How to Improve Data Validation in Five Steps

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1 Introduction

Social scientists are awash with data. According to a recent estimate, humans produce about 2.5 billion gigabytes of information every day, and 90 percent of the global data were created in only two years (IBM 2016). Governments also generate more data than ever before, with a growing number of agencies opening their archives and allowing users to access public records directly or via APIs (e.g., Al-Ubaydli and McLaughlin 2017; McDonnell et al. 2019).

In this context, researchers have developed a series of tools to obtain, clean, and store data files. R and Python, two open source programming languages, have become the *de facto* standards for downloading and manipulating data (Magoulas and Swoyer 2020; Perkel 2018). Reproducible scripts are now a common feature in academic studies, so researchers can easily share and verify their analyses (Höffler 2017; Key 2016). Scholars can also store data and code in public repositories, such as GitHub or the Harvard Dataverse, which guarantee that academic materials will be preserved for future reference (King 2007).

Although there has been significant progress in data analytics, data validation techniques have received little attention in academia. Data validation is defined as "[...] *an activity verifying whether or not a combination of values is a member of a set of acceptable combinations*" (ESSnet ValiDat Foundation 2018, 8). One reason for this omission is that data quality procedures are not as standardised as other statistical methods, so users often need to create *ad hoc* semantic rules to compile new data (McMann et al. 2016). Moreover, scholars have to engage with several sources of information to establish conceptual

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validity and translate abstract concepts into plausible numeric values (Munck and Verkuilen 2002; Schedler 2012).

In this paper, I present five steps to help scholars improve their data validation process. My idea is to offer a short check-list that is useful to both data developers and reviewers, so all parties involved in the validation procedures have a common understanding of what constitutes good practices in the field. My suggestions are based on the standards set by Eurostat, an agency that provides statistical information to the European Union (EU), and on recommendations by Gerring (2001), McMann et al. (2016), and Schedler (2012). I discuss how to create testable validation functions, how to increase construct validity, and how to incorporate qualitative knowledge in statistical measurements. I present the concepts according to their level of abstraction, with the last three demanding more theorisation than the first two, and I provide practical examples on how scholars can add the suggestions below to their work.

2 Five Steps Towards Better Data Validation Processes

2.1 Step 1: Technical Consistency

Ensuring technical consistency is perhaps the easiest task in the data validation process, yet it is often overlooked even by experienced scholars. Technical consistency means that the data should be machine-readable and as intuitive as possible to humans. More specifically, scholars have to ensure that their data do not produce parsing errors, that values corresponding to variables and observations are clearly identified, and that other researchers can analyse the data as soon as they receive them.

The computer science literature has some important suggestions in this regard. First, data should be "tidy", that is, in a format where each column represents one variable, each row represents one observation, and each observational unit forms a table (Wickham 2014, 4). Although the definition seems intuitive, scholars sometimes break these rules when building a new dataset. It is not uncommon to see multiple variables stored as a single column (e.g., race and gender together) or one variable divided into many columns (e.g., one column per level of income). Fortunately, most datasets can be tidied up with simple operations, such as pivoting tables, splitting or combining columns, or filtering values. Please refer to Wickham and Grolemund (2016) for more information on how to clean messy data.

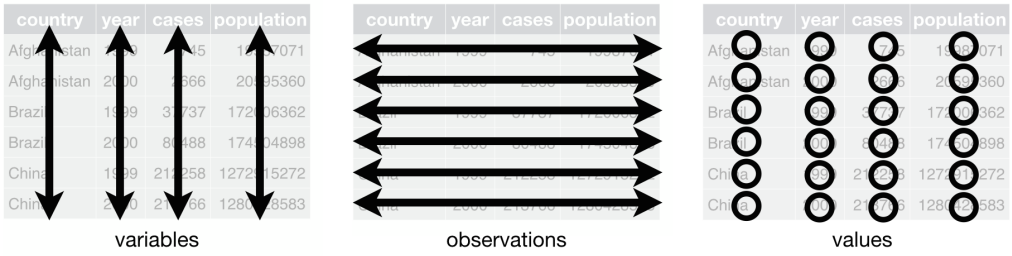

Figure 1: A tidy dataset. Source: Wickham and Grolemund (2016).

It is important to add an identifying variable (primary key) that is unique across all records (van der Loo and de Jonge 2019, 1). This is particularly relevant when scholars need to merge different datasets, as the primary keys have to be the same across all tables. Also, variables should have appropriate cell formats, or the machine may not be able to parse the values correctly. For instance, users should store strings as character vectors, numbers as numeric values (floating points or integers), binary indicators as boolean vectors (`TRUE` or `FALSE`), and categorical variables as factors (ESSnet ValiDat Foundation 2018, 10). Whenever possible, save tabular data in pure text format as any software can read it. Comma-separated values files (`.csv`) have wide support across many operating systems and can be easily opened in Excel, R, and Python with no errors.

Variables containing textual data or times and dates need special attention as they are prone to encoding issues. There are dozens of character encoding standards, but a recent survey shows that Unicode Transformation Format – 8-bit (UTF-8) is used on 96% of all internet websites (W3 Techs 2020). In this sense, scholars should use UTF-8 to store text variables as it currently is the world's most popular text encoding. UTF-8 is able to convert characters from many alphabets and its recent version also stores emojis. Regarding times and dates, scholars are advised to record time in the ISO 8601 standard ISO. The ISO standard uses the Gregorian calendar and a 24-h timescale (Van der Loo and De Jonge 2018, 52). Dates are stored in the `YYYY-MM-DD` format, in which `YYYY` represents the year, `MM` the month, and `DD` the day. Time of day should be expressed as `hh:mm:ss`, for hour, minute, and second, respectively.

Although not strictly required, it is recommended that researchers use version control to keep track of changes and ensure the technical consistency of their data files. Git is the most popular version control system. While it was first designed to manage computer code, Git allows users to record and recall any

particular version of a given document, and it works well with pure text files like `.csv`. This increases transparency in academic research, as others can trace all steps of the data management process and serve as a reliable back up in the case of data loss (Ram 2013). Moreover, contributors can modify the files and merge them to the main Git repository, which facilitates collaboration and review at every stage of the research project. Since users can quickly revert to previous versions of a file, the process is risk-free. For more information about Git, please visit https://git-scm.com.

2.2 Step 2: Logical Consistency

The second step involves the elaboration of logical validation rules to assess the consistency of recorded values. In contrast with technical integrity, logical consistency requires *a priori* knowledge from a particular scientific field, so these validation methods are domain-specific by design. However, these specific rules can be evaluated using a general framework based on boolean statements. In other words, scholars may use validation functions that produce a set of `TRUE` or `FALSE` responses to check whether the variables are in line with their theoretical expectations (van der Loo and de Jonge 2019, 3).

For instance, if a researcher measures the average population age and GDP per capita, the data should have no negative values or include zero. An `if` statement can verify whether the observations conform to that rule:

- IF `age` ≤ 0 OR `gdp_per_capita` ≤ 0 == `FALSE`
- ELSE == `TRUE`

Scholars can use similar validations functions to check the logical validity of any variable for which prior information is available. Users can also combine conditional statements and check the quality of related variables with a single function. As an example, if a dataset contains information about the location of the subjects, such as city and street name, one can assume that the postal code is the same if the two values are identical (van der Loo and de Jonge 2019, 12). Translating the rules into conditional expressions, the code would be:

- IF $\texttt{city}_{[i]}$ == $\texttt{city}_{[j]}$ AND $\texttt{street}_{[i]}$ == $\texttt{street}_{[j]}$
- THEN $\texttt{postal}_{[i]} \equiv \texttt{postal}_{[j]}$

There are cases, however, for which no exact information on the true values exist. But social scientists can still verify the consistency of their data using conditional rules. Instead of focusing on a particular boolean outcome, researchers should estimate upper and lower bounds for the variable they want to check. One way to do so is via Monte Carlo simulations. The ESSnet ValiDat Foundation (2018, 72) proposes an easy yet effective method to estimate logical consistency bounds for a given variable. First, create a set of values S that seems plausible according to the related literature. Second, add disturbances to the dataset S by simulating cases with measurement error, missing values, mistakes in the data entry process, or other statistical issues that are common to that type of data. This yields a variable S'. Then, apply the consistency test to S'. In the final step, repeat this process several times and change the number of wrong observations to create a distribution of rule statistics from the simulated S'_n variables. This method produces the lower and upper bounds required for the data, assuming that S correctly approximates the true values of the chosen variable.

While in the section I discuss how rules can be applied to new datasets, they may also provide interesting insights when used to evaluate existing data. One possible avenue for research is to compare whether certain conditional statements produce different outcomes in datasets that measure the same phenomena, such as level of democracy or changes in political regimes. Observations that do not conform to the rules should be contrasted and explained, and if that is the case, imputed to credible values. Indeed, de Waal (2017) suggests that imputation methods that both preserve statistical properties of the variables and conform to rule restrictions are the best way to fill missing data, even if so far they are difficult to estimate.

Testing data with conditional expressions provides another benefit for researchers. Since logical rules can be defined in advance, they may be included in a preregistration plan. Registering the study design before data collection or analysis reduces the chances of "data dredging", where researchers release only the analyses that support their hypotheses (Klein et al. 2018). Preregistration increases the credibility of the findings and may be even submitted directly for publication in the form of registered reports (Chambers 2013). Journals can evaluate the research design before scholars know the results, and the manuscript's acceptance is independent of the final data. As of late 2020, 275 journals use registered reports as a regular or one-off submission option (Center for Open Science 2020).

2.3 Step 3: Content Validity

Content validity refers to whether the variables correspond to the theoretical concepts they intend to measure. This is a difficult task as there are no hard-and-fast rules on how to map concepts into values. Here I follow Gerring (1999; 2001; 2011) and suggest that researchers should check if their variables meet six criteria: resonance, domain, differentiation, fecundity, consistency, and causal utility. I explain each of them in further detail below.

Resonance means that the variable name brings to mind the core idea of a concept. A good name is one that includes a simple word that is used in common language and quickly conveys the point the authors are trying to make. Terms that resonate are akin to mnemonic devices, something that helps readers to remember what the variable means long after they see it (Gerring 1999, 370). Concepts like "social capital" or "civic culture" might be difficult to measure, but they do invoke an intuitive understanding of the concepts authors refer to (Bjørnskov and Sønderskov 2013).

Domain considers whether relevant parties agree with the concept being measured. The idea of domain is similar to that of resonance, but it describes how particular audiences, mainly area specialists, interpret the concept one intends to describe (McMann et al. 2016, 9). For example, the domain of "democracy" as measured by political indices may differ substantially from what the lay community generally understands as the "government of the people" (Munck and Verkuilen 2002). In that respect, the concept should embrace as many domains as possible, although it should strive first for internal validity and consistency (Tortola 2017, 241). Thus, it is essential that the researcher has a firm idea of what his or her target public expects from the concept.

Differentiation indicates that the variable should include the unique aspects of a given concept. In other words, it entails that one should find what makes a concept distinct from related terms, and the sharper those boundaries are, the stronger the validity of the concept. As Gerring (1999, 375) notes, a useful definition of "state" has to single out what characteristics are particular to states and do not appear in other forms of social organisation, such as tribes or empires. Many concepts in the social sciences cause confusion precisely because they include traits that are not exclusive to these categories. For instance, if one defines "armed conflict" as "the use of force by the state or civilians against other groups", it is not possible to differentiate such cases from episodes of lynchings or genocide.

Similarly, *fecundity* indicates that the variable is parsimonious and excludes all information that is not related to the concept. It refines the differentiation attribute and highlights that it is not only required for scholars to affirm what the concept is, but also to show what *it is not* (Gerring 2001, 92). This exercise involves counterfactual thinking, and it is not always clear which unrealised outcome scholars should focus on. One suggestion may be to start with competing definitions and remove characteristics that conflate the original concept with similar behaviours. For instance, a corruption variable should exclude private benefits that do not originate from someone's governmental position (McMann et al. 2016, 10).

Consistency is an attribute that signals whether a concept retains its validity across different settings (McMann et al. 2016, 11). An indicator of liberal democracy should be able to explain not only Western regimes, but to identify liberal traits in countries that do not share a similar background and retain its consistency over time. In this sense, the variable should preferably measure sufficient attributes of the concept, which can be easily identified in other cases.

Lastly, *causal utility* means that researchers are able to test hypotheses in which the concept described is either the main cause or the expected effect (Gerring 1999, 367). In most cases, concepts designed to be employed as independent variables require fewer attributes to be causally useful than those created to be dependent variables (Gerring 2011, 130). While it is hard to ensure that a concept is completely exogenous from other theoretical constructs, authors should avoid a definition where known confounders connect the concept to background factors (Gerring 2011, 130).

2.4 Step 4: Data Generation Validity

This step corresponds to the relationship between the concepts the researcher wants to translate into numeric values and the data generating process. In particular, scholars need to be aware that their data generating process may be biased or unreliable (McMann et al. 2016, 12). Problems may arise either when gathering new data or using secondary sources. Here I focus on two common threats to data generation validity, low intercoder reliability and data aggregation challenges.

With regards to novel datasets, scholars should address whether coders have inadvertently introduced their own views during the data collection stage. Although intercoder reliability does not guarantee that the data are correct, disagreements between coders raise a red flag about the validity of the recorded

values (Kolbe and Burnett 1991, 248). A first step is to calculate intercoder agreement using two popular statistics, Cohen's Kappa and Krippendorff's Alpha (Lombard et al. 2002). While these tests have their limitations, they are easy to estimate and are available in many statistical languages. R users have the `irr` package (Gamer et al. 2019), which provides functions to estimate those statistics for any dataset. Scholars are also expected to report the results of these tests in their materials, as well as a justification for the minimum acceptable level of intercoder reliability they have adopted (Lombard et al. 2002, 600).

There are a few recommendations on how to proceed when intercoder agreement is low. First, provide training and clear guidelines to the raters. Allowing them to discuss and explain to each other where they disagree can also bring substantial increases to intercoder reliability (O'Connor and Joffe 2020). Second, if time allows, implement multiple coding rounds and modify the coding frame accordingly until intercoder agreement reaches a desired level (MacPhail et al. 2016). A final suggestion would be to apply item-response theory (IRT) models to convert ordinal data to latent variables, as they allow for intercoder variation in skill and in perceived scale differences (Marquardt and Pemstein 2018).

When the data come from secondary sources and the scholar wants to combine them into an index, it is good practice to describe how aggregation rules may change the results. Loss of information is inevitable when aggregating attributes into an index, so scholars need to first clarify which of the attributes will be combined and for what reason. There is where theory comes in, as aggregation rules should always be theoretically motivated. For instance, it is unclear whether additivity, the default method for merging low-level attributes, is the best aggregation rule for most indices, or why scholars do not assign unequal weights to their attributes more often (Munck and Verkuilen 2002, 24). As long as the steps are theoretically consistent, researchers can use very different methods for index construction.

There are cases, nevertheless, where one has no *a priori* knowledge about what features to include in an aggregate measure. It can either be because the current literature offers little guidance on the topic or because features are multicollinear. One suggestion is to use Bayesian factor analysis (BFA) as a technique to model latent traits (Conti et al. 2014). While researchers have long used principal component analysis (PCA) to reduce the dimensionality of a dataset, BFA has several advantages over PCA. BFA propagates uncertainty in the estimates, allows for correlated factors and control variables, and can either decide automatically or let users include as many factors as they see fit into the index. The R package `BayesFM` (Piatek 2020) performs the analysis presented here.

2.5 Step 5: Convergent Validity

The last step concerns how well the variables compare with well-documented cases. McMann et al. (2016) suggest that researchers should evaluate their dataset against other sources that cover the same topics, including qualitative studies. We can borrow the idea of validation functions discussed above and apply the same logic here. But as I noted above, as the statements come from domain knowledge, authors and reviewers should be familiar with the specialised literature in order to check the consistency of the convergence rules.

Consider a data set with two variables, `gender` and `salary`. Suppose that a previous case study in the same location states with high confidence that 20% of males have earnings lower than $2,000 per month. We can formulate a validation rule set as follows:

- IF `gender == "male"`
- THEN $\frac{count(\texttt{salary} > 2{,}000)}{count(\texttt{salary})} = 0.2$

The example shows how researchers can integrate previous information to their estimates. Authors can select the case studies they want to analyse using different criteria. Seawright and Gerring (2008) offer an interesting comparison between seven case selection methods and the corresponding large-N statistical reasoning behind the choices. The first method is the selection of *typical* cases, ones that best represent the intended relationship. This is the equivalent of analysing low-residual observations, those which are very close to the fitted statistical curve. Authors can choose *diverse* cases if they are interested in obtaining a range for their variables. This is similar to checking the spread of a statistical distribution. Third, *extreme* cases describe observations that lie at the tails of a distribution. *Deviant* cases are akin to outliers in statistical modelling. *Influential* cases are those which are often not representative, but have a particular effect caused by independent variables. The last two cases are: *most similar*, which parallels matching techniques in large-N studies; and *most different*, its opposite. Please refer to Seawright and Gerring (2008) for more information on case selection strategies.

Finally, authors should explain the reasons behind eventual divergences between their measurements and current theoretical expectations. That said, it is recommended that authors investigate why outliers occur and test whether coder characteristics or measurement construction explain these differences. McMann et al. (2016, p. 27-36) provide an empirical case study on how to assess convergent validity.

3 Conclusion

Data validation is a crucial yet undertheorised topic in the social sciences. While estimation methods have made significant progress over the last decades, data validation procedures remain largely absent from university courses and academic textbooks. This is at odds with the famous saying that "80% of data analysis is spent on the process of cleaning and preparing the data" (Wickham 2014, 1) and with the growing number of datasets social scientists have amassed recently. My goal in this short paper was not to provide an abstract view of the data validation process, but to offer a few pieces of practical advice that social scientists may find useful when creating a new dataset or assessing the properties of existing ones. I divided the data validation process in five steps, from technical consistency to convergent validity, and added reading suggestions for authors who would like to read more about the topics discussed here.

I encourage authors to pay special attention to issues of logical consistency and content validity, which are particularly difficult parts of the data validation process. Translating concepts into numeric values is more art than science, even more so in areas where many foundational ideas remain contested. Thus, careful theoretical considerations are key to better measurement. Another important part of the data validation process is reproducibility. All steps of the data collection process should be documented and shared along with the final results. Reproducible research leads to timely feedback, quality reviews, and stronger academic collaborations, so scholars have an incentive to adopt reproducible methods in their work. Computer science and its many successful open source projects provide good evidence in favour of greater research transparency. As stated by Eric Raymond (2001, 30), a software developer, "given enough eyeballs, all bugs are shallow". Maybe the same is true in our discipline.

References

Al-Ubaydli, O. and McLaughlin, P. A. (2017). RegData: A Numerical Database on Industry-Specific Regulations for All United States Industries and Federal Regulations, 1997–2012. *Regulation & Governance*, 11(1):109–123.

Bjørnskov, C. and Sønderskov, K. M. (2013). Is Social Capital a Good Concept? *Social Indicators Research*, 114(3):1225–1242.

Center for Open Science (2020). Registered Reports: Peer Review before Results are Known to Align Scientific Values and Practices. https://www.cos.io/initiatives/registered-reports.

Chambers, C. D. (2013). Registered Reports: A New Publishing Initiative at Cortex. *Cortex*, 49(3):609–610.

Conti, G., Frühwirth-Schnatter, S., Heckman, J. J., and Piatek, R. (2014). Bayesian Exploratory Factor Analysis. *Journal of Econometrics*, 183(1):31–57.

de Waal, T. (2017). Imputation Methods Satisfying Constraints. In *Work Session on Statistical Data Editing*, Working Paper 5. United Nations Economic Commission for Europe.

ESSnet ValiDat Foundation (2018). Methodology for Data Validation 2.0. https://ec.europa.eu/eurostat/cros/system/files/ess_handbook_-_methodology_for_data_validation_v2.0_-_rev2018_0.pdf.

Gamer, M., Lemon, J., Fellows, I., and Singh, P. (2019). *irr: Various Coefficients of Interrater Reliability and Agreement*. R package version 0.84.1.

Gerring, J. (1999). What Makes a Concept Good? A Criterial Framework for Understanding Concept Formation in the Social Sciences. *Polity*, 31(3):357–393.

Gerring, J. (2001). *Social Science Methodology: A Criterial Framework*. Cambridge: Cambridge University Press.

Gerring, J. (2011). *Social Science Methodology: A Unified Framework*. Cambridge: Cambridge University Press.

Höffler, J. H. (2017). Replication and Economics Journal Policies. *American Economic Review*, 107(5):52–55.

IBM (2016). 10 Key Marketing Trends For 2017. ftp://ftp.www.ibm.com/software/in/pdf/10_Key_Marketing_Trends_for_2017.pdf.

Key, E. M. (2016). How Are We Doing? Data Access and Replication in Political Science. *PS: Political Science & Politics*, 49(2):268–272.

King, G. (2007). An Introduction to the Dataverse Network as an Infrastructure for Data Sharing. *Sociological Methods and Research*, 36(2):173–199.

Klein, O., Hardwicke, T. E., Aust, F., Breuer, J., Danielsson, H., Hofelich Mohr, A., IJzerman, H., Nilsonne, G., Vanpaemel, W., and Frank, M. C. (2018). A Practical Guide for Transparency in Psychological Science. *Collabra: Psychology*, 4(1):1–15.

Kolbe, R. H. and Burnett, M. S. (1991). Content-Analysis Research: An Examination of Applications with Directives for Improving Research Reliability and Objectivity. *Journal of Consumer Research*, 18(2):243–250.

Lombard, M., Snyder-Duch, J., and Bracken, C. C. (2002). Content Analysis in Mass Communication: Assessment and Reporting of Intercoder Reliability. *Human Communication Research*, 28(4):587–604.

MacPhail, C., Khoza, N., Abler, L., and Ranganathan, M. (2016). Process Guidelines for Establishing Intercoder Reliability in Qualitative Studies. *Qualitative research*, 16(2):198–212.

Magoulas, R. and Swoyer, S. (2020). 5 Key Areas for Tech Leaders to Watch in 2020. https://www.oreilly.com/radar/oreilly-2020-platform-analysis/.

Marquardt, K. L. and Pemstein, D. (2018). IRT Models for Expert-Coded Panel Data. *Political Analysis*, 26(4):431–456.

McDonnell, R. M., Duarte, G. J., and Freire, D. (2019). congressbr: An R Package for Analyzing Data from Brazil's Chamber of Deputies and Federal Senate. *Latin American Research Review*, 54(4).

McMann, K. M., Pemstein, D., Seim, B., Teorell, J., and Lindberg, S. I. (2016). Strategies of Validation: Assessing the Varieties of Democracy Corruption Data. *V-Dem Working Paper*, 23.

Munck, G. L. and Verkuilen, J. (2002). Conceptualizing and Measuring Democracy: Evaluating Alternative Indices. *Comparative Political Studies*, 35(1):5–34.

O'Connor, C. and Joffe, H. (2020). Intercoder Reliability in Qualitative Research: Debates and Practical Guidelines. *International Journal of Qualitative Methods*, 19:1609406919899220.

Perkel, J. M. (2018). Why Jupyter is Data Scientists' Computational Notebook of Choice. *Nature*, 563(7732):145–147.

Piatek, R. (2020). *BayesFM: Bayesian Inference for Factor Modeling*. R package version 0.1.4.

Ram, K. (2013). Git Can Facilitate Greater Reproducibility and Increased Transparency in Science. *Source Code for Biology and Medicine*, 8(1):1–8.

Raymond, E. (2001). *The Cathedral & the Bazaar, Revised Edition*. Sebastopol: O'Reilly.

Schedler, A. (2012). Judgment and Measurement in Political Science. *Perspectives on Politics*, 10(1):21–36.

Seawright, J. and Gerring, J. (2008). Case Selection Techniques in Case Study Research: A Menu of Qualitative and Quantitative Options. *Political Research Quarterly*, 61(2):294–308.

Tortola, P. D. (2017). Clarifying Multilevel Governance. *European Journal of Political Research*, 56(2):234–250.

Van der Loo, M. and De Jonge, E. (2018). *Statistical Data Cleaning with Applications in R*. Hoboken: Wiley Online Library.

van der Loo, M. P. and de Jonge, E. (2019). Data Validation Infrastructure for R. *arXiv preprint arXiv:1912.09759*.

W3 Techs (2020). Usage of Character Encodings Broken Down by Ranking. https://w3techs.com/technologies/cross/character_encoding/ranking.

Wickham, H. (2014). Tidy Data. *Journal of Statistical Software*, 59(10):1–23.

Wickham, H. and Grolemund, G. (2016). R for Data Science. https://r4ds.had.co.nz.