

A Tao of Data Wrangling: A Practical Routine for Getting Past the ‘Janitor Work’*

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This article focuses on a preliminary step in any ex-post data harmonization project—wrangling the pre-harmonized data—and suggests best practices for helping scholars avoid errors in this often-tedious work. To provide illustrations of these best practices, the article uses the examples of pre-harmonizing procedures used to produce the Standardized World Income Inequality Database (SWIID), a widely used database that uses Gini indices from multiple sources to create comparable estimates, and the Dynamic Comparative Public Opinion (DCPO) project, which creates a workflow for harmonizing aggregate public opinion data.

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1 A Wrangling Issue of Data Harmonization

Empowered by the spreading Internet and advancing computational power, researchers have entered an unprecedented age of data availability. A growing volume of social science research aims to take the benefit to extend the generality: they employ large quantities of data drawn from different sources. However, ensuring the quality of harmonized datasets remains a significant challenge in handling fitness to use and raw data quality monitoring among others (Slomczynski, Tomescu-Dubrow, and Wysmulek 2025). Beyond the focus on the harmonization process itself, we argue that quality assurance must begin *earlier* to the data-wrangling step where raw inputs are selected, processed, and prepared for harmonization.

The wrangling step determines the quality of data in the harmonization process, and the challenges is how to properly and transparently clean the increasing amount and diversity of data. The conventional approach usually involves a notorious bulk of manual work on indicator identification, data merging, data scaling, and so on (see, e.g., Lohr 2014). The tiresome task is easy to introduce errors in data collection procedure. Manual wrangling make a full reproducibility of research pipeline more difficulty and undermine the transparency (Liu and Salganik 2019).

These challenges are amplified when raw data comes from heterogeneous sources and have been processed using various software environments over time. This is a common scenario in secondary data collection. For example, older survey files stored in SPSS's ASCII or portable formats often require extensive restructuring before they can be merged with new format of data. Such undocumented transformations make it difficult to track changes and undermine transparency.

Finally, even meticulous documentation cannot eliminate the influence of human discretion embedded in manual processing. Such discretion leaves behind few traces, making it difficult for collaborators or reviewers to verify the wrangling process or trace sources of error.

In short, poor source data quality, the absence of reproducibility, and untrackable human discretion in manual janitor work have collectively became the largest obstacle on the way to data harmonization, which yet have thus far gained little attention.

In this article, we provide a practical routine taken the advantage of automatic programming and team work to reduce such data-entry errors and improve the reproducibil-

ity and transparency of the wrangling process for researchers and reviewers to check the errors. The routine includes three steps: data selection, data entry, and opening. We illustrate how researchers use this routine on statistical (*hard*) and opinion (*soft*) data with two ongoing harmonization efforts, the Standardized World Income Inequality Database (SWIID) and the Dynamic Comparative Public Opinion (DCPO) project.

2 A 3-Step Routine for Data Harmonization

Our routine aims to helping researchers reach three goals for scientific research:

1. To reduce the manual entry errors to improve the accuracy of the harmonized data and analytic data;
2. To incorporate as much available data as possible to provide a base for comparable data and increase generality of the inferences; and
3. To improve the reproducibility of data wrangling process for the sake of transparency.

The routine decomposes a data-wrangling process into three steps:

1. Team-based concept construct and data selection;
2. Data entry automation; and
3. “Second-order” opening.

To illustrate the above routine, we use two data harmonization projects as examples, SWIID and DCPO. SWIID is a long-running project that seeks to provide harmonized income inequality statistics for the broadest possible coverage of countries and years (Solt 2009, 2015, 2016, 2020). As of its most recent update at the time of this writing, its source data consists of some 27,000 observations of the Gini coefficient of income distribution in nearly 200 countries over as many as 65 years, collected from over 400 separate sources including international organizations, national statistics bureaus, and academic studies.

DCPO is both a method and a database. Scholarship on comparative public opinion only rarely benefits from relevant items asked annually by the same survey in many countries (see, e.g., Hagemann, Hobolt, and Wratil 2017). To address the lack of cross-national and longitudinal data on many topics, a number of works have presented latent variable models that harmonize available but incomparable survey items (see e.g., Caughey,

O’Grady, and Warshaw 2019; Claassen 2019; Kołczyńska et al. 2024). Along this line, DCPO not only provides latent variable measurements but also automatized and reproducible data collection (Solt 2020), which has been applied in a complete pipeline for a variety of topics such as gender egalitarianism (Woo, Goldberg, and Solt 2023), political interest (Hu and Solt 2024), and support for gay rights (Woo et al. 2024), among other aspects of public opinion and open it freely for global researchers (see more updated data collections at <https://dcpo.org/>).

In the following sections we first address the common challenges for the phases of data wrangling and explain how our routine can help deal with it illustrated with the data wrangling processes of the SWIID and DCPO projects.

2.1 Step 1: Team-Based Construct Building and Data Selection

Large scale of data selection and cleaning is almost always tedious, as something to be delegated to research assistants, to someone—indeed anyone, but usually research assistants (RA)—else (see Torres 2017). This manual procedure is easy to make mistakes and errors. Haegemans, Snoeck, and Lemahieu (2019, 1) has demonstrated examples of misrouted financial transactions and airline flights. In a more systematic examination, Barchard and Pace (2011) found that RA assigned in an experiment to carefully enter data manually, even those instructed to double-check their entries against the original, had error rates approaching 1% in just a single roughly half-hour session. The consequences of such errors can be pernicious.

Our antidote for this issue is a combination of team work and automation. We will focus more on the team work and discuss the latter in OSM 2.2. The goal here is to have consistent understanding on conceptualized construct, select valid data for later measurement and/or analyses, and reduce biases caused by inconsistent human judgment. A team work framework for this end requires a deliberative set and a dual-entry process.

A deliberative set requires the members in a research team—regardless several coauthors or a primary author with one or two RAs—to have a clear and coherent understanding of the research questions and associated data goals. These understandings will help the team members identify the right data to collect and discover extra useful data sources that are not in the initial plan.

In the SWIID program, for example, we told RAs that the goal of the research is to

generate comparable statistics of country-level economic inequality. We provide a list of sources mainly from national statistic bureaus for them to start, but we also told them that updated statistics for some countries may come from academic papers, published documents, and other sources, and they are free to add them in while making sure a valid link of the new sources are also recorded.

Ensuring team members to understand how the data would use later is also important, as they could have a better sense of what data are analyticable and a forward perspective of how many situations would the later entry part need to take care. In the SWIID project, we told the RAs that the inequality statistics be recorded in four formats: Gini index in disposable (post-tax, post-transfer) income, Gini in market (pre-tax, pre-transfer) income, absolute redistribution (market-income inequality minus net-income inequality), or relative redistribution (market-income inequality minus net-income inequality, divided by market-income inequality). So, for later unification work, they need not only to record the digits but also seek documents to explain the methods of the statistics.

The SWIID project requires update for almost every year and we also often hire new RAs. Therefore, the cross-check is done in a rolling basis usually by the rookies who are in charge of checking the old data and updating malfunctional links. This is both a learning process and a way to improve data accuracy.

In the DCPO project, clearly defining and agreeing upon the latent construct among team members is a critical first step for ensuring theoretical comparability across countries and over time (Koc and Kołczyńska 2025). This process begins with a shared conceptual foundation established through literature review and corresponding pre-defined potential dimensions of the latent opinion. Each team member is then assigned survey datasets from specific geographic regions and tasked with identifying potentially relevant items and potential dimensions based on both general theoretical guidance and region-specific knowledge. This structure ensures that the construct is informed by both global theory and local context.

Before data selection begins, team members undergo hands-on training on how the method work and what type of data and detail they need to collect, such as data format and weighting types, which provide a valuable help of later build the automative data preparation software.

Following the initial round of item selection and collection, the dural-entry section

comes in. In this stage, each team member reviews and re-codes the survey data originally handled by another member. The independently coded versions are then compared to detect discrepancies, which may arise from misinterpretations of the construct, ambiguous item wording, or common entry errors.

Disputed cases are flagged for group discussion. Some mismatches may indicate items that may not be conceptually equivalent across cultures or regions, and others suggest multidimensionality that requires theoretical disaggregation. For the latter, we either categorize such items into pre-defined dimensions and/or revise the codebook accordingly to add new dimensions—an iterative process aimed at improving construct validity, intercoder reliability, and reducing oversimplification of target variable (Slomczynski, Tomescu-Dubrow, and Wysmulek 2025).

Therefore, we broke down the cross-check step into several lab meetings interspersed during the data selection to collect new insights from each members’ selection works and make sure everyone were on the same page through the whole process. The process ends with a systemic cross-check of the final selected data among members.

In addition to reducing manual biases, teamwork also helps expand the data pool. Both SWIID and DCPO projects enrolled team members from countries other than the U.S. These members have well used their language and cultural advantages to discover more data recorded in non-English languages and improve the precision of the data selections. To some extent, data from different sources also help correct the biases caused by the designers’ cultural backgrounds.

2.2 Step 2: Data Entry Automation

Formatting data is arguably the easiest step to involve manual errors and controversies. The best solution is to automate the entry process taken the advantages of the programming languages and application programming interfaces (APIs) of the data source.

In the DCPO case, data entry is fully automated through the R-based software, `DCPOtools` (Solt, Hu, and Tai 2018). This software processes raw survey files directly, ensuring reproducible data entry. It converts various file formats to R-readable objects, extracts variables of interest, reorders response values, applies survey weights, and aggregates weighted respondents by country and year based on actual fieldwork dates.

To address theoretical comparability concerns, DCPO employs conservative filtering,

removing items appearing in fewer than five country-years in countries surveyed at least three times, minimizing the risk of sacrificing comparability for coverage (Koc and Kołczyńska 2025). `DCP0tools` standardizes country names using Arel-Bundock, Enevoldsen, and Yetman (2018)’s `countrycode` and ensures years reflect actual fieldwork dates, creating aggregated respondent data for the latent variable model.

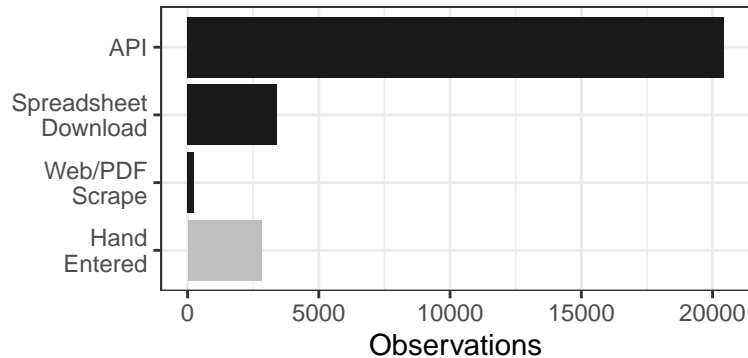


Figure 1: Income Inequality Observations by Method of Collection

While coding datasets and items into structured spreadsheets facilitates automation, an even better version starts the automation since the data selection step via programming and APIs. As shown in Figure 1, the current version of SWIID grapes 76% of the observations through API. In OSM 4.1, we also provide an incomplete list of R packages that can ease the processes to, for example, collect data with APIs and clean and transform data. Readers can also use the codes in this article’s replication file to explore more automation options for more specific needs.

When no API is available, the automation script downloads and reads any available spreadsheets (see Wickham 2016). In the absence of a spreadsheet, the process of scraping the data either directly from the web or, preferably, from a pdf file (see Sepulveda 2024) is automated. Together the collection of 90% of the source data is scripted. This means not only that the possibility of errors introduced by hand entry for a vast majority of observations is eliminated but also that the updates and revisions that are frequent in these data are automatically incorporated as they become available.¹

For data sources, such as those from academic articles or books, that have to be entered in hand, there is still rooms for automation. For the remaining 10% of the SWIID observations, for instance, we collected them using Sepulveda’s `tabulapdf` R package to avoid data-entry errors as long as they are in pdf (Sepulveda 2024). The advanced

Optical Character Recognition (OCR) can extend this method on data sources even in hard copies.

And finally, one source of SWIID contains crucial information encoded in the typeface of its tables (see Mitra and Yemtsiv 2006, 6); this information would be lost if the tables were read directly into R. We reapplied the approach from the data selection here to enter them twice into separate spreadsheets.² The dual-entry process allows for automated cross-checks of the newly entered data that increase the chances that errors are identified and corrected (see Barchard and Pace 2011).

2.3 Step 3: “Second-Order” Opening

Since the replication crisis, replication files for analytical results in academic articles has become a standard requirement for top-tier journals in political science (Chang and Li 2015; Open Science Collaboration 2015). Nevertheless, the continual raising controversies on the researcher degrees of freedom indicated that current open is still not adequate.³ Especially in relation with data harmonization, we eager researchers to conduct a, what we called, the “second-order” opening. That is, not only opening analytical steps (the “first-order”) but also the data generation process (the “second-order”), including data collection, data cleaning, and data wrangling, as mentioned above.

If researchers applied our suggestions of team-based construct building, systematic data selection, and automated data entry, the second-order opening becomes both feasible and efficient. Along with a clearly conceptualized theoretical framework, researchers can simply share their programming scripts for data downloading, formatting, and wrangling, ensuring that the full pipeline is documented and reproducible.

With developed scientific and technical publishing system, such as Quarto or R markdown, and version control platforms (e.g., Github) and open collaboration platforms (e.g., Open Science Framework, OSF), researchers can integrate the entire workflow—from raw data collection to final analysis—within a single, publicly trackable archive. We reached at this step for all the DCPO projects so far. Readers can find a Github repo for the research from scratch, and every wave of data update in the corresponding OSF project.⁴

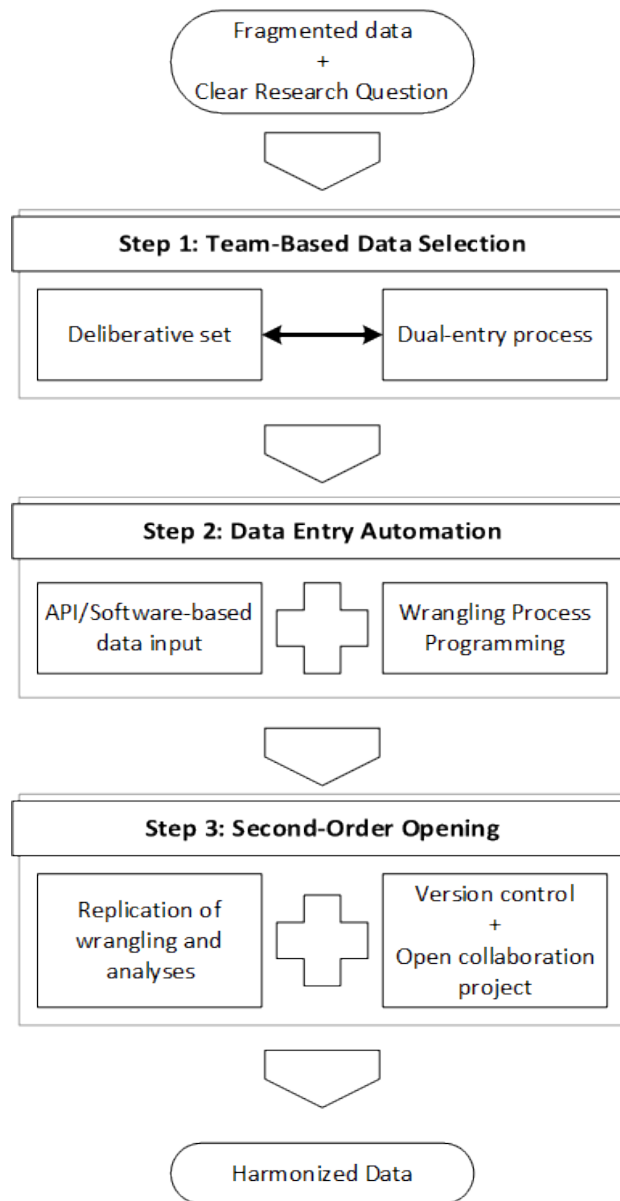


Figure 2: The 3-Step Routine of Data Wrangling Before Harmonization

3 Discussion

Figure 2 presents the whole process of the 3-step routine of data wrangling for later harmonization phase. Implementing these practices requires effort, just as in many open-science endeavors (see Engzell and Rohrer 2021). Though labor-intensive, the double-entry method reduces error rates thirty-fold (Barchard and Pace 2011, 1837), justifying the investment. Teamwork distributes tasks, reducing fatigue-related errors, while allowing discrepancies to be resolved through discussion.

Social scientists now benefit from standardized harmonization workflows (Slomczynski, Tomescu-Dubrow, and Wysmulek 2025) and automated data processing (Kritzinger, Lutz, and Boomgaarden 2025). Researchers can reuse high-quality harmonized datasets, enhancing efficiency and comparability. Open-source software packages like those used by the SWIID and DCP0tools have already automated many data preparation tasks. With large language models emerging, intelligent agents may soon handle parts of these routines, potentially advancing automation to new levels (Kritzinger, Lutz, and Boomgaarden 2025).

A final point we would like to clarify is that, in our three-step routine, researchers remain central to harmonization. As illustrated in the SWIID and DCPO examples, researchers are responsible for all critical decisions from clarifying research questions and building theoretical constructs to conducting version control and developing replication materials. Early and critical steps, such as construct development and codebook refinement, must be conducted iteratively to achieve high intercoder reliability. Even with automated data entry, human validation remains essential for verifying variable formats and value ranges. Computing environments should be documented to minimize system-related discrepancies (Liu and Salganik 2019).

For ex-post harmonization projects, careful attention to pre-harmonization stages substantially contributes to overall dataset quality. While some error is inevitable, with responsible researcher oversight, data-entry errors can be minimized while transparency, openness, and research credibility continue to grow.

Notes

¹ The R community has often built software to ease the access of APIs and make the batch work for multiple waves of data in a more comfortable and efficient way (see Blondel 2018; Lahti et al. 2017; Lugo 2017; Magnusson, Lahti, and Hansson 2014; Wickham, Hester, and Ooms 2018).

²Most often this has been done by two different investigators, but sometimes sequentially by a single researcher.

³See a summary of the “researcher degrees of freedom” literature in Hu, Tai, and Solt (2024).

⁴See a comprehensive example applied the second-order opening strategy in Tai, Hu, and Solt (2024).

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4 Supplementary Materials

4.1 R packages for data wrangling

Here are the tables of example R packages that researchers can use to collect, clean, and transform data. The tables were generated by the `pkgsearch::pkg_search()` function

with the keywords relating to data downloading (`?@tbl-download`), wrangling (`?@tbl-clean`), and transforming (`?@tbl-transform`). The packages are ranked based on the ‘score’ metric that reflects both textual relevances with the keyword and package popularity in the last month. Only the top twenty packages and only the maintainers’ names are shown. We encourage readers to use the codes in this paper’s replication file to explore more useful packages. We also recommend readers to refer to the “CRAN Task View: Reproducible Research” page for more useful tools to achieve the first-order and second-order opening.

Table 1: Example packages for downloading data with API

| package | title | maintainer |
|------------------|---|------------------------|
| giscoR | Download Map Data from GISCO API - Eurostat | Diego Hernangómez |
| rwebstat | Download Data from the Webstat API | Vincent Guegan |
| crypto2 | Download Crypto Currency Data from 'CoinMarket- | Sebastian Stoeckl |
| | Cap' without 'API' | |
| RKaggle | 'Kaggle' Dataset Downloader 'API' | Benjamin Smith |
| csodata | Download Data from the CSO 'PxStat' API | Conor Crowley |
| hansard | Provides Easy Downloading Capabilities for the UK | Evan Odell |
| | Parliament API | |
| cranlogs | Download Logs from the 'RStudio' 'CRAN' Mirror | Gábor Csárdi |
| clinicalomicsdbR | Interface with the 'ClinicalOmicsDB' API, Allowing | John Elizarraras |
| | for Easy DataDownloading and Importing | |
| wdi2 | Download World Development Indicators from the | Christoph Scheuch |
| | World BankIndicators API | |
| GDELTtools | Download, Slice, and Normalize GDELT V1 Event | Stephen R. Haptonstahl |
| | and Sentiment APIData | |
| neonUtilities | Utilities for Working with NEON Data | Claire Lunch |
| piggyback | Managing Larger Data on a GitHub Repository | Carl Boettiger |
| Quandl | API Wrapper for Quandl.com | Dave Dotson |
| nasapower | NASA POWER API Client | Adam H. Sparks |
| rstudioapi | Safely Access the RStudio API | Kevin Ushey |
| rdhs | API Client and Dataset Management for the Demo- | OJ Watson |
| | graphic and HealthSurvey (DHS) Data | |
| fishtree | Interface to the Fish Tree of Life API | Jonathan Chang |
| ridigbio | Interface to the iDigBio Data API | Jesse Bennett |
| tradestatistics | Open Trade Statistics API Wrapper and Utility Pro- | Mauricio Vargas |
| | gram | |
| FlickrAPI | Access to Flickr API | Koki Ando |
| easycensus | Quickly Find, Extract, and Marginalize U.S. Census | Cory McCartan |
| | Tables | |
| shutterstock | Access 'Shutterstock' REST API | Metin Yazici |
| wbstats | Programmatic Access to Data and Statistics from the | Jesse Piburn |
| | World BankAPI | |
| gwasrapidd | 'REST' 'API' Client for the 'NHGRI'-'EBI' 'GWAS' | Ramiro Magno |
| | Catalog | |
| ecos | Economic Statistics System of the Bank of Korea | Seokhoon Joo |

Continued on next page

Table 1: Example packages for downloading data with API (Continued)

| | | |
|-----------------|--|--------------------------|
| rscopus | Scopus Database 'API' Interface | John Muschelli |
| I14Y | Search and Get Data from the I14Y Interoperability | Felix Luginbuhl |
| | Platform ofSwitzerland | |
| riingo | An R Interface to the 'Tiingo' Stock Price API | Davis Vaughan |
| PurpleAir | Query the 'PurpleAir' Application Programming In- | Cole Brokamp |
| | terface | |
| kaigiroku | Programmatic Access to the API for Japanese Diet | Akitaka Matsuo |
| | Proceedings | |
| mgpStreamingSDK | Interact with the Maxar MGP Streaming API | Nathan Carr |
| GetLattesData | Reading Bibliometric Data from Lattes Platform | Marcelo Perlin |
| worldbank | Client for World Banks's 'Indicators' and 'Poverty | Maximilian Mücke |
| | andInequality Platform (PIP)' APIs | |
| BFS | Get Data from the Swiss Federal Statistical Office | Felix Luginbuhl |
| jsonlite | A Simple and Robust JSON Parser and Generator for | Jeroen Ooms |
| | R | |
| trud | Query the 'NHS TRUD API' | Alasdair Warwick |
| rinat | Access 'iNaturalist' Data Through APIs | Stéphane Guillou |
| zen4R | Interface to 'Zenodo' REST API | Emmanuel Blondel |
| yfinancer | 'Yahoo Finance' API Wrapper | Giovanni Colitti |
| opendotaR | Interface for OpenDota API | Kari Gunnarsson |
| Visual- | Visualize Downloads from 'CRAN' Packages | Marcelo Ponce |
| ize.CRAN.Down- | | |
| loads | | |
| PurpleAirAPI | Historical Data Retrieval from 'PurpleAir' Sensors via | Heba Abdelrazzak |
| | API | |
| pacu | Precision Agriculture Computational Utilities | dos Santos Caio |
| cbsodataR | Statistics Netherlands (CBS) Open Data API Client | Edwin de Jonge |
| MetaculR | Analyze Metaculus Predictions and Questions | Joseph de la Torre Dwyer |
| kosis | Korean Statistical Information Service (KOSIS) | Seokhoon Joo |
| trellor | Access the Trello API | Jakub Chromec |
| naptanr | Call the 'NaPTAN' API Through R | Francesca Bryden |
| rscorecard | A Method to Download Department of Education Col- | Benjamin Skinner |
| | lege ScorecardData | |
| inegiR | Integrate INEGI's (Mexican Stats Office) API with R | Eduardo Flores |

Table 2: Example packages for wrangling data with API

| package | title | maintainer |
|----------------|---|-----------------------|
| discretization | Data Preprocessing, Discretization for Classification | HyunJi Kim |
| helda | Preprocess Data and Get Better Insights from Ma- | Simon Corde |
| | chine LearningModels | |
| recipes | Preprocessing and Feature Engineering Steps for Mod- | Max Kuhn |
| | eling | |
| dunlin | Preprocessing Tools for Clinical Trial Data | Joe Zhu |
| dataprep | Efficient and Flexible Data Preprocessing Tools | Chun-Sheng Liang |
| smallsets | Visual Documentation for Data Preprocessing | Lydia R. Lucchesi |
| rtry | Preprocessing Plant Trait Data | Olee Hoi Ying Lam |
| PupilPre | Preprocessing Pupil Size Data | Aki-Juhani Kyröläinen |
| mpactr | Correction of Preprocessed MS Data | Patrick Schloss |

Continued on next page

Table 2: Example packages for wrangling data with API (Continued)

| | | |
|---------------|--|------------------------|
| bdpar | Big Data Preprocessing Architecture | Miguel Ferreira-Díaz |
| webtrackR | Preprocessing and Analyzing Web Tracking Data | David Schoch |
| tsrobprep | Robust Preprocessing of Time Series Data | Michał Narajewski |
| VWPre | Tools for Preprocessing Visual World Data | Vincent Porretta |
| binst | Data Preprocessing, Binning for Classification and Re- | Chapman Siu |
| | gression | |
| PreProcessing | Various Preprocessing Transformations of Numeric | Swamiji Pravedson |
| | Data Matrices | |
| esmtools | Preprocessing Experience Sampling Method (ESM) | Jordan Revol |
| | Data | |
| RobLoxBioC | Infinitesimally Robust Estimators for Preprocessing - | Matthias Kohl |
| | Omics Data | |
| shinyrecipes | Gadget to Use the Data Preprocessing 'recipes' Pack- | Alberto Almuíña |
| | ageInteractively | |
| RGCxGC | Preprocessing and Multivariate Analysis of Bidimen- | Cristian Quiroz-Moreno |
| | sional GasChromatography Data | |
| mlr3pipelines | Preprocessing Operators and Pipelines for 'mlr3' | Martin Binder |
| EEM | Read and Preprocess Fluorescence Excitation- | Vipavee Trivittayasil |
| | Emission Matrix(EEM) Data | |
| cobalt | Covariate Balance Tables and Plots | Noah Greifer |
| clickR | Semi-Automatic Preprocessing of Messy Data with | David Hervas Marin |
| | Change Trackingfor Dataset Cleaning | |
| SerolyzeR | Reading, Quality Control and Preprocessing of MBA | Tymoteusz Kwiecinski |
| | (MultiplexBead Assay) Data | |
| PvSTATEM | Reading, Quality Control and Preprocessing of MBA | Tymoteusz Kwiecinski |
| | (MultiplexBead Assay) Data | |
| huge | High-Dimensional Undirected Graph Estimation | Haoming Jiang |
| klaR | Classification and Visualization | Uwe Ligges |
| datawizard | Easy Data Wrangling and Statistical Transformations | Etienne Bacher |
| dplyr | A Grammar of Data Manipulation | Hadley Wickham |
| pagoda2 | Single Cell Analysis and Differential Expression | Evan Biederstedt |
| biclust | BiCluster Algorithms | Sebastian Kaiser |
| ggplot2 | Create Elegant Data Visualisations Using the Gram- | Thomas Lin Pedersen |
| | mar of Graphics | |
| tidyr | Tidy Messy Data | Hadley Wickham |
| tibble | Simple Data Frames | Kirill Müller |
| prospectr | Miscellaneous Functions for Processing and Sample | Leonardo Ramirez-Lopez |
| | Selection ofSpectroscopic Data | |
| microeco | Microbial Community Ecology Data Analysis | Chi Liu |
| pammtools | Piece-Wise Exponential Additive Mixed Modeling | Andreas Bender |
| | Tools forSurvival Analysis | |
| ebal | Entropy Reweighting to Create Balanced Samples | Jens Hainmueller |
| ordinalRR | Analysis of Repeatability and Reproducibility Studies | Ken Ryan |
| | withOrdinal Measurements | |
| ff | Memory-Efficient Storage of Large Data on Disk and | Jens Oehlschlägel |
| | Fast AccessFunctions | |
| mlr3data | Collection of Machine Learning Data Sets for 'mlr3' | Marc Becker |
| lubridate | Make Dealing with Dates a Little Easier | Vitalie Spinu |
| daltoolbox | Leveraging Experiment Lines to Data Analytics | Eduardo Ogasawara |

Continued on next page

Table 2: Example packages for wrangling data with API (Continued)

| | | |
|----------------|--|------------------|
| mlrCPO | Composable Preprocessing Operators and Pipelines | Martin Binder |
| | for MachineLearning | |
| readr | Read Rectangular Text Data | Jennifer Bryan |
| CRMetrics | Cell Ranger Output Filtering and Metrics Visualiza- | Rasmus Rydbirk |
| | tion | |
| JointAI | Joint Analysis and Imputation of Incomplete Data | Nicole S. Erler |
| HiClimR | Hierarchical Climate Regionalization | Hamada S. Badr |
| gcxgclab | GCxGC Preprocessing and Analysis | Stephanie Gamble |
| simulariatools | Simulatia Tools for the Analysis of Air Pollution Data | Giuseppe Carlino |

Table 3: Example packages for transforming data with API

| package | title | maintainer |
|----------------|---|---------------------|
| yaml | Methods to Convert R Data to YAML and Back | Shawn Garbett |
| geojsonio | Convert Data from and to 'GeoJSON' or 'TopoJSON' | Michael Mahoney |
| jsonlite | A Simple and Robust JSON Parser and Generator for | Jeroen Ooms |
| | R | |
| reticulate | Interface to 'Python' | Tomasz Kalinowski |
| keyToEnglish | Convert Data to Memorable Phrases | Max Candocia |
| qtl2convert | Convert Data among QTL Mapping Packages | Karl W Broman |
| gtools | Various R Programming Tools | Ben Bolker |
| rmarkdown | Dynamic Documents for R | Yihui Xie |
| interleave | Converts Tabular Data to Interleaved Vectors | David Cooley |
| do | Data Operator | Jing Zhang |
| rio | A Swiss-Army Knife for Data I/O | Chung-hong Chan |
| data.tree | General Purpose Hierarchical Data Structure | Christoph Glur |
| wktmo | Converting Weekly Data to Monthly Data | You Li |
| GDPuc | Easily Convert GDP Data | Johannes Koch |
| nuts | Convert European Regional Data | Moritz Hennicke |
| wearables | Tools to Read and Convert Wearables Data | Peter de Looft |
| xml2relational | Converting XML Documents into Relational Data | Joachim Zuckarelli |
| | Models | |
| TidyMultiqc | Converts 'MultiQC' Reports into Tidy Data Frames | Michael Milton |
| odk | Convert 'ODK' or 'XLSForm' to 'SPSS' Data Frame | Muntashir-Al-Arefin |
| spbabel | Convert Spatial Data Using Tidy Tables | Michael D. Sumner |
| exp2flux | Convert Gene EXPression Data to FBA FLUXes | Daniel Osorio |
| ecocomDP | Tools to Create, Use, and Convert ecocomDP Data | Colin Smith |
| tbl2xts | Convert Tibbles or Data Frames to Xts Easily | Nico Katzke |
| LAIr | Converting NDVI to LAI of Field, Proximal and Satel- | Francesco Chianucci |
| | lite Data | |
| broom.mixed | Tidying Methods for Mixed Models | Ben Bolker |
| ILRCM | Convert Irregular Longitudinal Data to Regular Inter- | Atanu Bhattacharjee |
| | vals and Perform Clustering | |
| intergraph | Coercion Routines for Network Data Objects | Michał Bojanowski |
| gtfs2gps | Converting Transport Data from GTFS Format to | Pedro R. Andrade |
| | GPS-Like Records | |
| RJSONIO | Serialize R Objects to JSON, JavaScript Object No- | Yaoxiang Li |
| | tation | |
| vcfR | Manipulate and Visualize VCF Data | Brian J. Knaus |
| MissingHandle | Handles Missing Dates and Data and Converts into | Mr. Sandip Garai |
| | Weekly and Monthly from Daily | |

Continued on next page

Table 3: Example packages for transforming data with API (Continued)

| | | |
|--------------|---|----------------------|
| orsk | Converting Odds Ratio to Relative Risk in Cohort | Zhu Wang |
| | Studies with Partial Data Information | |
| sjlabelled | Labelled Data Utility Functions | Daniel Lüdecke |
| dplyr | A Grammar of Data Manipulation | Hadley Wickham |
| tidytree | A Tidy Tool for Phylogenetic Tree Data Manipulation | Guangchuang Yu |
| pack | Convert Values to/from Raw Vectors | Joshua M. Ulrich |
| ggplot2 | Create Elegant Data Visualisations Using the Gram- | Thomas Lin Pedersen |
| | mar of Graphics | |
| string2path | Rendering Font into 'data.frame' | Hiroaki Yutani |
| tdata | Prepare Your Time-Series Data for Further Analysis | Ramin Mojab |
| DDIwR | DDI with R | Adrian Dusa |
| CADF | Customer Analytics Data Formatting | Ludwig Steven |
| tidyr | Tidy Messy Data | Hadley Wickham |
| tibble | Simple Data Frames | Kirill Müller |
| redquack | Transfer 'REDCap' Data to Database | Dylan Pieper |
| mltools | Machine Learning Tools | Ben Gorman |
| tinytable | Simple and Configurable Tables in 'HTML', 'LaTeX', | Vincent Arel-Bundock |
| | 'Markdown', 'Word', 'PNG', 'PDF', and 'Typst' For- | |
| | mats | |
| mergen | AI-Driven Code Generation, Explanation and Execu- | Altuna Akalin |
| | tion for DataAnalysis | |
| unpivotr | Unpivot Complex and Irregular Data Layouts | Duncan Garmonsway |
| jsonld | JSON for Linking Data | Jeroen Ooms |
| mergenstudio | 'Mergen' Studio: An 'RStudio' Addin Wrapper for the | Jacqueline Jansen |
| | 'Mergen'Package | |