Data Smells Are Sneaky

Nicolas Hahn[a] and Afonso Sales[b]
School of Technology, PUCRS, Porto Alegre, RS, Brazil

Keywords: Data Smells, Simulation, Technical Debt in AI, Data Debt, Data Quality, Anomaly Detection.

Abstract: Data is the primary source for developing AI-based systems, and poor-quality data can lead to technical debt and negatively impact performance. Inspired by the concept of code smells in software engineering, data smells have been introduced as indicators of potential data quality issues, and can be used to evaluate data quality. This paper presents a simulation aimed at identifying specific data smells introduced in the unstructured format and detected in a tabular form. By introducing and analyzing specific data smells, the research examines the challenges in their detectability. The results underscore the need for robust detection mechanisms to address data smells across different stages of a data pipeline. This work expands the understanding of data smells and their implications, provinding new foundations for future improvements in data quality assurance for AI-driven systems.

1 INTRODUCTION

Data is the primary source for developing AI-based systems, where data analysis and validation are essential first steps for machine learning practitioners. Data quality issues can arise from multiple sources, including data entry errors, insufficient cleaning or inherent biases. Mitigating these issues requires a well-structured data quality management approach, encompassing profiling, cleansing, and data enrichment (Munappy et al., 2019). Despite the availability of tools and techniques supporting feature engineering and data transformation in AI pipelines (Recupito et al., 2022), the demand for robust quality assurance practices continues to grow (Ehrlinger and Wöß, 2022). Poor data quality not only diminishes immediate analytics effectiveness but also introduces data debt - a form of technical debt specific to data - which can degrade overall system performance and cascade issues throughout the pipeline (Foidl and Felderer, 2019). This data debt, particularly when driven by data quality issues or anomalies, significantly impacts AI-enabled systems, reducing model accuracy and affecting downstream processes (Bogner et al., 2021).

In analyzing technical debt specific to data, data smells can be viewed through an analogy to code smells. Code smells are warning signs in code, often indicating suboptimal design or programming practices that increase the likelihood of future issues (Santos et al., 2018). Such smells are widely recognized as markers of potential faults that may accumulate over time, leading to technical debt within codebases (Fowler and Beck, 1999; Van Emden and Moonen, 2012). In a similar manner, data smells signal latent data quality issues that arises from ineffective data management practices, posing risks that may compromise data reliability and usability in the future (Foidl et al., 2022). Although many other types of data quality issues have been extensively studied and addressed in research (Gong et al., 2019; Gray et al., 2011; Mansouri et al., 2021; Wang and Abraham, 2015), understanding of data smells - along with their impact and precise definitions - remains an evolving area. Recent contributions have expanded the foundational data smells catalog proposed by Foidl et al. (2022), with additional classifications introduced by Recupito et al. (2024) to further explore these indicators.

In contrast to traditional software, where changes primarily occur in code, machine learning systems mature through changes in data, models, and code (Sato et al., 2019). The feedback loop in machine learning systems is also generally longer, and, given their highly interconnected nature, any change within one stage of the lifecycle can trigger ripple effects across the entire pipeline (Sculley et al., 2015). While data pipelines can improve productivity and enhance data quality (Munappy et al., 2020), poorly designed or error-prone pipelines may fail to detect data qual-

[a] https://orcid.org/0009-0001-2551-1574
[b] https://orcid.org/0000-0001-6962-3706

Hahn, N. and Sales, A.
Data Smells Are Sneaky.
DOI: 10.5220/0013285500003929

In *Proceedings of the 27th International Conference on Enterprise Information Systems (ICEIS 2025) - Volume 1*, pages 479-488
ISBN: 978-989-758-749-8; ISSN: 2184-4992

ity issues, potentially leading to low-quality data output (Zhang et al., 2022). Such issues can propagate through various processing stages, remaining undetected until they eventually impact results. Testing these changes poses an additional challenge, as all three components - data, model, and code - require evaluation, and a full training and testing cycle may require substantial time, resource, and financial costs. As machine learning pipelines scale to production environments, the supporting infrastructure becomes increasingly complex. Therefore, identifying and addressing potential issues early in the data analysis phase becomes highly valuable, as this enables faster, easier, and more cost-effective remediation.

This paper aims to investigate data smells through a simulation study. By controlling the data generation process, we specify which data smells are introduced and examine how these are detected. Additionally, we include non-tabular data to observe how data smells originating in unstructured formats are affected once transformed into tabular form. For the detection process, we use the open-source detectors provided by Foidl et al. (2022) for tabular data, and we mapped these same smells in the unstructured data before tabular conversion. This study is guided by the following research questions:

- *RQ1: Do data smells present in unstructured data remain detectable when the data is converted into tabular form?*
- *RQ2: Does the detection process accurately reflect the data smells present within the data?*

The remaining paper is structured as follows. Section 2 provides the background, detailing the concept of data smells, data debt, and the probability distributions employed in the data generation process, and it also reviews related works, establishing connections to this study and identifying gaps addressed by our approach. Section 3 outlines the simulation study methodology, including the specific data smells introduced and the detection mechanism used. Section 4 presents the results, highlighting key findings and their implications for data quality assurance. In Section 5, we discuss threats to validity, addressing the limitations of the tools and methods employed and how they impact the study's conclusions while providing insights into the replicability and future extension of the research. And, finally, Section 6 concludes the paper with a concise summary of the findings and proposes directions for future research.

2 BACKGROUND

This section begins by defining key concepts central to this study, including data smells and data debt, in Section 2.1, highlighting their significance in data quality and AI systems. Following this, Section 2.2 reviews related works, providing context and identifying gaps that this research aims to address.

2.1 Data Smells and Data Debt

Data smells are indicators of potential data quality issues, characterized by data values that suggest problems regardless of context, and are often a result of suboptimal practices. Poor data management practices, commonly observed in early-stage startups, can exacerbate the emergence of data smells, acting as barriers to maintaining data quality (Melegati et al., 2019). The term first appeared in the grey literature in 2014, introduced by Harris (2014), who emphasized the importance of critically evaluating data prior to deriving results and conclusions. Shortly thereafter, Iubel (2014) adopted the term and proposed 13 data smells specific to the data journalism domain on GitHub. A more comprehensive catalog was introduced by Foidl et al. (2022), identifying 36 data smells organized into four main categories: Believability Smells, Consistency Smells, Encoding Smells, and Syntactic Smells. Later, Recupito et al. (2024) expanded this catalog, adding 12 new data smells and three additional categories: Redundant Value Smells, Distribution Smells, and Miscellaneous Smells. Figure 1 illustrates the catalog from Foidl et al. (2022), with new additions from Recupito et al. (2024) highlighted in bold.

Data smells exhibit a moderate degree of suspicion, meaning they are not immediately flagged as problematic upon initial inspection. For example, the word "Paris" might seem unremarkable, as it represents a well-known city. However, complications may arise when specific geographical information is required, as there are at least two cities named Paris — one in France and another in the USA. A key characteristic of data smells is their context independence: they represent universal issues that can manifest in any domain, potentially affecting any data-driven system. Additionally, data smells can remain unnoticed for extended periods, only to cause problems later, such as less accurate classification models or incorrect descriptive statistics. Finally, data smells often arise from poor data management and engineering practices. Therefore, the implementation of quality assurance methods can significantly improve the quality of processed data.

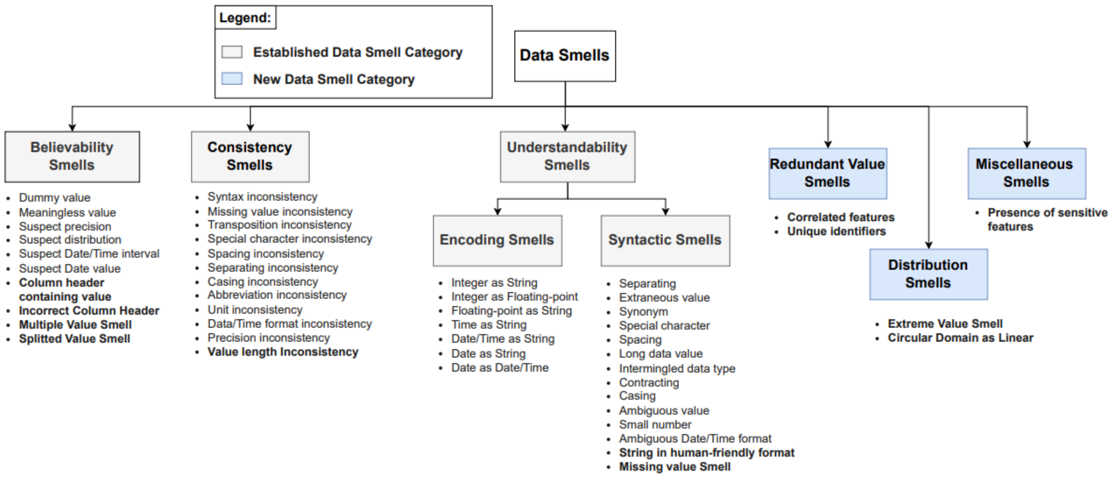


Figure 1: Data Smell Catalogue Expanded by Recupito et al. (2024).

Several studies have explored the concept of data debt in AI-enabled systems. Sculley et al. (2015) introduced the idea of technical debt in the context of the data used to build AI models. They examined the dependencies within data, highlighting the risks posed by unstable data dependencies, where changes could lead to unpredictable consequences for the entire system, as well as underutilized data dependencies within an AI pipeline. Bogner et al. (2021) subsequently conducted a systematic mapping study to explore the types of data smells. Data debt is the most recurrent type of AI-specific debt of all the types of technical debt explored for AI-enabled systems. In a case study, Munappy et al. (2019) explored data management challenges in deep learning systems, focusing on critical issues related to data structure, including deduplication and the management of heterogeneous data in terms of encoding and format. Bosu and MacDonell (2013) performed a systematic literature review on data quality research within empirical software engineering, revealing that only a small number of 23 studies addressed the three key activities of data quality management: data collection reporting, data preprocessing, and the identification of data quality issues. Yoon and Bae (2010) evaluated six different techniques to face outliers anomalies in the context of software project data, discovering that data cleaning techniques on artificial datasets are a considerable solution for this type of data quality issue. Liebchen and Shepperd (2008) expanded on earlier literature reviews, identifying new challenges in data quality management for software engineering, and noted an increasing interest among practitioners in exploring techniques that can automatically detect data quality issues. These studies put the basis for further investigation into the complexities of data debt.

2.2 Related Work

Data problems are widely explored in the literature. However, there is not a consensus on the terms that are used to refer to these problems: dirty data (Kim et al., 2003; Li et al., 2011), data error (Abedjan et al., 2016), data defect (Josko et al., 2019), data anomaly (Foorthuis, 2018; Sukhobok et al., 2017), data quality problem (Oliveira et al., 2005). For a comprehensive overview of the broader concepts of data quality and data handling, refer to the works of Batini and Scannapieco (2016), as well as Ilyas and Chu (2019). Additionally, Heck (2024) presents the current state of data engineering focused on AI-based systems.

The work developed by Roman et al. (2022) involved creating a demo site for data acquisition via sensors in photovoltaic cells (solar panels), addressing data quality issues such as missing data, inconsistent timing, unknown conditions, changes in the experiment environment, and not large enough experiment. This study intends to observe the behavior and potential issues present in a real-world scenario. The difference is that the authors work involved developing a small solar power generation station, while this study was restricted to a computational simulation.

Bayram et al. (2023) presented a framework called DQSOPs (*Data Quality Scoring Operations*), which provides a quality score for data in production within DataOps workflows. For the score, two approaches are presented: ML prediction-based and standard-based, involving data quality dimensions such as accuracy, completeness, consistency, timeliness, and skewness. Additionally, the cited data quality issues involve only numerical values. Although a direct relationship is not presented, it is possible to identify the connection between data quality dimensions and the data smells presented by Foidl et al. (2022) (*e.g.*, data anomaly).

Also, the work developed by Ter Hofstede et al. (2023) presents a discussion on the challenges related to data quality from both research and practical perspectives. Additionally, it is noteworthy that the authors present the existing problems and possible solutions for proper data cleaning.

The work presented by Shome et al. (2022) involved analysis of 25 datasets from Kaggle - an online repository - to identify recurrent data smells on public datasets. The scope of their work was restricted to structured data, i.e., tabular data. Also, their analysis revealed technical debt in the dataset due to lack of best practices and standardised procedures in upstream processes.

Golendukhina et al. (2022) explored the impact of data smells in a real-world business travel data scenario, using the taxonomy from Foidl et al. (2022) to identify data smells across the data pipeline. They highlighted three stages where data smells occur:

1. **Data Sources.** Originally, some of the data smells come from the raw data. Inconsistent data value entries by different users, different sources and differing data management methods.
2. **Data Transformation.** The next group of data smells arises in the data transformation stage. Issues like date/time represented as strings, numbers as strings, and inconsistent missing values from different tools and programming languages used.
3. **Data Enrichment.** The majority of data smells are produced in the data enrichment phase, often due to insufficient validation in earlier phases. However, data smells can also be produced from clean data, e.g., if time zones are not considered. Although spotting data smells in some cases might be challenging, analysis of the products of such data can facilitate the process.

The study emphasizes the significant impact of the data pipeline on data quality and suggests that data validation strategies are needed on different stages of the pipeline.

Finally, Recupito et al. (2024) extended the data catalog from Foidl et al. (2022) up to 50 data smells, including new categories. Also, using the data studied by Le Quy et al. (2022) and a subset of the data quality metrics described by Elouataoui et al. (2022), they identified a positive correlation between the presence of *Extreme Value Smells* and the *Readability* quality metric.

3 SIMULATION STUDY

To investigate data smells and address our research questions, we conducted a simulation study of data at different pipeline stages, considering *correct data*, *raw data*, and *tabular data*. Figure 2 illustrates the entire process, highlighting each phase from initial data generation to the final detection step, allowing us to analyze the presence of data smells.

We opted for numeric data due to its flexibility and ease of controlled generation with variability. We start by the generation phase, detailed as follows:

1. **Choose Generation Process.** Numeric data can be generated in two primary types - integers and floating-point numbers - using either arbitrary values or probability distributions. The strategy chosen depends on the intended representation of the data:
   - *sequential*: For scenarios requiring simple identifiers (*e.g.*, user IDs), we generate arbitrary values as a sequence of positive integers, such as $1, 2, 3, \ldots$.
   - *probability distribution*: For data with specific contextual meanings, such as the count or timing of system failures, we can use:
     - The Poisson distribution (parameter λ) to model the average number of failures per time interval, generating non-negative integers.
     - The Exponential distribution (parameter λ) for estimating the average time between failures, generating non-negative floating-point numbers.
     - The Uniform distribution (continuous or discrete) for generating values within a specified range (*e.g.*, $(0, 1)$ or $(1, 100)$), which can be integers or floating points as needed.

   For further details on these probability distributions, refer to Casella and Berger (2001).
2. **Choose Probability Distribution's Parameters Values.** When generating data through probability distributions, we specify distribution parameters based on the chosen distribution. For this study, we limit our scope to Uniform, Poisson, and Exponential distributions, as they are sufficient to create varied, realistic numeric data.

Also, we will generate these data in batches to consider a scenario that the data is not static, but on a streaming environment, reflecting real-world scenarios where data may change over time. The resulted data values of these phase represents the category of *correct data*, because they are the original data without any intervention nor errors, and, consequently, without any data smell.

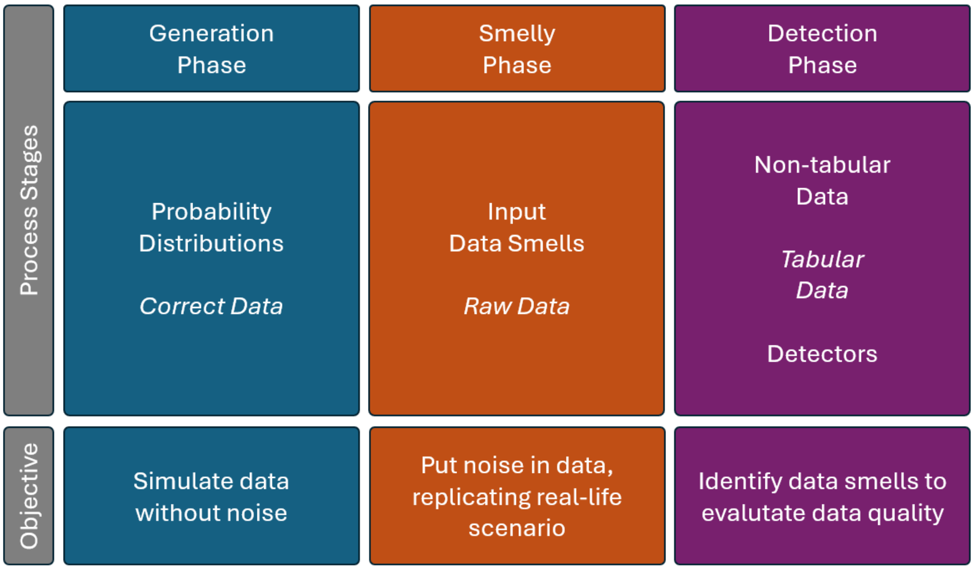


Figure 2: Methodology diagram ilustrating the entire process.

Next, we follow to the smelly phase, that we introduce different data smells in the numeric vector generated *correct data*. To avoid any transformation that may occur when data is in a structured tabular form (*e.g.*, convert data values to attend a specific table schema), we chose to put data smells on the numeric vectors resulted by the generated phase. The data smells considered are detailed below:

- **Duplicate Value Smell** (DupVS)**.** This smell occurs when the same data value is repeated multiple times. They are detectable by instance and are applied at all data types. We imputed on the vector by repeating the previous instance.
- **Dummy Value Smell** (DumVS)**.** This smell characterizes a situation in which a kind of substitute value is used due to several reasons (*e.g.*, unknown values, computation errors, surpassing "not NULL" constraints, *etc.*). They are detectable by instance and are applied at the data types Text, Numeric, Date/Time. We imputed in the vector by putting the values 999 (batch 1) and -1 (batch 2).
- **Suspect Precision Smell** (SPS)**.** This smell arises when a data value has a large number of decimal places. They are detectable by instance and are applied at the data type Numeric. We imputed by adding standard Gaussian noise on the $1e-5$ decimal point.
- **Integer/Floating-point Number as String Smell** (IFSS)**.** This smell occurs when an integer/floating-point number is encoded as a string. They are detectable by instance and are applied at the data type Numeric. We imputed by converting the instance to string.
- **Integer as Floating-Point Number** (IFS)**.** This smell occurs when an integer is encoded as a floating-point number. They are detectable by instance and are applied at the data type Numeric. We imputed by converting the instance to floating-point number.
- **Missing Value Smell** (MVS)**.** This smell occurs when the data value is missing. They are detectable by instance and are applied to all data types. We imputed by removing the instance from the vector.
- **Extreme Value Smell** (EVS)**.** This smell occurs when some of the values strongly differ from the data distribution. They are detected by partition and are applied mainly at the data type Numeric. We imputed by multiplying the respective instance by 10,000.
- **Suspect Sign Smell** (SSS)**.** This smell occurs when there is a value with the opposite sign of the majority of the data values. They are detected by partition and are applied at the data type Numeric. We did not imput, but it can be detected because the dummy value -1 that we imputed.

The data generated in this phase is referred to as *raw data* since it includes data collected at the source, with smells present but without any transformations applied. Later, we organize these values into a structured, tabular format, resulting on the *tabular data*. Each batch is processed separately to prevent schema overwriting.

In the final phase, the detection phase, we aimed to compare data smells present in both the *raw data* and *tabular data*. For the *tabular data*, we utilized the Rule-Based Data Smell Detection tool provided by Foidl et al. (2022). For the *raw data*, we tracked all introduced smells throughout the data generation process, providing a direct reference for comparison.

4 RESULTS

We generated two batches of size $n = 1,000$ for each probability distribution. Our main goal was to have numeric vectors that represent "realistic" data. Also, imputing data smells on data before tabulate let us compare the incidence of data smells on different cases. Each of the seven data smells was imputed with an incidence between 1% and 5%, and they were mapped so we can compare them in both *raw data* and *tabular data*. Table 1 ilustrates the setup for the data generated with all the smells.

After tabulating the data, we utilized the Rule-Based Data Smell Detection. In our tests, the only smell that the tool was able to accurately detect all instances was the Missing Value Smell. Figure 3 shows the smells detected on batch 1 of the vector generated by the Poisson distribution (remember that data generated from this distribution has non-negative integer values). As we can see in Figure 3, the only smells detected were MVS, EVS and IFS. However, the only instance detected as an EVS was a combination of the dummy value 999 multiplied by $10,000$. Also, the IFS was overly detected, showing that the integers were converted to floating-point numbers when they were processed by the tool. Next, we evaluated the results for batch 2 of the vector generated by the Poisson distribution (Figure 4). The smells detected were MVS, SSS, EVS and IFS. The dummy value -1 was detected as SSS instead of DumVS, and this is expected because they were the only negative values of the vector. Again, the IFS was overly detected, showing that the integers were converted to floating-point numbers when they were processed by the tool. However, the detection results for the EVS were better than for batch 1, accurately detecting 31/35 of the EVS imputed.

We repeated the detection process to all tabulated data generated, and the results are shown in Tables 2 and 3.

It is noteworthy that no instances of IFSS were detected, indicating that these smells were addressed during the data tabulation process and the schema's conversion of string values to float. Also, it wasn't detected any instance with SPS, indicating that the tool needs improvement to identify this smell.

With these results, we can answer our research questions:

- **RQ1.** It depends. Even when data smells are not explicitly detected, they may still be present. Some, such as IFSS, are corrected during the processing stages. Smells such as DumVS and Missing Value persist and are easily identifiable (though identifying the specific dummy value used for DumVS may require additional analysis). However, others, such as IFS, may even be inadvertently inserted into the vector.
- **RQ2.** Overall, no. As previously mentioned, cases such as DumVS and MVS are relatively easier to detect. However, EVS can blend with the data, rendering it "invisible" to detectors. Additionally, DupVS may be overly detected without necessarily representing a "real" data smell, as the original data might legitimately contain multiple instances of the same value. Finally, IFS was overly detected in our tests due to the conversion of integers to floats.

5 THREATS TO VALIDITY

The choice of instrumentation is a critical factor affecting the validity of the conclusions, particularly in detecting data smells. This study utilized the rule-based detection tool provided by Foidl et al. (2022) for tabular data due to its standardized approach, but the absence of comparable tools for non-tabular data represents a significant limitation.

Another threat arises from the simulation-based methodology, which may not fully capture the complexities and variability of real-world data pipelines, such as the development of Minimum Viable Products (MVPs) in software startups (Melegati et al., 2020; Chanin et al., 2018). While the controlled environment enabled precise analysis, it inherently lacks the unpredictability and diversity of operational data systems. Additionally, the study focused exclusively on numerical data and a limited set of data smells, which restricts the generalizability of the findings to other data types.

Finally, the reliance on specific probability distributions and parameter values in the data generation process may not encompass all possible scenarios encountered in practical applications. Future work should address these limitations by expanding the scope of data types, exploring detection tools for unstructured data, and validating findings against diverse, real-world datasets to ensure broader applicability and robustness of the conclusions.

Table 1: Data generated with $n = 1{,}000$ for each batch, with the respective parameter values of the probability distributions. The frequency of each smell imputed is the same for all the vectors.

prob_dist	batch	params	DumVS	DupVS	SPS	IFSS	IFS	MVS	EVS
exponential	1	$\lambda = 1$	27	33	39	24	-	48	35
	2	$\lambda = 10$	27	33	39	24	-	48	35
poisson	1	$\lambda = 1$	27	33	-	24	10	48	35
	2	$\lambda = 10$	27	33	-	24	10	48	35
uniform_int	1	a = - 1, b = 1	27	33	-	24	10	48	35
	2	a = -10, b = 10	27	33	-	24	10	48	35
uniform	1	a = - 1, b = 1	27	33	39	24	-	48	35
	2	a = -10, b = 10	27	33	39	24	-	48	35

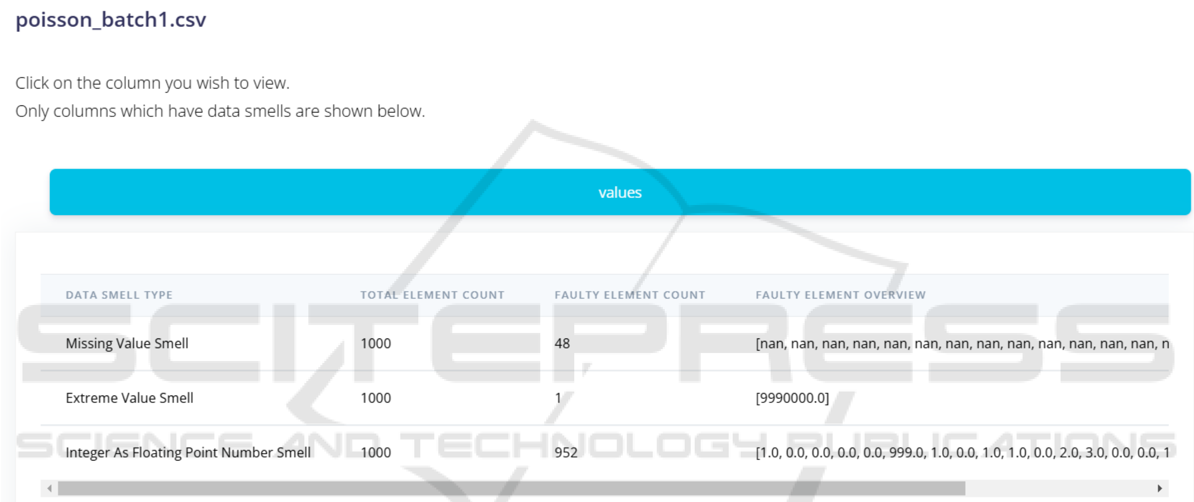
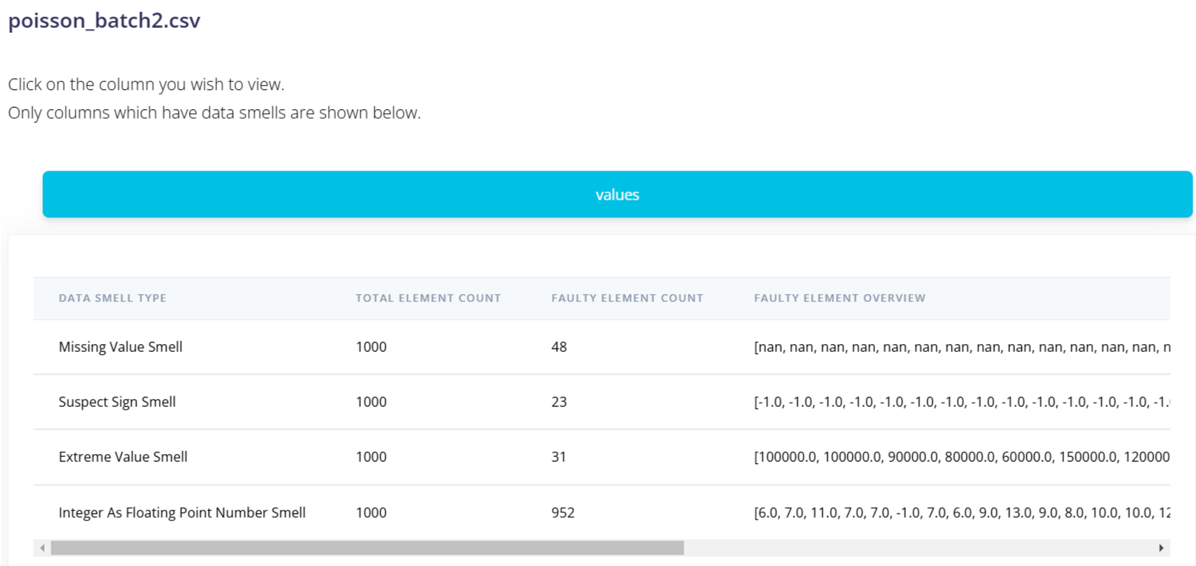


Figure 3: Data smells detected by the Rule-Based Data Smell tool on batch 1 of the vector generated by the Poisson distribution.

Table 2: Results of the detection process for *tabular data*. For each data smell, we have the incidence imputed (originated from *raw data* and detected).

prob_dist	batch	DumVS		DupVS		SPS		IFSS	
		imputed	detected	imputed	detected	imputed	detected	imputed	detected
exponential	1	27	0	33	0	39	0	24	0
	2	27	0	33	0	39	0	24	0
poisson	1	27	0	33	0	-	0	24	0
	2	27	0	33	0	-	0	24	0
uniform_int	1	27	0	33	0	-	0	24	0
	2	27	0	33	0	-	0	0	0
uniform	1	27	0	33	0	39	0	24	0
	2	27	0	33	0	39	0	24	0



poisson_batch2.csv

Click on the column you wish to view.
Only columns which have data smells are shown below.

values

DATA SMELL TYPE	TOTAL ELEMENT COUNT	FAULTY ELEMENT COUNT	FAULTY ELEMENT OVERVIEW
Missing Value Smell	1000	48	[nan, nan, nan, nan, nan, nan, nan, nan, nan, nan, nan, nan, nan, n
Suspect Sign Smell	1000	23	[-1.0, -1.0, -1.0, -1.0, -1.0, -1.0, -1.0, -1.0, -1.0, -1.0, -1.0, -1.0, -1.0, -1.
Extreme Value Smell	1000	31	[100000.0, 100000.0, 90000.0, 80000.0, 60000.0, 150000.0, 120000
Integer As Floating Point Number Smell	1000	952	[6.0, 7.0, 11.0, 7.0, 7.0, -1.0, 7.0, 6.0, 9.0, 13.0, 9.0, 8.0, 10.0, 10.0, 12

Figure 4: Data smells detected by the Rule-Based Data Smell tool on batch 2 of the vector generated by the Poisson distribution.

Table 3: Results of the detection process for *tabular data*. For each data smell, we have the incidence imputed (originated from *raw data* and detected).

prob_dist	batch	IFS		MVS		EVS		SSS	
		imputed	detected	imputed	detected	imputed	detected	imputed	detected
exponential	1	-	0	48	48	35	1	-	0
	2	-	0	48	48	35	16	-	23
poisson	1	10	952	48	48	35	1	-	0
	2	10	952	48	48	35	31	-	23
uniform_int	1	10	952	48	48	35	1	-	0
	2	10	952	48	48	35	26	-	0
uniform	1	-	0	48	48	35	1	-	0
	2	-	0	48	48	35	24	-	0

6 CONCLUSION

This study provided a comprehensive exploration of data smells in numerical data, leveraging a controlled simulation environment to examine their detectability across unstructured and structured formats. The findings reveal significant variability in detection outcomes, with some smells, such as *Missing Value Smell*, being accurately identified, while others, such as *Extreme Value Smell* and *Integer as Floating-point Number Smell*, differed markedly from the imputed incidence, with misclassifications or over-detections. These discrepancies points the challenges inherent in ensuring data quality within AI pipelines and highlight the need for more advanced detection mechanisms.

The study's focus was confined to numerical data and a few types of *data smells*, using rule-based detectors. Therefore, it was enough to ilustrate that these smells are present in our data in both unstructured and structured format, and, consequently, on different stages of a data pipeline. Integrating agile practices, such as Behavior-Driven Development (BDD), may facilitate improved collaboration and more effective identification of data quality issues (Nascimento et al., 2020).

Future research could expand the scope to include a broader array of *data smells*, explore and develop better detection methods, and investigate other data types, such as Text and Date/Time. By advancing these areas, we can better understand and mitigate the risks posed by *data smells*, ultimately enhancing the reliability and quality of data-driven systems. This research contributes to the understanding of *data smells* and their implications, creating opportunities for future innovations in data quality assurance.

DATA AVAILABILITY

The scripts used to analyze and generate data, charts, and tables discussed when addressing our research goals are publicly available at GitHub: https://github.com/nmhahn/sneaky_smells.

ACKNOWLEDGEMENTS

This paper was supported by the Ministry of Science, Technology, and Innovations, with resources from Law No. 8.248, dated October 23, 1991, within the scope of PPI-SOFTEX, coordinated by Softex, and published in the Residência em TIC 02 - Aditivo, Official Gazette 01245.012095/2020-56.

REFERENCES

Abedjan, Z., Chu, X., Deng, D., Fernandez, R. C., Ilyas, I. F., Ouzzani, M., Papotti, P., Stonebraker, M., and Tang, N. (2016). Detecting data errors: where are we and what needs to be done? *Proc. VLDB Endow.*, 9(12):993–1004.

Batini, C. and Scannapieco, M. (2016). *Data and Information Quality: Dimensions, Principles and Techniques*. Springer Publishing Company, Incorporated, 1st edition.

Bayram, F., Ahmed, B. S., Hallin, E., and Engman, A. (2023). Dqsops: Data quality scoring operations framework for data-driven applications. In *Proceedings of the 27th International Conference on Evaluation and Assessment in Software Engineering*, EASE '23, page 32–41, New York, NY, USA. Association for Computing Machinery.

Bogner, J., Verdecchia, R., and Gerostathopoulos, I. (2021). Characterizing technical debt and antipatterns in ai-based systems: A systematic mapping study. *2021 IEEE/ACM International Conference on Technical Debt (TechDebt)*, pages 64–73.

Bosu, M. F. and MacDonell, S. G. (2013). Data quality in empirical software engineering: a targeted review. In *Proceedings of the 17th International Conference on Evaluation and Assessment in Software Engineering*, pages 171–176.

Casella, G. and Berger, R. (2001). *Statistical Inference*. Duxbury Resource Center, Australia ; Pacific Grove, CA : Thomson Learning.

Chanin, R., Sales, A., Santos, A. R., Pompermaier, L. B., and Prikladnicki, R. (2018). A collaborative approach to teaching software startups: findings from a study using challenge based learning. In Sharp, H., de Souza, C. R. B., Graziotin, D., Levy, M., and Socha, D., editors, *Proceedings of the 11th International Workshop on Cooperative and Human Aspects of Software Engineering, ICSE 2018, Gothenburg, Sweden, May 27 - June 03, 2018*, pages 9–12. ACM.

Ehrlinger, L. and Wöß, W. (2022). A survey of data quality measurement and monitoring tools. *Frontiers in Big Data*, 5.

Elouataoui, W., El Alaoui, I., el Mendili, S., and Youssef, G. (2022). An advanced big data quality framework based on weighted metrics. *Big Data and Cognitive Computing*, 13.

Foidl, H. and Felderer, M. (2019). Risk-based data validation in machine learning-based software systems. In *Proceedings of the 3rd ACM SIGSOFT International Workshop on Machine earning Techniques for Software Quality Evaluation*, MaLTeSQuE 2019, page 13–18, New York, NY, USA. Association for Computing Machinery.

Foidl, H., Felderer, M., and Ramler, R. (2022). Data smells: categories, causes and consequences, and detection of suspicious data in ai-based systems. In *Proceedings of the 1st International Conference on AI Engineering: Software Engineering for AI*, CAIN '22, page 229–239, New York, NY, USA. Association for Computing Machinery.

Foorthuis, R. (2018). A typology of data anomalies. In *International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems*, pages 26–38. Springer.

Fowler, M. and Beck, K. (1999). *Refactoring: Improving the Design of Existing Code*. Addison-Wesley object technology series. Addison-Wesley.

Golendukhina, V., Foidl, H., Felderer, M., and Ramler, R. (2022). Preliminary findings on the occurrence and causes of data smells in a real-world business travel data processing pipeline. In *Proceedings of the 2nd International Workshop on Software Engineering and AI for Data Quality in Cyber-Physical Systems/Internet of Things*, SEA4DQ 2022, page 18–21, New York, NY, USA. Association for Computing Machinery.

Gong, L., Jiang, S., and Jiang, L. (2019). Tackling class imbalance problem in software defect prediction through cluster-based over-sampling with filtering. *IEEE Access*, 7:145725–145737.

Gray, D., Bowes, D., Davey, N., Sun, Y., and Christianson, B. (2011). The misuse of the nasa metrics data program data sets for automated software defect prediction. volume 2011.

Harris, J. (2014). Distrust your data. https://source.opennews.org/articles/distrust-your-data.

Heck, P. (2024). What about the data? a mapping study on data engineering for ai systems. In *Proceedings of the IEEE/ACM 3rd International Conference on AI Engineering - Software Engineering for AI*, CAIN '24, page 43–52, New York, NY, USA. Association for Computing Machinery.

Ilyas, I. F. and Chu, X. (2019). *Data Cleaning*. Association for Computing Machinery, New York, NY, USA.

Iubel, N. (2014). Ensuring accuracy in data journalism. https://github.com/nikeiubel/data-smells/wiki/Ensuring-Accuracy-in-Data-Journalism.

Josko, J. M. B., Ehrlinger, L., and Wöß, W. (2019). Towards a knowledge graph to describe and process data defects. *DBKDA 2019*, 65.

Kim, W., Choi, B.-J., Hong, E., Kim, S.-K., and Lee, D. (2003). A taxonomy of dirty data. *Data Min. Knowl. Discov.*, 7:81–99.

Le Quy, T., Roy, A., Iosifidis, V., Zhang, W., and Ntoutsi, E. (2022). A survey on datasets for fairness-aware machine learning. *WIREs Data Mining and Knowledge Discovery*, 12(3):e1452.

Li, L., Peng, T., and Kennedy, J. (2011). A rule based taxonomy of dirty data. *GSTF INTERNATIONAL JOURNAL ON COMPUTING*, 1.

Liebchen, G. and Shepperd, M. (2008). Data sets and data quality in software engineering. *Proceedings - International Conference on Software Engineering*.

Mansouri, T., Moghadam, M. R. S., Monshizadeh, F., and Zareravasan, A. (2021). Iot data quality issues and potential solutions: A literature review. *CoRR*, abs/2103.13303.

Melegati, J., Chanin, R., Sales, A., Prikladnicki, R., and Wang, X. (2020). MVP and experimentation in software startups: a qualitative survey. In *46th Euromicro Conference on Software Engineering and Advanced Applications, SEAA 2020, Portoroz, Slovenia, August 26-28, 2020*, pages 322–325. IEEE.

Melegati, J., Chanin, R., Wang, X., Sales, A., and Prikladnicki, R. (2019). Enablers and inhibitors of experimentation in early-stage software startups. In Franch, X., Männistö, T., and Martínez-Fernández, S., editors, *Product-Focused Software Process Improvement - 20th International Conference, PROFES 2019, Barcelona, Spain, November 27-29, 2019, Proceedings*, volume 11915 of Lecture Notes in Computer Science, pages 554–569. Springer.

Munappy, A., Bosch, J., Olsson, H. H., Arpteg, A., and Brinne, B. (2019). Data management challenges for deep learning. In *2019 45th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)*, pages 140–147.

Munappy, A. R., Bosch, J., and Olsson, H. H. (2020). Data pipeline management in practice: Challenges and opportunities. In *Product-Focused Software Process Improvement: 21st International Conference, PROFES 2020, Turin, Italy, November 25–27, 2020, Proceedings*, page 168–184, Berlin, Heidelberg. Springer-Verlag.

Nascimento, N., Santos, A. R., Sales, A., and Chanin, R. (2020). Behavior-driven development: A case study on its impacts on agile development teams. In *ICSE '20: 42nd International Conference on Software Engineering, Workshops, Seoul, Republic of Korea, 27 June - 19 July, 2020*, pages 109–116. ACM.

Oliveira, P., Rodrigues, F., Rangel Henriques, P., and Galhardas, H. (2005). A taxonomy of data quality problems. *Journal of Data and Information Quality - JDIQ*.

Recupito, G., Pecorelli, F., Catolino, G., Moreschini, S., Nucci, D. D., Palomba, F., and Tamburri, D. A. (2022). A multivocal literature review of mlops tools and features. In *2022 48th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)*, pages 84–91.

Recupito, G., Rapacciuolo, R., Di Nucci, D., and Palomba, F. (2024). Unmasking data secrets: An empirical investigation into data smells and their impact on data quality. In *Proceedings of the IEEE/ACM 3rd International Conference on AI Engineering - Software Engineering for AI*, CAIN '24, page 53–63, New York, NY, USA. Association for Computing Machinery.

Roman, D., Pultier, A., Ma, X., Soylu, A., and Ulyashin, A. G. (2022). Data quality issues in solar panels installations: a case study. In *Proceedings of the 2nd International Workshop on Software Engineering and AI for Data Quality in Cyber-Physical Systems/Internet of Things*, SEA4DQ 2022, page 24–25, New York, NY, USA. Association for Computing Machinery.

Santos, J. A. M., Rocha-Junior, J. B., Prates, L. C. L., Do Nascimento, R. S., Freitas, M. F., and De Mendonça, M. G. (2018). A systematic review on the code smell effect. *Journal of Systems and Software*, 144:450–477.

Sato, D., Wider, A., and Windheuser, C. (2019). Continuous delivery for machine learning. https://martinfowler.com/articles/cd4ml.html.

Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., Chaudhary, V., Young, M., Crespo, J.-F., and Dennison, D. (2015). Hidden technical debt in machine learning systems. In Cortes, C., Lawrence, N., Lee, D., Sugiyama, M., and Garnett, R., editors, *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc.

Shome, A., Cruz, L., and van Deursen, A. (2022). Data smells in public datasets. In *Proceedings of the 1st International Conference on AI Engineering: Software Engineering for AI*, CAIN '22, page 205–216, New York, NY, USA. Association for Computing Machinery.

Sukhobok, D., Nikolov, N., and Roman, D. (2017). Tabular data anomaly patterns. In *2017 International Conference on Big Data Innovations and Applications (Innovate-Data)*, pages 25–34.

Ter Hofstede, A. H. M., Koschmider, A., Marrella, A., Andrews, R., Fischer, D. A., Sadeghianasl, S., Wynn, M. T., Comuzzi, M., De Weerdt, J., Goel, K., Martin, N., and Soffer, P. (2023). Process-data quality: The true frontier of process mining. *J. Data and Information Quality*, 15(3).

Van Emden, E. and Moonen, L. (2012). Assuring software quality by code smell detection. In *2012 19th Working Conference on Reverse Engineering*, pages xix–xix. Citeseer.

Wang, H. and Abraham, Z. (2015). Concept drift detection for streaming data. In *2015 international joint conference on neural networks (IJCNN)*, pages 1–9. IEEE.

Yoon, K.-A. and Bae, D.-H. (2010). A pattern-based outlier detection method identifying abnormal attributes in software project data. *Information and Software Technology*, 52(2):137–151.

Zhang, H., Cruz, L., and Van Deursen, A. (2022). Code smells for machine learning applications. In *Proceedings of the 1st international conference on AI engineering: software engineering for AI*, pages 217–228.