



cleanR: Maid for Cleaning Datasets in R

Anne H. Petersen

Biostatistics

Department of Public Health

University of Copenhagen

Claus Thorn Ekstrøm

Biostatistics

Department of Public Health

University of Copenhagen

Abstract

Data cleaning and -validation are the first steps in any data analysis, as the validity of the conclusions from the analysis hinges on the quality of the input data. Mistakes in the data can arise for any number of reasons, including erroneous codings, malfunctioning measurement equipment, inconsistent data generation manuals and many more. Ideally, a human investigator should go through each variable in the dataset and look for potential errors — both in input values and coding — but that process can be very time-consuming, expensive and error-prone by itself.

We describe an R package which implements an extensive and customizable suite of quality assessment tools to be applied to a dataset in order to identify potential problems in its variables. The results can be presented in an auto-generated, non-technical, stand-alone overview document, intended to be perused by an investigator with an understanding of the variables in the data and the experimental design, but not necessarily knowledge of

R. Thereby, **cleanR** aids the dialogue between data analysts and field experts, while also providing easy documentation of reproducible data cleaning steps and data quality control. Moreover, the **cleanR** solution changes the data cleaning process from the usual ad hoc approach to a systematic, well-documented endeavor. **cleanR** also provides a suite of more typical R tools for interactive data quality assessment and -cleaning. **Hvad henvises der til med denne sætning?**

Keywords: data cleaning, quality control, R.

1. Introduction

Though data cleaning might be regarded as a somewhat tedious activity, adequate data cleaning is crucial in any data analysis. With ever-growing dataset sizes and complexities, statisticians and data analysts find themselves spending a large portion of their time on data cleaning and on data wrangling. While a computer should never provide an unsupervised

decision on what should be done to potential errors in the dataset, it can be an extremely useful tool in tracking down and flagging potential erroneous data and in providing information for humans to easier identify errors based on the context.

Online tools such as OpenRefine (<http://openrefine.org/>) and R-packages such as **plyr**, and **data.table** have made data wrangling a lot easier, but only a handful of packages such as **editrules**, **validate**, **DataCombine**, and **janitor** attempt to implement systematic, reproducible data cleaning. These packages use different approaches for data cleaning: **editrules** and **validate** provide frameworks for setting up and checking constraints on the variables, while **DataCombine** and **janitor** both provide a few functions for identifying problems (e.g, duplicates, dates coded as numbers, etc.) in data.

While these tools attempt to alleviate the ubiquitous ad hoc approach to data cleaning they are primarily intended for the data savvy users and less on the general researcher with a knowledge about the specific field and context of the available data. The **cleanR** package tries to address this by providing a framework that both allows for extendable, systematic, reproducible data cleaning, and summarizing findings for researchers from other fields such that they can act as human experts when tracking down potential errors.

Data cleaning is a time consuming endeavor, as it inherently requires human interaction since every dataset is different and the variables in the dataset can only be understood in the proper context of their origin. This often requires a collaborative effort between an expert in the field and a statistician or data scientist, which may be why the process of proper data cleaning is not always undertaken. In many situations, these errors are discovered in the process of the data analysis (e.g., a categorical variable with numeric labels for each category may be wrongly classified as a quantitative variable or a variable where all values have erroneously been coded to the same value), but in other cases a human with knowledge about the data context area is needed to identify possible mistakes in the data (e.g., if there are 4 categories for a variable that should only have 3).

The **cleanR** approach to data cleaning and -quality assessment is governed by two fundamental paradigms. First of all, there is no need for data cleaning to be an ad hoc procedure. Often, we have a very clear idea of what flags are raisable in a given dataset before we look at it, as we were the ones to produce it in the first place. This means that data cleaning can easily be a well-documented, well-specified procedure. In order to aid this paradigm, **cleanR** provides easy-to-use, automated tools for data quality assessment in R on which data cleaning decisions can be build. This quality assessment is presented in an auto-generated overview document, readable by data analysts and field experts alike, thereby also contributing to a inter-field dialogue about the data at hand. Oftentimes, e.g. distinguishing between faulty codings of a numeric value and unusual, but correct, values requires problem-specific expertise that might not be held by the data analyst. Hopefully, having easy access to data descriptions through **cleanR** will help this necessary knowledge sharing.

While **cleanR**'s primary raison d'être is auto-generating data quality assessment overview documents, we still wish to emphasize that it is *not* a tool for unsupervised data cleaning. This qualifies as the second paradigm of **cleanR**: Data cleaning decisions should always be made by humans. Therefore, **cleanR** does not supply any tools for “fixing” errors in the data. However, we do provide interactive functions that can be used to identify potentially erroneous entries in a dataset and that can make it easier to solve data issues, one variable at a time.

This manuscript is structured as follows: First, in Section 2, we introduce the representative of the first paradigm, namely the `clean()` function, which generates data cleaning overview documents. In the **cleanR** package, we have provided a number of default cleaning steps that cover the data cleaning challenges, we find to be most common. Next, in Section 3, we present the interactive mode of **cleanR**, as motivated by the second paradigm above. But, as any data analyst knows, every dataset is different, and some datasets might include problems that cannot be detected by our data checking functions. In Section 4, we turn to the question of how such **cleanR** extensions can be made, such that they are integrable with the `clean()` function and with the other tools available in **cleanR**. At last, in Section 5 [proper ref](#), we discuss a number of examples of specific data cleaning challenges and how **cleanR** can be used to solve them.

2. Creating a data cleaning overview

The `clean()` function is the primary workhorse of **cleanR** and this is the only function needed by the user if the standard battery of tests are used to output the data cleaning summaries. The data cleaning output itself is an overview document, intended for reading by humans, in either pdf or html format. Appendix A provides an example of a data cleaning output document, produced by calling `clean()` on the dataset `toyData` available in **cleanR**. The first two pages of this data cleaning output are shown in Figure 2. `toyData` is a very small (15 rows and 6 variables), artificial dataset, whose only purpose is to illustrate the main capabilities of **cleanR**. The following commands load the dataset and produce the cleaning output:

```
> library(cleanR)
> data(toyData)
> toydata
```

	var1	var2	var3	var4	var5	var6
1	red	1	a	-0.65959383	1	Irrelevant
2	red	1	a	0.08671649	2	Irrelevant
3	red	1	a	-0.10951326	3	Irrelevant
4	red	2	a	0.08630221	4	Irrelevant
5	red	2	a	-1.84311184	5	Irrelevant
6	red	6	b	0.92210680	6	Irrelevant
7	red	6	b	1.01921086	7	Irrelevant
8	red	6	b	-0.92428326	8	Irrelevant
9	red	999	c	-0.65340163	9	Irrelevant
10	red	NA	c	0.21133941	10	Irrelevant
11	blue	4	c	0.91783009	11	Irrelevant
12	blue	82	.	0.10313983	12	Irrelevant
13	blue	NA		0.16954218	13	Irrelevant
14	<NA>	NaN	other	0.41967230	14	Irrelevant
15	<NA>	5	OTHER	0.77143836	15	Irrelevant

```
> clean(toyData)
```

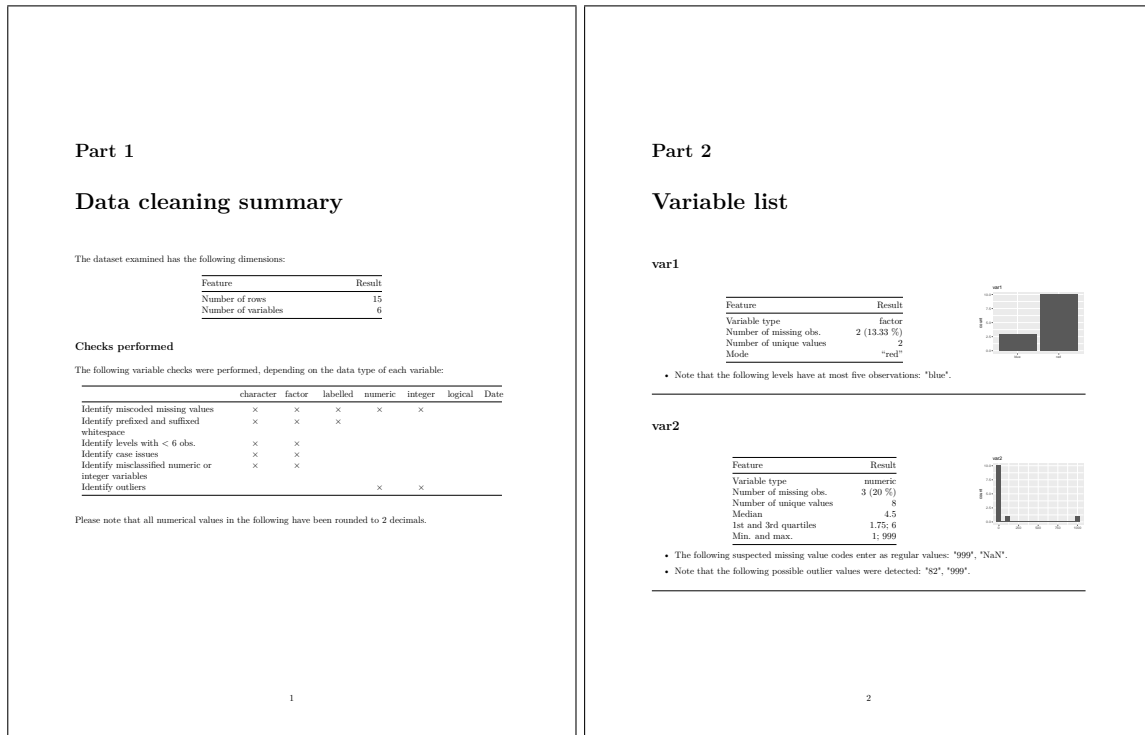


Figure 1: Example output from running `clean()` on the `toyData` dataset. First a summary of the full dataset is given and then type-dependent information on each variable is given in a table and a graph. Larger versions of the pages can be seen in Appendix A.

By default, an R markdown file and rendered pdf overview document is produced, saved to the disc (in the working directory) and opened for immediate inspection. Turning to Figure 2, we see that such a data cleaning output document consists of two parts. First, an overview of what was done is presented under the title *Data cleaning summary*. Secondly, each variable in the dataset is presented in turn using (up to) three tools in the *Variable list*: A table summarizing key features of the variable, a figure visualizing its distribution and potentially also a list of flagged issues. For instance, in the `numeric`-type variable `var2` from `toyData`, `clean()` has identified two values that are suspected to be miscoded missing values (999 and `NaN`), while two values were also flagged as potential outliers that should be investigated more carefully.

Though the `clean()` function is very easy to use, it should not be mistaken to be inflexible. A large number of function arguments allows for the cleaning overview document to be molded according to the user's needs.

The most commonly used arguments are summarized in Table 1 and they are grouped according to the part of the cleaning process they influence. In order to understand this distinction, a glimpse of the inner structure of `clean()` is shown in Figure 2. In the following we give examples on how to use these parameters to influence the output of `clean()`.

For example, to get a summary document in html format that only contains the variables with potential problems, and with a limit of maximum 10 printed potential errors for each

Argument	Description	Default value
Control input variable and summary		
<code>useVar</code>	What variables should be used?	NULL (corresponding to all variables)
<code>ordering</code>	Ordering of the variables in the data summary (as is or alphabetical)	"asIs"
<code>onlyProblematic</code>	Should only variables flagged as problematic be included in the <i>Variable list</i> ?	FALSE
<code>listChecks</code>	Should an overview of what checks were performed by listed in the <i>Data cleaning summary</i> ?	TRUE
Control summarize, visualize, and check steps		
<code>mode</code>	What steps should be performed for each variable (out of the three possibilities <i>summarize</i> , <i>visualize</i> , <i>check</i>)?	c("summarize", "visualize", "check")
<code>labelled_as</code>	How should variables of class <code>labelled</code> be handled (as factors, is missing values or by ignoring labels)?	"factor"
<code>smartNum</code>	Should numerical values with only a few unique levels be flagged and treated as a factor variable?	TRUE
<code>maxProbVals</code>	Maximum number of problematic values to print, if any are found in data checks	Inf
<code>maxDecimals</code>	Maximum number of decimals to print for numeric values in the variable list	2
<code>twoCol</code>	Should the summary table and visualizations be placed side-by-side (in two columns)?	TRUE
Control output and post-processing		
<code>output</code>	Type of output file to be produced (html, or pdf)	"pdf"
<code>render</code>	Should the output file be rendered from markdown?	TRUE
<code>openResult</code>	If a pdf/html file is rendered, should it automatically open afterwards, and if not, should the <code>rmarkdown</code> file be opened?	TRUE
<code>replace</code>	Overwrite an existing markdown file with the same name?	FALSE

Table 1: A selection of commonly used arguments to `clean()` separated into the parts they control.

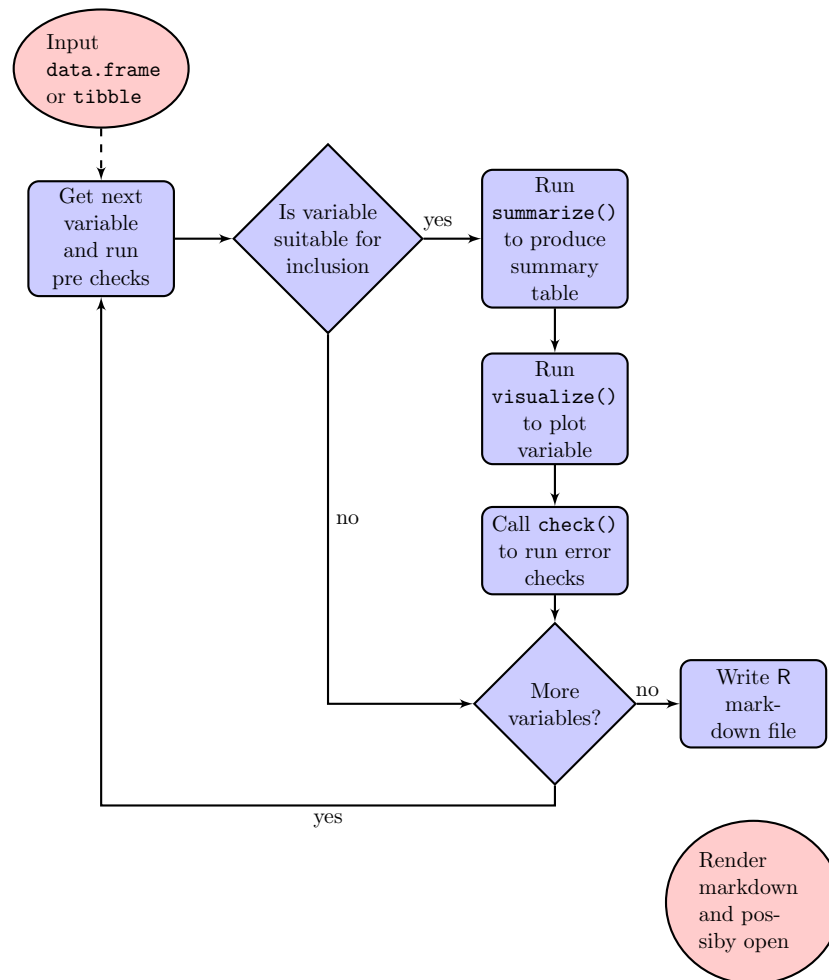


Figure 2: Overall illustration of the stages undertaken when running `clean()`. Each variable is checked for eligibility before running `summarize()`, `visualize()`, and `check()`, and the resulting R markdown file may be rendered and opened.

variable we can write (output not shown). Also, we can add the argument `replace=TRUE` in order to force `clean()` to overwrite any existing files produced by `clean()`.

```
> clean(toyData, output="html", onlyProblematic=TRUE, maxProbVals=10,
        replace=TRUE)
```

The final rendering of the generated markdown file is controlled with the `render` and `openResult` arguments which both default to `TRUE` *Bliver det ved med at være sandt?*. `render` determines if the R markdown file produced should be rendered using the `rmarkdown` package and `openResult` decides whether the output html or pdf file should be opened. The following command produces an R markdown file containing the data cleaning process information but the markdown file is not rendered into html and it is not opened.

```
> clean(toyData, output="html", render=FALSE, openResult=FALSE)
```

	Description	Variable classes						
		C	F	I	L	B	N	D
summaryFunctions								
centralValue	Compute median or mode	×	×	×	×	×	×	×
countMissing	Compute ratio of missing observations	×	×	×	×	×	×	×
minMax	Find minimum and maximum values			×			×	×
quartiles	Compute 1st and 3rd quartiles			×			×	×
uniqueValue	Count number of unique values	×	×	×	×	×	×	×
variableType	Data class of variable	×	×	×	×	×	×	×
visualFunctions								
basicVisual	Histograms and barplots using base R graphics	×	×	×	×	×	×	×
standardVisual	Histograms and barplots using ggplot2	×	×	×	×	×	×	×
checkFunctions								
identifyCaseIssues	Identify case issues	×	×					
identifyLoners	Identify levels with < 6 obs.	×	×					
identifyMissing	Identify miscoded missing values	×	×	×	×	×		
identifyNums	Identify misclassified numeric or integer variables	×	×					
identifyOutliers	Identify outliers			×		×	×	
identifyOutliersTBStyle	Identify outliers (Turkish Boxplot style)			×		×	×	
identifyWhitespace	Identify prefixed and suffixed whitespace	×	×		×			
isCPR	Identify Danish CPR numbers	×	×	×	×	×	×	×
isEmpty	Check if the variable contains only a single value	×	×	×	×	×	×	×
isKey	Check if the variable is a key	×	×	×	×	×	×	×

Table 2: List of all summary functions (used in the summary table for each variable in the output), visual functions (used for visualization of each variable), and check functions (used for data checks for each variable) currently implemented in **cleanR**. The variable classes C, F, I, L, B, N, and D, refer to **character**, **factor**, **integer**, **labelled**, **logical** (boolean), **numeric**, and **Date**, respectively.

cleanR uses three different types of functions for performing all steps in the above, namely `summaryFunctions`, `visualFunctions` and `checkFunctions`. By default, `clean()` runs all the summary, visualization, and check functions currently implemented for each variable type as part of the algorithm (see Figure 2). Table 2 lists all these functions but we can also use the `allSummaryFunctions()`, `allVisualFunctions()`, and `allCheckFunctions()` function in R to print an overview list. For example the implemented summary functions are:

```
> allSummaryFunctions()
```

name	description	classes
centralValue	Compute median or mode	character, Date, factor, integer, labelled, logical, numeric
countMissing	Compute ratio of missing observations	character, Date, factor, integer, labelled, logical, numeric
minMax	Find minimum and maximum values	integer, numeric, Date
quartiles	Compute 1st and 3rd quartiles	integer, numeric
uniqueValues	Count number of unique values	character, Date, factor, integer, labelled, logical, numeric
variableType	Data class of variable	character, Date, factor, integer, labelled, logical, numeric

Thus we can see, for example, that the summary table for a **numeric**, **integer**, or **Date** variable will include information about the minimum and maximum values, while all variable classes will produce some kind of information about the central tendency (i.e., mode or median).

We can control the default summaries and checks for each variable type through the `XXXSummaries` and `XXXChecks` arguments where **XXX** represents a variable type, e.g., `factorChecks` for factors, `numericChecks` for numeric variables, etc. These arguments accept a vector of summary or check functions that should be run for a particular variable type and the default values for each of these arguments (i.e., the functions from Table 2 that are applied) can be obtained through the `defaultXXXChecks()` and `defaultXXXSummaries()` functions, where **XXX** again refers to the variable type.

For example, the default summaries being used for a factor variable is


```
> defaultFactorSummaries()
```

```
[1] "variableType" "countMissing" "uniqueValues" "centralValue"
```

We can change the summaries (and similarly the checks) by setting the corresponding arguments when calling `clean()`. For example, to get only the variable type and the central tendency listed in the summary table of each variable we write

```
> clean(toyData, output="html",
        characterSummaries = c("variableType", "centralValue"),
        factorSummaries = c("variableType", "centralValue"),
        labelledSummaries = c("variableType", "centralValue"),
        numericSummaries = c("variableType", "centralValue"),
        integerSummaries = c("variableType", "centralValue"),
        logicalSummaries = c("variableType", "centralValue"),
        dateSummaries = c("variableType", "centralValue"))
```

In this particular case, where we specify the same set of summary functions for each variable type, we can use the simpler argument `allSummaries` which overrides the summary functions for all variable types. Thus, the same result as above could be obtained with

```
> clean(toyData, output="html",
        allSummaries = c("variableType", "centralValue"))
```

Similarly, the checks applied are set with the `XXXChecks` arguments. The default checks being applied to a factor is

```
> defaultFactorChecks()
```

```
[1] "identifyMissing"    "identifyWhitespace" "identifyLoners"
[4] "identifyCaseIssues" "identifyNums"
```

Now, if we only wanted to apply the identify whitespace function for factor variables then we would need to set the `factorChecks` accordingly

```
> clean(toyData, output="html",
        factorChecks = c("identifyWhitespace"))
```

or we could remove checks for factor altogether by setting the corresponding argument to `NULL` in which case factor variables will not be checked for any potential errors.

```
> clean(toyData, output="html", factorChecks = NULL)
```

As indicated in Figure 2 there are two stages where `clean()` applies function(s) to each of the variables:

1. In the precheck functions
2. As part of the summarize/visualize/check (SVC) steps

Each of these stages are controllable using appropriate function arguments in `clean()`, and above we have shown examples of how to tweak them to modify the data cleaning outputs. However, if for instance the dataset at hand requires completely different visualizations then more control is needed, and Section 4 explains how to modify, and expand the possibilities by producing new functions quite easily.

3. Using cleanR interactively

While overview documents are great for presenting and documenting the data cleaning checks, it may be natural to work more interactively through the data cleaning process. **cleanR** also provides more standard R interactive tools, such as functions that print results to the console or returns the information as an object for later use. This section describes how to use the functions `check()`, `summarize()` and `visualize()` to work interactively with **cleanR**.

3.1. Data cleaning by hand: An example

Let's say we wish to look further into a certain variable from `toyData`, namely `var2`. The data cleaning summary found some issues in this variable, and we would like to recall what these issues were. This can be done using the `check()` command

```
> check(toyData$var2)

$identifyMissing
The following suspected missing value codes enter as regular values: 999, NaN.
$identifyOutliers
Note that the following possible outlier values were detected: 82, 999.
```

Note that the arguments specifying which checks to perform, as described in the previous section, are in fact passed to `check()`, and thus they can also be used here. For instance, if we only want to check for potentially miscoded missing values, we can use the relevant `XXXChecks` argument (e.g., `numericChecks`, `factorChecks`, etc. as described in Section 2) to provide a vector of the check functions that should be applied. Recall that Table 2 or the `allCheckFunctions()` provides overviews of the available check functions.

```
> check(toyData$var2, numericChecks = "identifyMissing")

$identifyMissing
The following suspected missing value codes enter as regular values: 999, NaN.
```

An equivalent way to call only a single, specific `checkFunction` such as `identifyMissing` (see 2 for a list of check functions) is by using it directly on the variable, e.g.,

```
> identifyMissing(toyData$var2)
```

The following suspected missing value codes enter as regular values: 999, NaN.

The result of a `checkFunction` is an object of class `checkResult`. By using the structure function, `str()`, we can look further into its components:

```
> missVar2 <- identifyMissing(toyData$var2)
> str(missVar2)
```

List of 3

```
$ problem      : logi TRUE
$ message      : chr "The following suspected missing value codes enter as
                  regular values: \\\"999\\\", \\\"NaN\\\"."
$ problemValues: num [1:2] 999 NaN
- attr(*, "class")= chr "checkResult"
```

The most important thing to note here is that while the printed message is made for easy reading, the actual values of the variable causing the issue are still obtainable in the element `problemValues`. If we for instance decide that the values 999 and NaN in `var2` are in fact miscoded missing values, we can easily replace them with NAs:

```
> toyData$var2[toyData$var2 %in% missVar2$problemValues] <- NA
> identifyMissing(toyData$var2)
```

No problems found.

Similarly, the `visualize()` and `summarize()` functions can be used to run the corresponding visualizations and summaries for each variable. See Figure 3.1 for the visualization output.

```
> visualize(toyData$var2)
> summarize(toyData$var2)
```

	Feature	Result
[1,]	"Variable type"	"numeric"
[2,]	"Number of missing obs."	"3 (20 %)"
[3,]	"Number of unique values"	"8"
[4,]	"Median"	"4.5"
[5,]	"1st and 3rd quartiles"	"1.75; 6"
[6,]	"Min. and max."	"1; 999"

As we saw with the `check()` function, the summary can be modified by providing the relevant `XXXSummaries` arguments. Setting the `numericSummaries` argument we can control the summary output by providing a vector of functions to run for a particular summary. To only get the minimum and maximum we set `numericSummaries=c("minMax")`.

```
> summarize(toyData$var2, numericSummaries=c("minMax"))
```

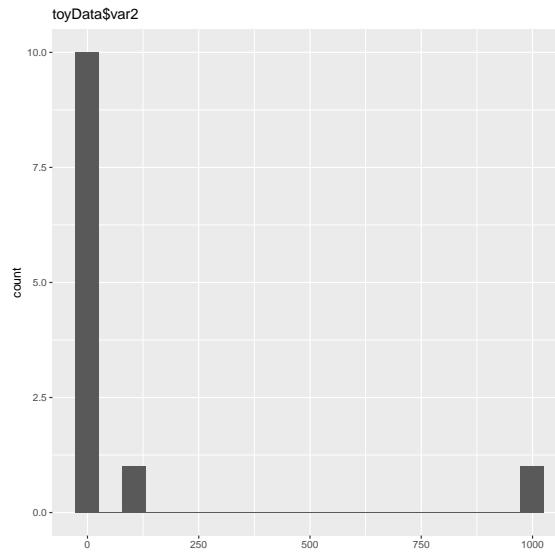


Figure 3: Output from running `visualize()` on the variable `var2` from the `toyData` dataset.

Feature	Result
[1,] "Min. and max."	"1; 999"

4. Extending cleanR

cleanR can be used as a user-friendly, self-contained package as shown in the previous section. However, **cleanR** is fully customizable and `clean()` is mainly a tool for formatting the results from various checking-, summary- and visualization functions. Thus, the actual work underlying a **cleanR** output file can be anything — depending on the arguments given to `clean()` — and user made functions are easily added to the `summarize/visualize/check`-function arguments as discussed previously (e.g., `factorSummaries`, or `numericChecks`). However, the functions used in the `summarize/visualize/check` steps need to adhere to a specific structure to be called from these three steps, and therefore, we will now present how `summaryFunctions`, `visualFunctions` and `checkFunctions` are made.

This section consists of two parts. First, we describe how the `clean()` function can be extended by adding custom prechecks, summaries, checks and visualizations. In order to do this, one needs to create functions with a specific structure required by **cleanR**. This can be done with different levels of strictness. If the custom functions are only to be used part of the corresponding arguments of `clean()` then only the input/output structures of the functions need to be fixed.

However, new user-defined functions can also be registered locally to be part of the full machinery of **cleanR**, and these function will be recognized and behave in the same way as the build-in functions on **cleanR**. The presentation below is given in the format of function templates, written in pseudo-code. These templates are designed for getting the full functionality, but note that Table 3 serves as a reference to the minimal requirements, while also presenting

	summaryFunction	visualFunction	checkFunction
Input (required)	v - a variable vector ...	v - a variable vector vnam - the variable name (as character string) doEval - a logical (TRUE/FALSE) controlling the output type of the function	v - a variable vector nMax - an integer (or Inf), controlling how many problematic values are printed, if relevant ...
Input (optional)	maxDecimals - number of decimals printed in outputted numerical values. Describe some aspect of the variable, e.g. a central value, its dispersion or level of missingness.	-	maxDecimals - number of decimals printed in outputted numerical values. Check a variable for a specific issue and, if relevant, identify the values in the variable that cause the issue.
Purpose		Produce a distribution plot.	A list with entries \$problem - a logical identifying whether an issue was found \$message - a character string (possibly empty) describing the issue that was found, properly escaped and ready for use in <code>rmarkdown</code>
Output (required)	A list with entries \$feature - a label for the summary value (as character string) \$result - the result of the summary (as character string)	A character string with R code for producing a plot. This code should be standalone, i.e. should include the data if necessary.	A <code>checkResult</code> object (an attributed list with entries \$problem, \$message and \$problemValues, the latter being either NULL or the problem causing values, as they were found in v, whichever is relevant.
Output (recommended)	A <code>summaryResult</code> object (i.e. an attributed list with entries \$feature, \$result and \$value, the latter being the values from \$result in their original format).	If doEval is TRUE: A plot that will be opened by the graphic device in R.	If doEval is FALSE: A text string with R code, as described above.
Tools available for producing the function	<code>summaryResult()</code>	-	<code>messageGenerator()</code> <code>checkResult()</code>

Table 3: Reference information for creating new functions to be used as part of the summarize, visualize, and check steps. The three columns correspond to each of the three function types.

the "full" versions of the function types. We end this section with a worked example of how to use custom made functions in practice, where four new summarize/visualize/check functions are defined and used, both interactively and in `clean()`.

4.1. Function templates

Writing a summaryFunction

As mentioned above, **cleanR** provides a dedicated class for `summaryFunctions`. However, this does not imply that they are particularly advanced or complicated to create; in fact, they are nothing but regular functions with a particular input/output-structure. Specifically, they all follow the template below:

```
mySummaryFunction <- function(v, ...) {
  res <- [result of whatever summary we are doing]
```

```
summaryResult(list(feature = "[Feature name]", result = res))
}
```

The last function called here, `summaryResult()`, changes the class of the output, thereby making a `print()` method available for it. Note that `v` is a vector and that `res` should be either a character string or something that will be printed as one. In other words, e.g. integers are allowed, but matrices are not. Though a lot of different things can go into the `summaryFunction` template, we recommend only using it for summarizing the features of a variable, and leaving tests and checks for the `checkFunctions` (presented below).

Adhering to the template above is sufficient for using the freshly made `mySummaryFunction()` in `clean()`, but we recommend furthermore adding the new function to the overview of all summary functions by converting it to a proper `summaryFunction` object. This is done by calling the `summaryFunction` function with the user-defined function as first argument, and additional arguments `description` which adds explanatory flavour text as an attribute of the function, and `classes` which determines which classes the user-defined function should be applied to (also stored as an attribute).

```
mySummaryFunction <- summaryFunction(mySummaryFunction,
  description = "[Text describing what the summaryFunction does]",
  classes = c([vector of data types that the function is intended for]))
```

which adds the new function to the output of an `allSummaryFunctions()` call. If the `description` argument is left unspecified, the name of the function (which in this case is `"mySummaryFunction"`) will be filled in and stored as an attribute. What happens if the `classes` argument is not specified depends on the type of `mySummaryFunction`. If `mySummaryFunction` is a S3 generic function with associated methods, the call to `summaryFunction()` will automatically produce a vector of the names of the classes for which the function can be called. If `mySummaryFunction` is not an S3 generic and `classes` is left unspecified, the attribute will simply be empty. Note that the helper function `allClasses()` might be useful for filling out the `classes` argument, as it simply lists all available classes in **cleanR**:

```
> allClasses()

[1] "character" "Date"      "factor"    "integer"   "labelled"
[6] "logical"   "numeric"
```

If we run the `allSummaryFunctions()` function we can see that the new function has been registered (output slightly abbreviated):

```
> allSummaryFunctions()

-----
name              description                                     classes
-----
mySummaryFunction [Text describing what the summaryFunction does]  numeric
.
.
.
```

Writing a visualFunction

`visualFunctions` are the functions that produce the figures in a **cleanR** output document. Writing a `visualFunction` is slightly more complicated than writing a `summaryFunction`. This follows from the fact that `visualFunctions` need to be able to output standalone code for plots in order for `clean()` to build standalone **rmarkdown** files. We recommend using the following structure:

```
myVisualFunction <- function(v, vnam, doEval) {
  thisCall <- call("[the name of the function used to produce the plot]",
    v, [additional arguments to the plotting function])
  if (doEval) {
    return(eval(thisCall))
  } else return(deparse(thisCall))
}
```

In this function, `v` is the variable to be visualized, `vnam` is its name (which should generally be passed to `title` or `main` arguments in plotting functions) and `doEval` controls whether the output is a plot (if `TRUE`) or a character string of standalone code for producing a plot (if `FALSE`). Implementing the `doEval = TRUE` setting is not strictly necessary for a `visualFunction`'s use in `clean()`, but it makes it easier to assess what visualization options are available, and obviously, it is crucial for interactive usage of `myVisualFunction()`. In either case, it should be noted that all the parameters listed above, `v`, `vnam` and `doEval`, are mandatory, so they must be left as is, even if they are not in use. See Table 3.

Similarly to the summary function, we call `visualFunction()` to register our newly created function. Like before, it accepts the user-defined function as the first argument, and two additional arguments description which adds explanatory flavour text as an attribute of the function, and a vector which determines which classes the user-defined function should be applied to (which is also stored as an attribute).

```
myVisualFunction <- visualFunction(myVisualFunction,
  description = "[Some text describing the visualFunction]",
  classes = c([data types that this function is intended for]))
)
```

Again, registering the visualization function allows it to be used without manually adding it to the list of visualizations.

Writing a checkFunction

The last, but perhaps most important, **cleanR** function type is the `checkFunction`. These are the functions that flag issues in the data in the check step and control the overall flow of the data cleaning process in the precheck stage. A `checkFunction` follows one of two overall structures, depending on the type of check. Either, it tries to identify problematic values in the variable (as e.g., `identifyMissing()` does) or it performs a check concerning the variable as a whole (e.g. the functions used for prechecks and the function `identifyNums()`). We present templates for both types of `checkFunctions` below separately, but it should be emphasized that formally, they belong to the same class.

First, a template for the full-variable check function type, where we first define the function and subsequently register it as a check function using `checkFunction()`:

```
myFullVarCheckFunction <- function(v, ...) {
  [do your check]
  problem <- [is there a problem? TRUE/FALSE]
  message <- "[message describing the problem, if any]"
  checkResult(list(problem = problem,
    message = message,
    problemValues = NULL))
}

myFullVarCheckFunction <- checkFunction(myFullVarCheckFunction,
  description = "[Some text describing the checkFunction]",
  classes = c([the data types that this function is intended to be used for])
)
```

Again, as with `summaryFunctions` and `visualFunctions`, the change of function class by use of `checkFunction()` is not strictly necessary. Note however, that if `myFullVarCheckFunction` is to be used in the `summarize/visualize/check` steps in `clean()`, the `description` attribute will be printed in the overview table in the *Data cleaning summary* part of the output document. If problematic values are to be identified, the template from above should be expanded to follow a slightly more complicated structure:

```
myProbValCheckFunction <- function(v, nMax, maxDecimals, ...) {
  [do your check]
  problem <- [is there a problem? TRUE/FALSE]
  problemValues <- [vector of values in v that are problematic]
  problemStatus <- list(problem = problem,
    problemValues = problemValues)

  problemMessage <- "[Message that is printed prior to listing
    problem values in the cleanR output,
    ending with a colon]"

  outMessage <- messageGenerator(problemStatus, problemMessage, nMax)

  checkResult(list(problem = problem,
    message = outMessage,
    problemValues = problemValues))
}

myProbValCheckFunction <- checkFunction(myProbValCheckFunction,
  description = "[Some text describing the checkFunction]",
  classes = c([the data types that this function is intended to be used for])
)
```

For this template, the argument `maxDecimals` is not in use. This argument is used to round

off the `problemValues` passed to `messageGenerator()`, if they are numerical. This is done by substituting the `problemStatus` assignment above with the following code: Denne foregående sætning forstår jeg ikke helt. Måske skal messagegenerator have en sætning eller to med på vejen? (Og det spiller lidt sammen med nedenstående)

```
problemStatus <- list(problem = problem,
  problemValues = round(problemValues, maxDecimals))
```

It is worth mentioning the helper function `messageGenerator()`, which aids in consistent styling of all `checkFunction` messages. This function simply pastes together the `problemMessage` and the `problemValues`, with the latter being quoted and sorted alphabetically. If `nMax` is not `Inf`, only the first `nMax` problem values will be pasted onto the message, accompanied by a comment about how many problem values were left out (if any). Note that printing quotes in **rmarkdown** requires an extensive amount of character escaping, so opting for `messageGenerator()` really is the easiest solution.

4.2. A worked example

We will now build four new functions and show both how they can be used interactively and how they can be integrated with the `clean()` function. These four new functions are:

isID A new `checkFunction` intended for use in the precheck-stage. This function checks whether a variable consists exclusively of long (> 10 characters/digits) entries that are all of equal length, as this might be personal identification codes that we do not wish to print out in the data summary.

mosaicVisual A new `visualFunction` that produces mosaic plots. This function will be used in the *visualize* step of `clean()`.

countZeros A new `summaryFunction` that counts the number of occurrences of the value 0 in a variable. This function will be used in the *summarize* step of `clean()`.

identifyColons A new `checkFunction` that flags variables in which values have colons that appear before and after alphanumerical characters. This is practical for identifying autogenerated interaction effects. This function will be used in the *check* step of `clean()`.

These functions are defined in turn below, and afterwards, an example of how they can be called from `clean()` is provided.

isID — a new checkFunction without problem values

First, let's define the `isID()` function. As this function is not supposed to list problematic values in the variable, it falls within the category of `checkFunctions` represented by `myFullVarCheckFunction()` in the above. We do not particularly wish to use this function interactively, so we will stick to the minimal requirements of a `checkFunction` used in `check()` (see Table 3). The function can then be defined by

```
isID <- function(v, nMax = NULL, ...) {
  out <- list(problem = FALSE, message = "")
```

```

# Should work for all but logical and Date variables
if (class(v) %in% setdiff(allClasses(), c("logical", "Date"))) {
  v <- as.character(v)
  lengths <- c(nchar(v))
  # Check that all lengths are the same and greater than 10 characters
  if (all(lengths > 10) & length(unique(lengths)) == 1) {
    out$problem <- TRUE
    out$message <- "Warning: This variable seems to contain ID codes."
  }
}
out
}

```

This is essentially all we need to do in order to include this function as a precheck-function in `clean()`, so we will leave it as is and move on to the next function, namely `mosaicVisual`.

mosaicVisual — a new visualFunction

R contains a function, `mosiacplot`, which produces mosaic plots. We intend to use this existing high-level plotting function as part of the new visualization function. We will define the new function such that it gets the full **cleanR** functionality. This can be done using the following code.

```

mosaicVisual <- function(v, vnam, doEval) {
  # Setup the call using the existing function mosaicplot
  thisCall <- call("mosaicplot", table(v), main = vnam, xlab = "")
  if (doEval) {
    # Return the graphics
    return(eval(thisCall))
  } else return(deparse(thisCall)) # Else return the code for the call
}

```

This function can now be called directly or used in `clean()` and we will show an example below. Depending on the `doEval` argument *skal doEval have en default value ovenfor?*, either a text string with code or a plot is produced. The plot resulting from the following call is found in Figure 4:

```
> mosaicVisual(toyData$var1, "variable 1", doEval = TRUE)
```

Even though `mosaicVisual()`, as written above, follows the style of a `visualFunction`, it is not yet truly one and therefore, it will not appear in a `allVisualFunctions()` call. In order to get this functionality, we need to change its object class. This can be done by writing

```

mosaicVisual <- visualFunction(mosaicVisual,
                               description = "Mosaic plots using graphics",
                               classes = allClasses())

```

Here, we use the function `allClasses()` to quickly obtain a vector of all the seven variable classes addressed in **cleanR**. Note that if `mosaicVisual` were an S3 generic function, this

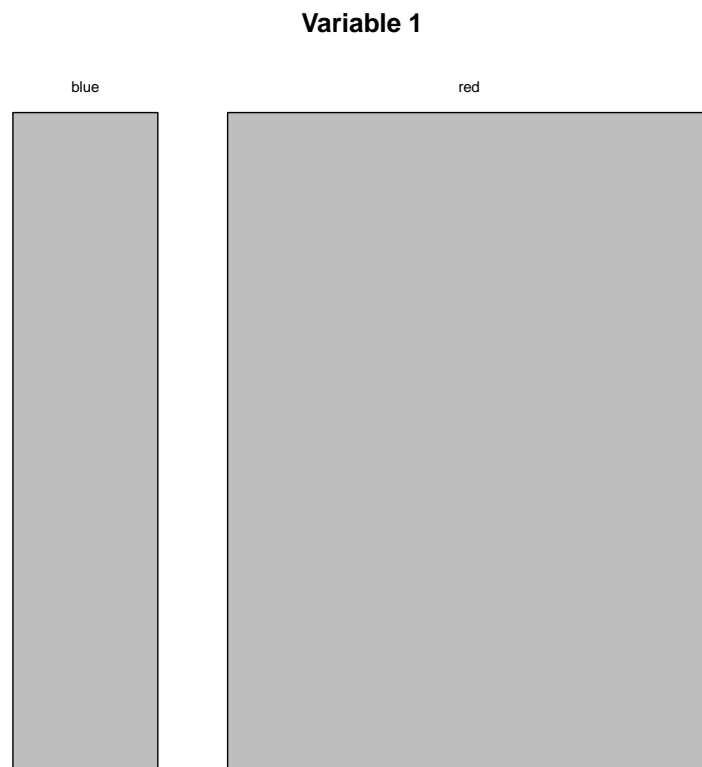


Figure 4: Mosaic plot generated by the user-defined visualization function `mosaicVisual`.

argument could have been left as `NULL` and then the classes for which methods are available would be added automatically.

As `mosaicVisual` is now a full-blooded `visualFunction`, it will also be included in the `allVisualFunctions()` output table:

```
> allVisualFunctions()
```

name	description	classes
mosaicVisual	Mosaic plots using graphics	character, Date, factor, integer, labelled, logical, numeric
basicVisual	Histograms and barplots using graphics	character, Date, factor, integer, labelled, logical, numeric
standardVisual	Histograms and barplots using ggplot2	character, Date, factor, integer, labelled, logical, numeric

Now that we are done with the definition of `mosaicVisual()` we can turn to the next function in line, `countZeros`.

countZeros — a new summaryFunction

This `summaryFunction` is defined in the following lines of code:

```
countZeros <- function(v, ...) {
  res <- length(which(v == 0))
  summaryResult(list(feature = "No. zeros", result = res, value = res))
}
```

As this function computes an integer (the number of zeros), there is no difference between the entries `$result` and `$value`. If, on the other hand, the result had been a character string, extra formatting might be required in the `$result` entry (such as escaping of quotation marks), and in this scenario, the two entries would have differed. As the result is returned as a `summaryResult` object, a printing method is automatically called when `countZeros` is used interactively:

```
> countZeros(c(rep(0, 5), 1:100))
```

```
No. zeros: 5
```

As with `mosaicVisual()`, we change the class of this function in order to make it appear in `allSummaryFunctions()` calls. But now we wish to emphasize that the function is not intended to be called on all variable types, as zeros have different roles in `Dates` and in `logical` variables:

```
> countZeros <- summaryFunction(countZeros,
  description = "Count number of zeros",
  classes = c("character", "factor", "integer",
    "labelled", "numeric"))
```

identifyColons - a new *checkFunction* with problem values

The last function mentioned above is `identifyColons()`. We define it using the helper function `messageGenerator()` to obtain a properly escaped message, and we use `checkResult` to make its output print neatly:

```
identifyColons <- function(v, nMax = Inf, ... ) {
  v <- unique(na.omit(v))
  problemMessage <- "Note: The following values include colons:"
  problem <- FALSE
  problemValues <- NULL

  # Use regular expressions to identify colons between two words
  problemValues <- v[sapply(gregexpr("[:xdigit:][:xdigit:]", v),
    function(x) all(x != -1))]

  if (length(problemValues) > 0) {
    problem <- TRUE
  }

  problemStatus <- list(problem = problem,
    problemValues = problemValues)
  # Use the messagegenerator function to produce the output
  # message from the problemStatus and problemMessage
  outMessage <- messageGenerator(problemStatus, problemMessage, nMax)

  checkResult(list(problem = problem,
    message = outMessage,
    problemValues = problemValues))
}

identifyColons <- checkFunction(identifyColons,
  description = "Identify colons surrounded by alphanumeric characters",
  classes = c("character", "factor", "labelled"))
```

As with the previous two functions, we also change its class. Note, however, that for `checkFunctions`, the function description will appear in the document produced by `clean()` (in the *Data cleaning summary* section of the output), so now this is not only done for the sake of the `allCheckFunctions()` output.

Calling the new summarize/visualize/check functions from clean()

Now, we are ready to use these new functions in a `clean()` call. The extended **cleanR** output

document should have the following modifications, relative to the standard **cleanR** output:

- We want to add the new pre-check function, `isID`, to the already existing pre-checks.
- We wish to change the plot type for all variables to the new mosaic plot.
- We want the new summary function, `countZeros`, to be added to the summaries performed on all variable types but `Date` and `logical`.
- We want the new check function, `identifyColon`, to be added to the checks performed on `character`, `factor` and `labelled` variables.

These options are specified as follows:

```
> data(testData)
> clean(testData,
  # Add the new pre-check function
  preChecks = c("isKey", "isEmpty", "isID"),
  # Change the visual
  allVisuals = "mosaicVisual",
  # Add the new checks for specific data types
  characterSummaries = c(defaultCharacterSummaries(), "countZeros"),
  factorSummaries = c(defaultFactorSummaries(), "countZeros"),
  labelledSummaries = c(defaultLabelledSummaries(), "countZeros"),
  numericSummaries = c(defaultNumericSummaries(), "countZeros"),
  integerSummaries = c(defaultIntegerSummaries(), "countZeros"),
  characterChecks = c(defaultCharacterChecks(), "identifyColons"),
  factorChecks = c(defaultFactorChecks(), "identifyColons"),
  labelledCheck = c(defaultLabelledChecks(), "identifyColons"))
```

The outputted document is found in [Appendix B](#).

5. Using cleanR in specific situations

Finally, we will present a few examples of how to make **cleanR** solve specific issues related to data cleaning. First, we discuss the challenges related to cleaning large datasets, particularly in terms of memory use and computation speed. Next, we show how **cleanR** can be used for problem-flagging. Lastly, we discuss how the **cleanR** output document can be included in other **rmarkdown** documents as a way to produce clear and concise documentation of a dataset.

5.1. Cleaning large datasets

If the dataset becomes very large, the standard use of `clean()` outlined above might not be ideal. If there is a vast number of variables, creation of the **rmarkdown** document might be quite slow, while a large number of observations generally will affect the rendering time of the document. In this section, we give a few practical examples of ways to deal with large data, while wishing to still produce (potentially very long) data cleaning overview documents. Note

that the interactive tools of **cleanR** can be used as usual or sequentially in small subsets of the large dataset, if no such overview documents are needed.

Handling the figures

Though figures give a nice overview of each variable, they are also quite heavy objects in terms of memory allocation. Therefore, it might be beneficial to not include figures in the **cleanR** outputs for very large datasets. This is controlled via the `mode` argument:

```
> clean(toyData, mode = c("summarize", "check"))
```

If figures are indeed needed, a different approach is to choose the less memory heavy standard R figure style instead of the **ggplot2** figures that are the default option in `clean()`. This can be done by setting the `allVisuals = "basicVisual"` argument:

```
> clean(toyData, allVisuals = "basicVisual")
```

Of course, even less heavy plots might be achieved by writing new `visualFunctions`, using the guidelines from section 4.1. For instance, a future extension of **cleanR** might be the inclusion of ASCII plots, as e.g. represented in the R package **txtplot**.

Economic memory use

Another solution, which is especially relevant to Windows users due to the unfortunate combination of memory control in this operating system and RStudio is simply splitting the two steps performed by `clean()`, namely producing the **rmarkdown** file and rendering it afterwards. If the **rmarkdown** file is very long, as it will typically be for very large datasets, having this file opened in memory wastes precious memory capacities. Therefore, we advice users to instead split the two steps. This can be done in the following manner:

```
> clean(toyData, render = FALSE, openResult = FALSE)
> render("cleanR_toyData.Rmd", quiet = FALSE)
```

This also deals with the fact that **cleanR** can produce **rmarkdown** files that supersedes the upper size limit.

5.2. Using **cleanR** for problem flagging

If the data is large, but memory issues and computation time are less of an issue than the human time it takes to look through the data cleaning document, a viable solution might be not to include all information about all variables. Or even for more reasonably sized datasets, sometimes a brief overview of the most pressing issues can be useful. This can be achieved by using the `onlyProblematic` argument in `clean()`. By specifying `onlyProblematic = TRUE`, only variables that raise a flag in the checking steps will be summarized and visualized. But perhaps we are not even interested in obtaining general information about these variables, but only in getting a quick overview of the problems they might have. This can be done by also controlling the `mode` argument:

```
> clean(toyData, onlyProblematic = TRUE, mode = c("check"))
```

Now only the checking results are printed, and only for variables where problems were identified. An even more minimal output can be generated by also leaving out the checking results — then `clean()` essentially just produces a list of the variable names that should be investigated further:

```
> clean(toyData, onlyProblematic = TRUE, mode = NULL)
```

Of course, this can also be done without generating an overview document, by direct, interactive use of the `check()` function. When called on a `data.frame`, this function produces a list (of variables) of lists (of checks) of lists (or rather, `checkResults`). Thus, the overall problem status of each variable can easily be unravelled using the list manipulation function `sapply()`:

```
> toyChecks <- check(toyData)
> foo <- function(x) {
>   any(sapply(x, function(y) y[["problem"]]))
> }
> sapply(toyChecks, foo)
```

```
var1 var2 var3 var4 var5 var6
TRUE TRUE TRUE TRUE TRUE FALSE
```

and we find that only the final variable, `var6`, for which all observations have the value "Irrelevant", is problem-free.

5.3. Include cleanR document in other files

Sometimes, a **cleanR** document might be a useful addition to a more general overview document, including also for example pairwise association plots, time series plots, or exploratory analysis results. To this end, it is possible to produce a **cleanR** document that can readily be included in other **rmarkdown** files. This is done by using the `standAlone` argument in `clean()`, which removes the preamble from the outputted **rmarkdown** file. Please note, that it is still necessary to indicate which **rmarkdown** type is being created; the pdf and html **rmarkdown** styles are unfortunately not identical.

If it is important that the embedded **cleanR** document can be rendered to either of these two file types, we recommend setting `twoCols = FALSE` and `output = html` in `clean()`, thereby essentially removing almost all output type specific formatting code from the generated **rmarkdown** file.

On the other hand, if a pdf document is to be produced, a few extra lines need to be added to the preamble of the master **rmarkdown** document — otherwise, the two-column layout code will produce an error. The following is an example of how such a master document preamble YAML might look like and how the `cleanR_toyData.Rmd` file can then be included:

```
---
output: pdf_document
documentclass: report
header-includes:
```



```

- \renewcommand{\chaptername}{Part}
- \newcommand{\fullline}{\noindent\makebox[\linewidth]{\rule{\textwidth}{0.4pt}}}
- \newcommand{\bminione}{\begin{minipage}{0.75 \textwidth}}
- \newcommand{\bminitwo}{\begin{minipage}{0.25 \textwidth}}
- \newcommand{\emini}{\end{minipage}}
---

```{r, child = 'cleanR_toyData.Rmd'}
```

```

In this example, the `cleanR_toyData.Rmd` file could have been created as follows:

```
> clean(toyData, standAlone = FALSE)
```

and the more minimal, html-style **rmarkdown** file described above can be produced using

```
> clean(toyData, standAlone = FALSE, output = "html", twoCols = FALSE)
```

6. Concluding remarks

In this paper we have introduced the R package **cleanR** for performing reproducible error detection and data cleaning summaries. The package provides a general and extendable framework for identifying potential errors and for creating human-readable summary documents that will help investigators to identify possible errors in the data.

Noget mere ind her?

While the current release is stable, the authors have an interest in further developing the functionality of **cleanR** by providing more summary, visual, and check function as part of the default package. We are also currently considering adding options to handle repeated measurement, where the visualizations — in particular — might be improved by visualizing measurements over time. In addition, an online **shiny** application where user that are not R-savvy can upload their data and get a data cleaning document is currently planned.

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Alle pakker. Andet?

A. Appendix A: cleaning the toyData data frame

Part 1

Data cleaning summary

The dataset examined has the following dimensions:

| Feature | Result |
|---------------------|--------|
| Number of rows | 15 |
| Number of variables | 6 |

Checks performed

The following variable checks were performed, depending on the data type of each variable:

| | character | factor | labelled | numeric | integer | logical | Date |
|--|-----------|--------|----------|---------|---------|---------|------|
| Identify miscoded missing values | × | × | × | × | × | | |
| Identify prefixed and suffixed
whitespace | × | × | × | | | | |
| Identify levels with < 6 obs. | × | × | | | | | |
| Identify case issues | × | × | | | | | |
| Identify misclassified numeric or
integer variables | × | × | | | | | |
| Identify outliers | | | | × | × | | |

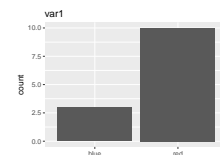
Please note that all numerical values in the following have been rounded to 2 decimals.

Part 2

Variable list

var1

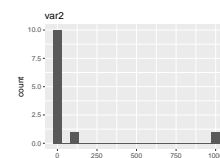
| Feature | Result |
|-------------------------|-------------|
| Variable type | factor |
| Number of missing obs. | 2 (13.33 %) |
| Number of unique values | 2 |
| Mode | "red" |



- Note that the following levels have at most five observations: "blue".

var2

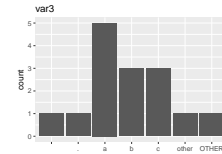
| Feature | Result |
|-------------------------|----------|
| Variable type | numeric |
| Number of missing obs. | 3 (20 %) |
| Number of unique values | 8 |
| Median | 4.5 |
| 1st and 3rd quartiles | 1.75; 6 |
| Min. and max. | 1; 999 |



- The following suspected missing value codes enter as regular values: "999", "NaN".
- Note that the following possible outlier values were detected: "82", "999".

var3

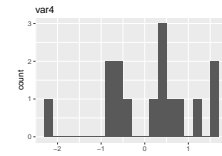
| Feature | Result |
|-------------------------|---------|
| Variable type | factor |
| Number of missing obs. | 0 (0 %) |
| Number of unique values | 7 |
| Mode | "a" |



- The following suspected missing value codes enter as regular values: " ", ".".
- The following values appear with prefixed or suffixed white space: " ".
- Note that the following levels have at most five observations: " ", ".", "a", "b", "c", "other", "OTHER".
- Note that there might be case problems with the following levels: "other", "OTHER".

var4

| Feature | Result |
|-------------------------|-------------|
| Variable type | numeric |
| Number of missing obs. | 0 (0 %) |
| Number of unique values | 15 |
| Median | 0.33 |
| 1st and 3rd quartiles | -0.62; 0.66 |
| Min. and max. | -2.21; 1.6 |



- Note that the following possible outlier values were detected: "1.12", "1.51", "1.6".

var5

- The variable is a key (distinct values for each observation).

var6

- The variable only takes one (non-missing) value: "Irrelevant". The variable contains 0 % missing observations.

This report was created by cleanR v0.5.1.

B. Appendix B: User-extended cleaning of testData

Part 1

Data cleaning summary

The dataset examined has the following dimensions:

| Feature | Result |
|---------------------|--------|
| Number of rows | 15 |
| Number of variables | 15 |

Checks performed

The following variable checks were performed, depending on the data type of each variable:

| | character | factor | labelled | numeric | integer | logical |
|---|-----------|--------|----------|---------|---------|---------|
| Identify miscoded missing values | × | × | × | × | × | |
| Identify prefixed and suffixed whitespace | × | × | × | | | |
| Identify levels with < 6 obs. | × | × | × | | | |
| Identify case issues | × | × | × | | | |
| Identify misclassified numeric or integer variables | × | × | × | | | |
| Identify non-suffixed nor -prefixed colons | | | | | | |
| Identify outliers | | | | × | × | |

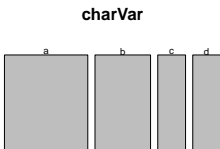
Please note that all numerical values in the following have been rounded to 2 decimals.

Part 2

Variable list

charVar

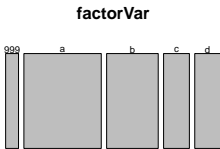
| Feature | Result |
|-------------------------|------------|
| Variable type | character |
| Number of missing obs. | 1 (6.67 %) |
| Number of unique values | 4 |
| Mode | "a" |
| No. zeros | 0 |



- Note that the following levels have at most five observations: "b", "c", "d".

factorVar

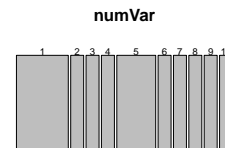
| Feature | Result |
|-------------------------|---------|
| Variable type | factor |
| Number of missing obs. | 0 (0 %) |
| Number of unique values | 5 |
| Mode | "a" |
| No. zeros | 0 |



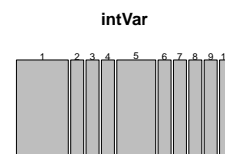
- The following suspected missing value codes enter as regular values: "999".
- Note that the following levels have at most five observations: "999", "b", "c", "d".

numVar

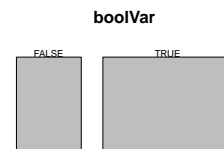
| Feature | Result |
|-------------------------|----------|
| Variable type | numeric |
| Number of missing obs. | 0 (0 %) |
| Number of unique values | 10 |
| Median | 5 |
| 1st and 3rd quartiles | 1.5; 6.5 |
| Min. and max. | 1; 10 |
| No. zeros | 0 |

**intVar**

| Feature | Result |
|-------------------------|----------|
| Variable type | integer |
| Number of missing obs. | 0 (0 %) |
| Number of unique values | 10 |
| Median | 5 |
| 1st and 3rd quartiles | 1.5; 6.5 |
| Min. and max. | 1; 10 |
| No. zeros | 0 |

**boolVar**

| Feature | Result |
|-------------------------|----------|
| Variable type | logical |
| Number of missing obs. | 3 (20 %) |
| Number of unique values | 2 |
| Mode | "TRUE" |

**keyVar**

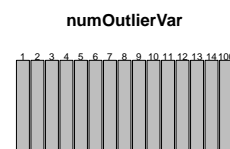
- The variable is a key (distinct values for each observation).

emptyVar

- The variable only takes one (non-missing) value: '1'. The variable contains 0 % missing observations.

numOutlierVar

| Feature | Result |
|-------------------------|-----------|
| Variable type | numeric |
| Number of missing obs. | 0 (0 %) |
| Number of unique values | 15 |
| Median | 8 |
| 1st and 3rd quartiles | 4.5; 11.5 |
| Min. and max. | 1; 100 |
| No. zeros | 0 |

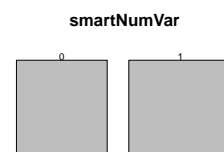


- Note that the following possible outlier values were detected: "100".

smartNumVar

- Note that this variable is treated as a factor variable below, as it only takes a few unique values.

| Feature | Result |
|-------------------------|---------|
| Variable type | numeric |
| Number of missing obs. | 0 (0 %) |
| Number of unique values | 2 |
| Mode | "1" |
| No. zeros | 7 |

**cprVar**

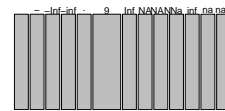
- Warning: This variable seems to contain ID codes!

cprKeyVar

- The variable is a key (distinct values for each observation).
- Warning: This variable seems to contain ID codes!

misclassifiedMissingVar

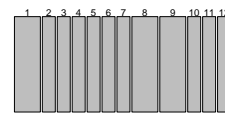
| Feature | Result |
|-------------------------|-----------|
| Variable type | character |
| Number of missing obs. | 0 (0 %) |
| Number of unique values | 14 |
| Mode | "9" |
| No. zeros | 0 |

misclassifiedMissingVar

- The following suspected missing value codes enter as regular values: "", "-", "-Inf", "-inf", ".", "9", "Inf", "NA", "NaN", "Na", "NaN", "inf", "na", "nan".
- Note that the following levels have at most five observations: "", "-", "-Inf", "-inf", ".", "9", "Inf", "NA", "NaN", "Na", "NaN", "inf", "na".
- Note that there might be case problems with the following levels: "-Inf", "-inf", "Inf", "NA", "NaN", "Na", "NaN", "inf", "na", "nan".

misclassifiedNumVar

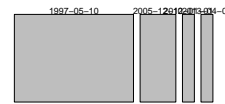
| Feature | Result |
|-------------------------|---------|
| Variable type | factor |
| Number of missing obs. | 0 (0 %) |
| Number of unique values | 12 |
| Mode | "1" |
| No. zeros | 0 |

misclassifiedNumVar

- Note that the following levels have at most five observations: "1", "10", "11", "12", "2", "3", "4", "5", "6", "7", "8", "9".
- Note: The variable consists exclusively of numbers and takes a lot of different values. Is it perhaps a misclassified numeric variable?

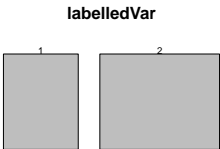
dateVar

| Feature | Result |
|-------------------------|------------------------|
| Variable type | Date |
| Number of missing obs. | 0 (0 %) |
| Number of unique values | 4 |
| Mode | "1997-05-10" |
| Min. and max. | 1997-05-10; 2013-04-02 |
| 1st and 3rd quartiles | 1997-05-10; 2005-12-10 |

dateVar

labelledVar

| Feature | Result |
|-------------------------|-------------|
| Variable type | labelled |
| Number of missing obs. | 2 (13.33 %) |
| Number of unique values | 2 |
| Mode | "2" |
| No. zeros | 0 |



This report was created by cleanR v0.6.2.

Affiliation:

Claus Thorn Ekstrøm

Biostatistics, Department of Public Health

University of Copenhagen

Denmark

E-mail: ekstrom@sund.ku.dk

URL: <http://staff.pubhealth.ku.dk/~ekstrom/>