimal deviation from the common workflows of ggplot and tidy data.

Last update:

CRAN 2019-02-15

Datasets:

- oceanbuoys
- pedestrian
- riskfactors

Further Information:

- Tierney, N. J., & Cook, D. H. (2018). Expanding tidy data principles to facilitate missing data exploration, visualization and assessment of imputations. arXiv preprint arXiv:1809.02264. [PDF \(on arXiv\)](#)
- [Vignettes](#)
- [Related visdat R-package](#)

Input:

data.frame, vector

Example:

```
library(naniar)

data(airquality)

print("print data set with NAs")
print(head(airquality))

## Replace "NA" values with values 10% lower
## than the minimum value in that variable.
## This is done by calling the geom_miss_point() function
ggplot2::ggplot(airquality,
                 ggplot2::aes(x = Solar.R,
                              y = Ozone)) +
  geom_miss_point()
```

Here you can have a interactive look at the example:

```
library(naniar)

data(airquality)

print("print data set with NAs")
print(head(airquality))

## Replace "NA" values with values 10% lower
## than the minimum value in that variable.
## This is done by calling the geom_miss_point() function
ggplot2::ggplot(airquality,
```

Run (Ctrl-Enter)

(a) Extract of global view

(b) Description sheet

Figure 4: R packages overview.

yet. We gathered publicly available data sets that have been used recurrently for comparison or illustration purposes in publications, R packages and tutorials. Most of these datasets are already included in R packages but some are available on other data collections. Figure 5 shows how the datasets are presented, with a detailed description shown for one of the dataset (“Ozone”, obtained by clicking on its name). The description follows the UCI Machine Learning Repository presentation (Dua and Graff, 2019), including a short description of the dataset, how to obtain it, external references describing the dataset in more details, and links to tutorials/lectures on our websites or to vignettes in R packages that use the dataset.

In addition, the Data sets page also references existing methods for generating missing data, given assumptions on their generation mechanisms (as in the R package **mice**).

2.5 Workflows

In the same spirit as the previous section, workflows present several illustrative and generic approaches given in form of R Markdown files. Currently there are three workflows available on the platform:

- *How to generate missing values?* Generate missing values under different mechanisms, on complete or incomplete data sets. Useful for simulation to compare methods.
- *How to do statistical inference with missing values?* Estimate linear and logistic regression parameters for Gaussian data.
- *How to impute missing values?* Impute missing values with conditional models or low-rank models.

There are two aims of these workflows: 1) they provide a practical implementation of concepts and methods discussed in the lectures and bibliography sections; 2) they are coded in a generic way, allowing for simple re-use on other data sets, for integration of other estimation or imputation methods. We encourage practitioners and researchers to use and adapt these workflows, to improve reproducibility and comparability of their work.

Of course, these workflows do not cover the entire spectrum of existing methods and data problems. The goal of this workflow section is to start the shift towards covering a larger spectrum of workflows, and to encourage the use of standardized procedures to evaluate and compare methods for estimation, prediction or imputation.

Incomplete data

The data sets listed below are either widely used in general in the missing data community or used for illustration of different methods handling missing values in the tutorials from the [Tutorials](#) and [R packages](#) sections. This presentation scheme is inspired by the [UCI Machine Learning Repository](#).

Click on a table entry to obtain further information about the data set.

Name	Data Types	Attribute Types	# Instances	# Attributes	% Missing entries	Complete data available	Year
Airquality	Multivariate, Time Series	Real	154	6	7	No	1973
chorizonDL	Multivariate	Integer, Real	606	110	15	Yes	1998
Health Nutrition And Population Statistics	Multivariate, Time Series	Integer, Real	15,022	397	54	No	2017
NHANES	Multivariate	Categorical, Integer, Real	10,000	75	37	No	2012
oceanbuoys	Multivariate, Time Series	Real	736	8	3	No	1997
Ozone	Multivariate	Categorical, Integer, Real	366	13	6	No	1976
<p>Los Angeles Ozone Pollution Data, 1976. This data set contains daily measurements of ozone concentration and meteorological quantities. It can be found in R in the mlbench package and is loaded by calling <code>data(Ozone)</code>.</p> <p>More information on the dataset.</p> <p>Tutorials illustrating methods on this data:</p> <ul style="list-style-type: none"> Julie Josse's course on missing values imputation using PC methods. Julie Josse's and Nick Tierney's tutorial on handling missing values. Download the data set from this tutorial: ozoneNA.csv Nick Tierney's nan1ar vignette for missing data visualization. 							
pedestrian	Multivariate, Time series	Categorical, Integer	37,700	9	2	No	2016

Figure 5: Data sets overview.

2.6 Additional content

This unified platform collects and edits the contributions of numerous individuals who have investigated the missing values problems, and developed methods to handle them for many years. To provide an overview of some of the main actors in this field, the list of all contributors who agreed to appear on this platform is given with links to their personal or to their research lab website.

We also provide links to other interesting websites or working groups, not necessarily working with R but with other programming languages such as Python (Van Rossum and Drake Jr, 1995) or SAS/STAT®.

The platform also provides two other features to engage the community:

1. a regularly updated list of events such as conferences or summer schools with special focus on missing values problems, and
2. a list of recurring questions together with short answers and links for more details for every question.

3 Perspectives and future extensions

By providing a platform and community to discuss missing data, software, approaches and workflows, we are providing a base from which we can grow.

3.1 Towards uniformization and reproducibility

One way to promote and encourage practitioners and researchers in their work with missing values is to provide community benchmarks and workflows centered around missing data. We will continue working on such workflows and the source code would be made available on the platform, and in doing so we hope to encourage users to continue benchmarking new methods and to present the results in a clear, fair, and reproducible way.

In addition, we plan to propose two types of data challenges - 1) imputation and estimation, and 2) analysis workflow. For the first challenge, the objective is to find the best imputation or estimation strategy. The community would be given a dataset with missing values, for which there is actually a hidden copy of the real values. The community is then tasked with creating imputed values, which are assessed against the original dataset with complete values, to determine which imputation is best. This is similar in spirit to the Netflix prize (Bennett et al., 2007) and the M4 challenge in the time series domain

(Makridakis et al., 2018). This benchmarking could be extended to other areas, such as parameter estimation, and predictive modeling with missing data.

Analysis workflow could form another community challenge, assessed in a similar way to existing “datathon” events where entries are assessed by an expert panel. Here the challenge could be to develop workflows and data visualizations from complex data. The data could have challenging features, and be combined from various data with complex structure, such as those data with several types of missingness, images, text, data, longitudinal data, and time series.

As has been demonstrated with data competition, involving the community brings forth many creative solutions and discussions that advance the field, and challenge existing strategies.

3.2 Pedagogical and practical guidance

In addition to the benchmarks and data challenges, we also plan to provide further guidance for both learning or teaching, and for applying the existing methods. For instance, an FAQ section is available on the platform, which answers prominent questions recurrent in lectures and talks, and for which the answers cannot always be found directly in the bibliography and lecture materials. Questions we receive on our platform, via the contact form or at other occasions, will also be posted there together with a concise answer.

3.3 Outreach

Despite the initial anchoring in the R community, we are currently working in collaboration with other communities, in particular with several developer teams of scikit-learn⁷ Pedregosa et al. (2011). Such collaborations will allow us to integrate new workflows, share respective experiences with missing values and to reach an even larger audience.

3.4 Participation and interaction

This platform is aimed to be for the community, in the sense that we welcome every comment and question, encourage submissions of new work, theoretical or practical, either through the provided contact form or directly via the GitHub project repository⁸. We have already received much useful feedback and contributions from the community, organized

⁷<https://scikit-learn.org/stable/index.html>

⁸<https://github.com/R-miss-tastic/website>

several remote calls and working sessions at statistics conferences. We are planning on regularly relaunching calls for new material for the platform, for instance through the R consortium blog⁹, R-bloggers¹⁰ and social media platforms. We also intend to use these channels to communicate more generally about the platform and the topic of missing values.

In order for the platform to be a reference to the community, it needs to provide regularly updated user friendly content. Crucial to this is creating sustainable solutions for the maintenance of the R-miss-tastic platform, which is being actively considered by the team. We welcome any community feedback on this topic.

The aim of this platform is to go further than only community participation, namely to seed meaningful community interactions, and make it a hub of communication amongst groups that rarely exchange, both within, and between academia and industry communities.

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