The Effects of Data Quality on ML-Model Performance

Experiment, Analysis, & Benchmark

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ABSTRACT

Modern artificial intelligence (AI) applications require large quantities of training and test data. This need creates critical challenges not only concerning the availability of such data, but also regarding its quality. For example, incomplete, erroneous or inappropriate training data can lead to unreliable models that produce ultimately poor decisions. Trustworthy AI applications require high-quality training and test data along many dimensions, such as accuracy, completeness, consistency, and uniformity.

We explore empirically the correlation between six of the traditional data quality dimensions and the performance of fifteen widely used ML algorithms covering the tasks of classification, regression, and clustering, with the goal of explaining ML results in terms of data quality. Our experiments distinguish three scenarios based on the AI pipeline steps that were fed with polluted data: polluted training data, test data, or both. We conclude the paper with an extensive discussion of our observations and recommendations, alongside open questions and future directions to be explored.

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1 DATA QUALITY AND AI

The rapid advances in the field of AI represent a great opportunity for further enhancement for many industries and sectors, some of which are critical in nature, such as autonomous driving and medical diagnosis. The potential for AI has been enhanced by the recent and future enormous growth of data. However, this precious data raises tedious challenges, such as data quality assessment, and, according to [18] data management, data democratization and data provenance. Until recently, both academia and industry were mainly engaged in improving or introducing new and improving existing ML-models, rather than finding remedies for any data challenges that fall beyond trivial cleaning or preparation steps.

Nevertheless, the performance of AI-enhanced systems in practice is proven to be bounded by the quality of the underlying training data [8]. Moreover, data have a long lifetime and their use is usually not limited to a specific task, but can continuously be fed into the development of new models to solve new tasks. These observations led to a shift in research focus from a model-centric to a data-centric approach for building AI systems1. In the last year alone, two workshops were held to discuss the potential of data-centric AI and to initiate an interdisciplinary field that needs expertise from both data management and ML communities2.

In the field of data management, data quality is a well-studied topic that has been a major concern of organizations for decades, leading to the introduction of standards and quality frameworks Battini and Scannapieco [4], Wang and Strong [53]. The recent advances in AI have brought data quality back into the spotlight in the context of building "data ecosystems" that cope with emerging data challenges posed by AI-based systems in enterprises [18]. Researchers pointed out such challenges, including data quality issues [20], data life cycle concerns [37], the connection to ML-OPs [39], and model management [43]. Furthermore, some studies presented a vision of data quality assessment tools [21], an automation of data quality verification [44] or a methodology to summarize the quality of a dataset as datasheets [16], nutritional labels [51] and data cards [52].

In this work, under the umbrella of data-centric AI, we revisit six selected data quality dimensions, namely consistent representation, completeness, feature accuracy, target accuracy, uniqueness, and target class balance. Our ultimate aim is to observe and understand the ML-models’ behavior in terms of data quality. We test a variety of commonly used ML-algorithms for solving classification, clustering, or regression tasks. We analyze the performance of five algorithms per task (15 algorithms in total) covering the spectrum from simple models to complex deep learning models (see Section 4).

Regarding data quality, we account for two aspects. First, data plays a different role at different stages of the AI pipeline: Some systems use pre-trained models and thus the only available data is the "serving" or "testing" data; in many other cases, data scientists also need "training" data to build the models from scratch. Second, training and testing data can be generated or collected by the same process from the same data source, which means that they have similar quality. In a more realistic case, training and testing data have a different quality, especially when using pre-trained models and different sources or collection processes. To that end, we consider in this study three scenarios: Training and testing data

1https://github.com/HazyResearch/data-centric-ai
2https://datacentricai.org/neurips21/ and https://hui.stanford.edu/events/data-centric-ai-virtual-workshop
have the same quality (Scenario 1); the training data have high quality (in terms of the studied quality dimensions) and lower quality testing data (Scenario 2); and finally, the testing data have a high quality and the data used to build the models are of a lower quality (Scenario 3). To vary data quality in each of these scenarios, we apply the notion of data pollution or corruption to create degraded quality versions from the dataset at hand. For each of the six data quality dimensions, we designed a parameterized data polluter to introduce respective data errors. While we used real-world data, for several of the datasets we had to manually create a clean version as a baseline to initiate the pollution process. In these cases, we report the performance of ML-models for both the “original” and the “baseline” datasets.

Research in the machine learning community has studied the effects of label noise and missing values, and the data management community has studied the effects of data cleaning on classification, as we discuss in Section 2. Nevertheless, this paper is the first systematic study of the effects of data quality dimensions not only for classification, but also for clustering and regression tasks. We studied the change of this effect also for low quality training data and not only for test data. Our work on real-world datasets with numerous experiments is a first step not only towards linking the ML-models performance to the underlying data quality, but also to understand and explain their connection.

Contributions. We present in this work a comprehensive experimental study that investigates the correlation between six data quality dimensions and the performance of fifteen ML algorithms, making the following contributions:

- Systematic empirical benchmarking to understand the correlation between data quality and ML-models performance under the umbrella of data-centric AI.
- Simulation of real life scenarios concerning data in ML-pipelines. We perform a targeted analysis for cases where serving data, training data, or both are of low quality.
- We provide practical insights and learned lessons for data scientists. In addition, we raise several questions and point out possible directions for further research.
- All polluters, ML-pipelines and all datasets are available online and can be easily extended with further quality dimensions, ML-models, or datasets.

Outline. First, we discuss related work in Section 2. Then, we formally define the six data quality dimensions together with a systematic pollution method for each in Section 3. In Section 4, we briefly introduce the fifteen algorithms for the three AI tasks of classification, regression, and clustering. We describe our experimental setup in Section 5. The results of the empirical evaluation, the core contribution of this paper, are discussed afterwards in Section 6. We conclude and suggest future work directions in Section 7.

2 RELATED WORK

First, we report briefly on the state of the art on data validation for ML. Then, we discuss related work that studies the influence of data quality on ML-models, namely by cleaning the data or by focusing on a specific error type like label noise.

Data validation. Several approaches have emerged to validate ML pipelines as well as the data fed to it, which includes training and serving data, i.e., the data used in production. These approaches use the concept of unit tests to help engineers diagnose model-quality issues originating from data errors. For instance, the validation systems implemented by [8] and the similar system by Schelter et al. [45] focus on validating serving data given a classification pipeline as a black box. Generally, validation systems check, on the one hand, for classical data quality dimensions, such as consistency and completeness, and on the other hand for ML-dependent dimensions, such as model robustness and privacy [5]. To help data scientists with the validation task, Schelter et al. [46] introduced the experimental library JENGA. It enables testing ML-model’s robustness under data errors in serving data, which is represented as the polluted test data in Scenario 2 in our experiments (Section 5.1). The authors use the concept of polluters or data corruptions as in our work. However, we were far ahead in our experiments when JENGA was published, but theoretically, we could have developed our experiments using JENGA.

Data cleaning. Li et al. [29] investigated the impact of cleaning training data, i.e., improving its quality, on the performance of classification algorithms. They obtained a clean version of the training data instead of systematically polluting it, as we did in this work. Furthermore, in their work, the robustness of the data cleaning method had an additional influence on how the classification performance changed with a training data of a higher quality. They focused on five error types: missing values, outliers, duplicates, in-consistencies, and mislabels. These error types correspond to DQ dimensions in our study (Section 3).

Label noise. The problem of label noise or mislabeling is one of the vital concerns of the ML-community that attracted an immense interest. This problem is in essence a data quality problem. Frénay and Verleysen [15] surveyed the literature related to classification using training data that suffers from label noise, which is equivalent to the target accuracy DQ dimension in our work. They distinguish several sources of noise, discuss the potential ramifications, and categorize the methods to address the problem into the classes label noise-robust, label noise cleansing, and label noise-tolerant. They conclude that label noise has diverse ramifications, including degrading in classification accuracy, high complexity learning models, and difficulty in specifying relevant features. Northcutt et al. [36] shifted the focus to label noise in test data and its effect on ML-benchmark results and thus on model selection. They estimated an average of 3.3% label noise in their test datasets and found that benchmark results are sensitive even to a small increase in the percentage of mislabeled data points, i.e., a smaller capacity models could have been sufficient if the test data was correctly labeled, but the label noise led to favoring a more complex model.

In summary, we present the first systematic study on how exactly both training and testing (serving) data quality affects not only classification but all the three ML tasks.
3 DATA QUALITY DIMENSIONS AND DATA POLLUTION

We present the definition of the six selected data quality dimensions, along with our methods to systematically pollute a dataset along those dimensions. In this work, we use the terms column and row to refer to the ML terms feature and sample, respectively. During the pollution, we assume that columns’ data types and the placeholders which represent missing values in each column are given.

3.1 Consistent Representation

A dataset is consistent in its representation if no column has two or more unique values that are semantically equivalent. I.e., each real-world entity or concept is referred to by only one representation. For example, in a column “city”, New York shall not be also represented as NYC or NY.

**Definition 1.** The degree of inconsistency of a column \( c \), denoted as \( \text{InCons}(c) \), is the ratio of the minimum number of replacement operations required to transform it into a consistent state and the number of rows in the dataset.

This definition applies only to categorical columns, i.e., strings or integers that encode categorical values, whereas numerical columns and dates are considered to be consistent and theirs \( \text{InCons}(c) = 0 \).

**Definition 2.** We define the degree of consistency of a dataset \( d \) with \( f \) columns as follows.

\[
\text{Consistency}(d) = 1 - \frac{1}{f} \sum_{i=1}^{f} \ln(\text{InCons}(c_i))
\]

**Pollution.** We have two inputs: First, the percentage of rows to be polluted \( \lambda_c \), defined by a value between 0 and 1, and second, for each unique value \( v \) of a pollutable column, the number of representations \( k_v \) for that value (including \( v \) itself). For each categorical column, we choose randomly the rows to be polluted. Then, we generate \( k_v - 1 \) new representations for each unique value \( v \) of its values. The new representations of a string value are produced as new non-existing values by appending a trailing ascending number to the end of the value, whereas for integers, new integers are added after the maximum existing one. These row’s entries at this column are replaced by a randomly picked fresh representation of the original value.

3.2 Completeness

The problem of missing values exists in many real-world datasets. Some of these values are actually missing, e.g., missing readings due to a failure in a sensor while others are represented by a placeholder, such as "unknown" or "NaN".

**Definition 3.** The completeness of a column \( c \) is the ratio of the number of non-missing values and \( n \), the total number of rows in this dataset. The completeness of a dataset \( d \) is defined as follows.

\[
\text{Completeness}(d) = 1 - \frac{1}{f} \sum_{i=1}^{f} \frac{\text{missing}(c_i)}{n}
\]

For ML, rows with a missing value for the target feature are usually removed from the dataset, as they cannot be used for training. Thus, we exclude the target feature while computing completeness.

**Pollution.** We inject missing values "completely at random" [31] according to a specified pollution percentage \( \lambda_c \) for each column. If there are already missing values in the column, we account for those values and inject only the remaining number of missing values necessary to reach \( \lambda_c \). A column-specific placeholder is used to represent all missing values injected into this column. The placeholder value does not carry information except that the value is missing. A typical placeholder is Not A Number (NaN). Many implementations of ML algorithms cannot handle NaN values. For this reason, we choose a representation as placeholders that can be used in computations, but lie outside the usual domain of a column and are still distinguishable from the actual non-missing values of the feature. For example, -1 for "age" column, or the string "empty" for "genre" categorical column in a movie table. We manually selected the used placeholders, as this task requires some domain knowledge to determine suitable values.

3.3 Feature Accuracy

ML-models learn correlations in datasets; thus it is desirable to have no errors in their values. However, real-world data may contain erroneous values from various sources, e.g., erroneous user input.

**Definition 4.** The feature (column) accuracy measures the deviation of its values from their respective ground truth values. For a categorical feature \( c \), we define the feature accuracy as follows.

\[
cFAcc(c) = 1 - \frac{\text{mismatches}(c)}{n}
\]

where \( \text{mismatches}(c) \) denotes the number of values in column \( c \) that are different from the ground truth and \( n \) is the number of rows in the dataset. For numerical ones, we define feature accuracy as follows.

\[
nFAcc(c) = 1 - \frac{\text{avg}_{\text{dist}}(c)}{\text{mean}_{\text{gt}}(c)}
\]

where \( \text{avg}_{\text{dist}}(c) \) is the average of the absolute distances between the ground truth and values in \( c \) and \( \text{mean}_{\text{gt}}(c) \) is the mean of the ground truth values of \( c \).

The feature accuracy of an entire dataset consists of two metrics: The average feature accuracy of all categorical features and the average feature accuracy of all numerical features.

**Pollution.** The pollution is executed differently depending on the feature type. For categorical features, the level of pollution \( \lambda_{fa} \) for a specific feature \( c \) determines the percentage of rows to be polluted. The randomly selected rows are polluted by exchanging the current category with a random, but different category from feature \( c \)’s domain. For numeric features, we add normally distributed noise to all rows of the feature \( c \): \( \text{noise}(c) = X \cdot \text{mean}_{\text{gt}}(c) \) where \( X \) is random samples drawn from the normal Gaussian distribution \( N(\mu, \sigma^2) \) with \( \mu = 0 \) and \( \sigma^2 = \lambda_{fa} \). The level of pollution \( \lambda_{fa} \) determines the standard deviation of the normal distribution and thus denotes how wide it is spread.

3.4 Target Accuracy

For each row in a dataset, the target feature contains either a class/label in classification tasks or a numeric value in regression tasks. There might be some incorrect labels due to human or machine error, e.g., an angry dog labeled as a "wolf". The definition of
the target accuracy of a dataset is equivalent to the definition of the feature accuracy of its target feature (see previous section). Nevertheless, the target feature is the most important feature because of its influence on prediction performance. Thus, it is beneficial to study its accuracy separately.

Pollution. Naturally, we used the same pollution method as for feature accuracy, based on the target type.

3.5 Uniqueness

Redundant data does not provide additional information to the ML-model for the training process. Thus, de-duplication is a common step in ML pipelines to avoid overfitting. Exact duplicates are easy to detect. Yet, this step still expensive, especially for large datasets.

**Definition 5.** The uniqueness of a dataset \(d\) is the fraction of unique rows within the dataset. We normalize the value as follows.

\[
\text{Uniqueness}(d) = \frac{\text{unique\_rows}(d) - 1}{n - 1}
\]

Pollution. To pollute a dataset along the uniqueness dimension, we first remove all existing exact duplicates. Then, we add exact duplicates of randomly selected rows to the dataset. The number of the added duplicates is determined by the duplication factor \(\rho\): For each class \(cl\) with \(n_{cl}\) rows, we add \(\text{dup}_{cl} = (\rho - 1) \cdot n_{cl}\) duplicates to avoid changing the class balance (next section). Thus, the size of the polluted dataset is \(n \cdot \rho\) and its uniqueness is \(1/\rho\). For each randomly selected row from a class \(cl\), we add \(x\) duplicates of this row and then continue sampling and adding duplicates to reach \(\text{dup}_{cl}\). We draw \(x\) from a pre-defined distribution: We try uniform, normal, and Zipf distributions, in addition to adding a single duplicate of each selected row.

3.6 Target Class Balance

Many ML approaches assume a relatively equal number of rows per target class, i.e., a balanced dataset, to achieve satisfactory performance. For example, the k-Means algorithm suffers from the “uniform effect”, i.e., it recognizes clusters of approximately uniform sizes even if it is not the case in the input data [27].

**Definition 6.** Given a dataset \(d\) with \(m\) target classes \(cl_1, ..., cl_m\) of \(n_{cl_1}, ..., n_{cl_m}\) rows per class, respectively, and \(\forall i, j : 1 \leq i < j \leq m \implies n_{cl_i} \leq n_{cl_j}\), the target class imbalance is defined as the sum of the pairwise differences between the number of rows per class:

\[
\text{ImBalance}(d) = \frac{1}{2} \sum_{i,j \in \{1, ..., m\}} |n_{cl_i} - n_{cl_j}|
\]

As the worst imbalance case, we assume a maximal imbalanced dataset \(w\) that has \([m/2]\) classes with \(n_{c_{\text{max}}}\) rows and the remaining classes have 0 rows, where \(n_{c_{\text{max}}}\) is the maximum number of rows that a class can have. The target class imbalance of such a dataset is \(e = \lfloor m/2 \rfloor \cdot \lfloor m/2 \rfloor \cdot n_{c_{\text{max}}}\).

**Definition 7.** The target class balance of a dataset \(d\) is the deviation from its imbalance score, normalized by the imbalance score of the worst case.

\[
\text{Balance}(d) = 1 - \frac{\text{ImBalance}(d)}{e}
\]

Pollution. We have two inputs for pollution: The degree of imbalance \(\lambda_{cb}\) and the number of rows in the polluted version \(\tilde{n}\). We can choose \(\tilde{n}\) arbitrarily as a multiplication of \(m\) or calculate it from the data as the number of rows from the original dataset, needed to produce the maximum pollution level. We use \(\lambda_{cb}\), which determines the severity of the class imbalance, to calculate the number of rows per class in the polluted version. The degree of imbalance \(\lambda_{cb}\) for any polluted dataset version satisfies:

\[
\lambda_{cb} = \frac{\text{ImBalance}(d)}{\tilde{n}}.
\]

To pollute, we order the target classes based on their sizes descending and for the classes with the same size, we use the class ID in ascending order. Using the defined order, we create a class imbalance with an equal difference \(\Delta\) for each consequent pair of classes. The used rows of each class are randomly selected, i.e., in the polluted dataset, the following holds: \(\forall 1 < j \leq m : (\tilde{n}_{c_{j-1}} \leq \tilde{n}_{c_j}) \wedge (\tilde{n}_{c_j} - \tilde{n}_{c_{j-1}}) = \Delta\). To create a class imbalance, we calculate the class size of a balanced dataset \(\tilde{n}/m\) with \(\tilde{n}\) rows and \(m\) classes. Then, we iteratively add/remove rows from the classes based on their order: We remove rows from all classes that are at indices \([m/2]-1\) and below, and add rows to all classes at indices above that, unless \(m\) is odd, then the size of the class at index \([m/2]\) stays constant.

4 MACHINE LEARNING TASKS

In this section, we introduce the 15 algorithms that we employed for the three tasks of classification, regression and clustering.

**Classification.** We picked a variety of classification algorithms that fall into different categories. We included two linear classification models: Logistic regression (LogR) [32] and support vector machine (SVM) [12]; a tree-based model: Decision tree (DT) [10]; a k-nearest neighbors (KNN) classifier [2]; and finally a neural network-based multi-layer perceptron (MLP) [50].

**Regression.** We use two linear-regression-based algorithms: linear regression (LR) [33] and ridge regression (RR) [22]; two tree-based algorithms: decision tree regression (DT) [10] and random forest regression (RF) [9]; and finally a deep-learning based algorithm: simple multi-layer perceptron (MLP) [50].

**Clustering.** We decided to use one algorithm from each of the five most commonly used categories of clustering algorithms [41]: The Gaussian Mixture Clustering algorithm [40] from the distribution-based family, the k-Means [47] and the k-Proto-types [24] algorithms from the centroid-based family, the Agglomerative Clustering algorithm [13] from the hierarchical family, the Ordering Points to Identify Cluster Structure (OPTICS) algorithm [3] from the density-based family and a Deep Autoencoder neural network from deep learning-based family [49].

5 EXPERIMENTAL SETUP

This chapter gives an overview of our implementation and introduces our datasets together with the parameterization and performance measures of the analyzed ML-models.

5.1 Implementation

The implementation of the polluters and ML pipelines are written in Python using scikit-learn and PyTorch.
We then pollute the training and test sets separately. We varied the k-Prototypes, Gaussian Mixture and Agglomerative algorithms. The target feature distribution in our regression datasets is mostly skewed.

For LR and RF, we set max_features = 1000 and optimized using the Adam optimizer [26] with a learning rate of 0.003 and mean squared error loss. The dataset is split into 80% train and 20% test data and loaded in batches of 128 shuffled samples. For all models that need a random seed, we used 42 as a seed.

### 5.3 Datasets

In our experiments, we use the nine datasets, shown in Table 1. We chose them from a variety of domains, sample sizes and characteristics. Our choice was also influenced by the ML-task that the dataset is used for.

#### Table 1: Overview of the used datasets after pre-processing.

| Name       | # Sample | # Feature | # Categorical | # Numerical | # Class |
|------------|----------|-----------|---------------|-------------|---------|
| Credit     | 1,000    | 20        | 13            | 7           | 2       |
| Contraceptive | 1,473    | 9         | 7             | 2           | 3       |
| Telco-Churn | 7,032    | 19        | 16            | 3           | 2       |
| Houses     | 1,460    | 79        | 46            | 33          | -       |
| IMDB       | 5,993    | 12        | 8             | 4           | -       |
| Cars       | 15,157   | 8         | 3             | 5           | -       |
| Bank       | 7,500    | 3         | 2             | 1           | 6       |
| Covertype  | 7,504    | 54        | 44            | 10          | 7       |
| Letter     | 7,514    | 16        | 0             | 16          | 26      |

**Classification.** IBM’s Telco Customer Churn dataset represents customers from a fictional telecommunications company. The target variable Churn describes whether the customer cancelled their contract within the last month. The German Credit dataset contains credits between the years 1973 and 1975 from a southern German bank. The target variable tells whether a customer complied with the conditions of the contract or not. The Contraceptive Method Choice dataset was part of the 1987 National Indonesia Contraceptive Prevalence Survey, asking non-pregnant married women about their contraceptive methods. The classification task is to determine the contraceptive method choice.

**Regression.** The Houses dataset contains features of houses in the city to determine their sales price. We use the dataset in the form it was presented in a Kaggle challenge. The IMDB dataset contains features and ratings for films and series that were retrieved from the IMDB website. The Cars dataset collects listings for used cars of different manufacturers. The sales price is the feature that shall be predicted. The data is stored in files grouped by manufacturer. We use only the data of VW.

**Clustering.** The Letter dataset contains statistical measures of character images. The Bank dataset contains different characteristics of a person and has a binary target stating whether a term deposit is subscribed. We use a subset of this dataset, taking the education level as the target and keeping only three features related to it to have more than two clusters. We removed all classes with less than 2,000 samples to avoid significant data loss when applying the target class balance polluter. The Covertype dataset consists of descriptive information about forested areas. All datasets used for the evaluation of clustering approaches were sampled as the last step of their preprocessing to reduce their size. We slightly varied the number of samples selected per dataset to be a multiple of the dataset’s class count larger than 7,500.
5.4 Models Performance

Classification. Accuracy is the most common performance metric in classification tasks, but it can be misleading in imbalanced datasets. Therefore, we use F1-score as it better accounts for class imbalance, which does exist in the used datasets. Usually, the F1-score is measured for a single target class, but as we do not make assumptions about the importance of the target class, we report the average of the F1-scores over all target classes.

Regression. Mean Squared Error is the commonly used metric to evaluate regression algorithms. However, it is highly dependent on the data domain, e.g., it is expected to be much larger for house prices than for movie ratings. As this makes comparisons of algorithm performance across datasets difficult, we use the Coefficient of Determination $R^2$, which measures the fraction of variance in the data that is explained by the regression model [28].

Clustering. The Mutual Information (MI) score describes how much information is shared between two clusters. This metric only recognizes if the same samples are grouped with the same other samples regardless of the actual target labels. We use an adapted version of MI called the Adjusted Mutual Information (AMI) [35].

6 RESULTS

Here, we discuss our observations grouped by ML-tasks and data quality dimensions. For all plots, the $x$-axis indicates the decreasing (training, testing, or both) data quality and the $y$-axis indicates the increasing ML-model performance metric. The quality of the baseline dataset (DQ=1) is indicated by a dotted vertical line. For most polluters, the original dataset and the baseline dataset are identical. Otherwise, the quality of the original dataset is indicated by a dashed horizontal line. For feature accuracy, we plotted the average of the two metrics described in Section 3.3. Finally, due to the definition of consistent representation, the data quality could increase again (instead of decreasing) with a higher pollution level. Thus, we add the degrees of pollution in the plots for such cases. Due to limited space, we include the plots only for one dataset per task. The full set of results can be found in our technical report.

6.1 Classification

For the three scenarios described in Section 5.1, we discuss here the effect of degrading the six data quality dimensions of three datasets, namely: Credit, Contraceptive and Telco-Churn on the performance of five classification algorithms, namely: LogR, SVM, DT, KNN and MLP. We include two baselines trained and tested on clean data, namely: a majority class and a class ratio classifiers.

Consistent Representation. Introducing new representations of the categorical values of the training dataset has a very limited impact on the performance of the studied classification algorithms on all datasets, as we see in Figure 1a for the Telco dataset. For Scenario 2, we observe a slight and slow decrease in the performance of all algorithms with the decrease in the test data consistency.

Comparing Figures 1b and 1c, we can see a better performance if both training and testing datasets are suffering from the same inconsistent representations. Considering inconsistent representations with only two representations per original value, we note less resilience by some of the algorithm’s and a clear decrease in their performance after polluting 50% of the values in Scenarios 1 and 2.

Completeness. Our intuition was that compromising the completeness of the training data in Scenario 1 leads to classifiers which are more and more biased towards the imputed placeholder values due to their sheer number. However, the results show a surprisingly limited decline in $F_1$, suggesting that the models are affected but not biased. The only exception is the SVM model on Telco dataset that drops drastically in performance once we pollute more than half the dataset, as we see in Figure 1d. In contrast, in Scenario 2 (Figure 1e), the degradation in prediction performance is faster and ends below the performance of the majority class baseline. Comparing the results on Scenario 3 to the other scenarios, we noticed that it seems the risk of classify incomplete serving data is less if the training has already been carried out on incomplete data.

Feature Accuracy. Training the classifiers on noisy data in Scenario 1 has a non-negligible impact on their performance that varies by the dataset. For the contraceptive dataset, the algorithms show a certain robustness until the quality reaches a threshold of 0.8, where the performance degrades more steeply and eventually falls below baseline performance between a quality of 0.4 and 0.2. A similar robustness can be noticed for the credit dataset except for the MLP which performs much worse (>10% drop in $F_1$-score) after introducing only a small amount of noise to the features.

Figure 1g shows a very interesting pattern: The linear models (SVM and LogR) seem very robust to degrading feature accuracy up to a certain point, where they suddenly lose performance rapidly until they meet with the majority class baseline. For Scenario 2 (Figure 1b), we can see that the performance linearly decreases with reduced feature quality of the serving data, while staying above baseline performance most of the time. There are no significant differences in the relative behavior of the algorithms, as their performance declines with roughly the same slope. Reducing the quality of the serving data to 0.5 causes a drop of about 10 percent in $F_1$-score for the linear models. For Scenario 3 (Figure 1i), we observe a similar behavior like in Scenario 1, but the linear models’ performance appears to improve once we pollute the training and serving data.

Target Accuracy. The target accuracy data quality dimension is especially relevant in the classification task, as it simulates labeling errors/noise in the data. For Scenario 1, there is almost a linear decline in performance for the contraceptive and credit dataset in response to decreasing the training dataset target accuracy. The Telco dataset (Figure 1j) shows a different behavior for the linear models, which steeply decline in performance around a target accuracy=0.5, while the other models follow a more linear pattern.

For all the datasets and all algorithms, we found that once the target accuracy of the training data is equal or worse than 1 divided by the number of classes, then the prediction performance is below the one from the class ratio baseline classifier. In addition, we note that up to 20 percent of training labels could be flipped without a performance’ losses of no more than 10 percent in $F_1$-score for most of the algorithms. The performance of the MLP and SVM also showed a very high variance across the five different seeds, which indicates that they are the most sensitive to incorrectly labeled
Figure 1: F-1 of the classification algorithms for Telco-Churn dataset.
samples. For Scenario 3 (Figure 1l), we observed a similar behavior of the algorithms like in Scenario 1, with one major difference: After polluting 1 divided by the number of classes of the rows both in the training and testing data the $F_1$ score starts to increase at different slopes for all algorithms regardless of the dataset. The results of Scenario 2 (Figure 1k) can be interpreted as the margin by which the performance is underestimated w.r.t. to the actual performance in clean data. This also follows a linear trend and is consistent across all datasets, with only slight differences in the slopes of the linear trend. Twenty percent more incorrectly labeled samples in the test set leads to an underestimation of up to about 10%, which shows that labeling the test set carefully is crucial.

**Uniqueness.** For all datasets, uniqueness does not have much of an impact on the performance of all classifiers in all scenarios. This can be seen in Figures 1m, 1n, and 1o. The largest drop in $F_1$ is observed for DT and MLP on the credit dataset. This drastic drop in performance is attributed to the size of the credit dataset, only 1000 records, where generalization is already difficult enough and introducing duplicates gives too much weight to single instances. On one hand, it is interesting that MLP performance already drops with 5% pollution in Scenarios 1 and 3 on the credit dataset. This suggests that de-duplication is an important pre-processing step before training an MLP on a small dataset. On the other hand, the results on the other datasets with linear models suggest that exact duplicates in both training and testing data do not significantly decrease the classification performance.

**Target Class Balance.** In Scenarios 1 and 3, once the imbalance affects more than half the rows for the binary classification datasets, all algorithms’ performance slowly drops towards the performance of the majority class baseline because they are trained on only a handful of samples from the minority class and therefore have no chance to actually learning the patterns of this class. Figures 1p and 1r shows the described behavior on the Telco-Churn dataset. All the algorithms behave similarly until this point, with only a few exceptions (mainly SVM and MLP). This suggests that the training data does not have to reflect the actual real-world-class balance, as long as it is equally or more balanced. For Scenario 2 (Figure 1q) we observe that the models are very robust against the distribution shift which moves towards a balance in class frequency and sometimes even increase their performance.

### 6.2 Regression

For the three scenarios described in Section 5.1, we discuss here the effect of degrading the six data quality dimensions of three datasets, namely: Houses, IMDB and Cars on the performance of five regression algorithms, namely: LR, RR, DT, RF and MLP. As LR and RR only differ by the regularization employed in RR, their performance lines in the result plots often overlap.

**Consistent Representation.** An increase of the representations of values in categorical columns leads to a decrease in $R^2$ of all algorithms. The severity of this decrease depends on the scenario. In Scenario 2 (Figure 2b), the performance decrease is the largest, especially for RR. In the two other scenarios, LR performance is dropping drastically, even for small percentage of pollution. Adding inconsistent representations during training but not during testing, i.e., Scenario 1 (Figure 2a) has a smaller effect. The effect of the pollution is smallest in Scenario 3 for the Houses (Figure 2c) and Cars dataset and for IMDB it is more similar to Scenario 1. Due to the one-hot encoding of categorical columns, LR is affected by the inherently discrete differences. The regularization of RR fixes this extreme behavior. The tree-based methods, DT and RF, are more stable in most cases, along with the MLP. The non-linearity of those methods weakens the effect of the inconsistencies.

**Completeness.** Reducing completeness of a dataset leads to a heavy performance degradation on all algorithms in all scenarios, as shown representatively in Figure 2 for the Houses dataset. The RF performance decreases the slowest. Next comes RR, being an ensemble method makes it more robust against missing values. For all datasets, the strongest decrease happens in Scenario 2 (Figure 2e). LR and RR are the most affected algorithms. This is because of the linear relation learned by those algorithms, which is easier to confuse with the newly inserted placeholders outside the columns’ domain.

The best performance is achieved in Scenario 3 (Figure 2f) indicating that models perform better on datasets with missing data if the missing data exists as well while the training. The effect of reducing the completeness differs per dataset. For example, the small size of the Houses dataset causes the algorithms to overfit and produce better results when both training and test set contain missing values. Larger datasets suffer less of such influence.

**Feature Accuracy.** Decreasing feature accuracy causes a clear performance degradation of the regression algorithms in all scenarios, as shown representatively in Figure 2 for the Houses dataset. Similar to completeness, the $R^2$ degradation is the highest in Scenario 2 (Figure 2h) and having inaccuracy also in the training data, i.e., in Scenario 3, leads to a better performance (Figure 2i). RF and RR are the most robust algorithms in Scenarios 1 and 3 for all datasets. For RF, the robustness is a result of the ensemble. LR and RR benefits of the normal distributed of the noise. The sudden performance drop of LR on the Houses dataset in both scenarios, shown in Figure 2, is due to the high number of features and low number of samples in this dataset. The regularization of RR seems to solve the problem.

For Scenario 1, the performance decrease in RF and LR (mostly)/RR is slower in higher quality ranges and faster in lower quality ranges as the differences between training and test set become too large. The behavior of the algorithms in Scenario 2 is similar but slower compared to the one showed in response to drop in completeness. In Scenario 3, those algorithms show more linearly decreasing performance. The DT algorithm is more sensitive to feature accuracy drop than on the other algorithms in Scenarios 1 and 3. The DT performance decreases especially fast on the IMDB dataset due to its large number of categorical columns. MLP is more robust than DT regarding feature accuracy.

**Target Accuracy.** We observe a strong $R^2$ degradation in response to decreasing target accuracy for all dataset and in all scenarios, like for feature accuracy and completeness, but at a different level. Scenario 1 shows the strongest degradation with a different speed at different dataset. For the Cars dataset with a low number of features and high number of records, we observe a heavy performance degradation for RF and DT, whereas the performance of LR/RR stays relatively constant as the noise is normally distributed.
Figure 2: $R^2$ of the regression algorithms for Houses dataset.
In contrast, there is a degradation of LR and RR performance for the Houses dataset (Figure 2j) because of the large number of features with low sample size. In general, MLP is the most resilience model for lowering target accuracy. Comparing within the LR-based and the tree-based families: RR performs better than LR, and RF outperforms DT, respectively. In lower quality ranges, the perceived performance in Scenario 3 (Figure 2) decreases slower or stagnates compared to Scenario 1. In Scenario 2, the performance declines gradually with the decrease in target accuracy, as the algorithms increasingly fail in predicting the emerging patterns caused by polluting only the test data.

**Uniqueness.** Decreasing uniqueness does not have a considerable effect on the performance of the algorithms, regardless of the scenario and the dataset. On the datasets with many samples, we see no effect at all. Datasets with a small sample size, like the Houses dataset (Figures 2m, 2n, and 2o), show a slight performance decrease with decreased uniqueness in Scenarios 1 and 3 due to an exaggerated influence of few samples on the training dataset, as they occur several times as a result of duplication.

Comparing the uniqueness with duplicate count sampled by normal distribution and uniqueness with all rows having duplicate count of 1, we do not see different behavior for the Cars dataset and IMDB dataset. For the Houses dataset, inserting duplicates following a normal distribution causes a larger degradation of all algorithms’ performance, especially for Scenario 2 and 3 that some samples appears regularly and thus have a relatively higher impact. As the Cars and IMDB dataset have fewer features and more samples compared to the Houses dataset, this explains the higher reliance of the algorithms.

**Target Class Balance.** Similar to uniqueness dimension, we observe a low effect of the target class imbalance increase in all scenarios on all datasets as shown in last row in Figure 2 for the House dataset. Two facts can justify this observation: First, regression datasets usually have a continuous target variable, i.e., a mostly normally distributed and therefore inherently unbalanced target variable. Second, we had to discretize the target feature and discard resulting classes with very few samples before applying pollution, as described in Section 5.1. Only with a high imbalance above 50%, we start to recognize a degraded performance of all algorithms.

### 6.3 Clustering

For the three scenarios described in Section 5.1, we discuss here the effect of degrading the six data quality dimensions of three datasets, namely: Bank, Covertype and Letter on the performance of five clustering algorithms, namely: Gaussian Mixture clustering, k-Means/k-Prototypes, Agglomerative clustering, OPTICS and Autoencoder. We start by a general observation: We observed that the Gaussian Mixture algorithm assumes data that follows a single distribution, i.e., the random peaks and drops in its performance are caused by its sensitivity to the distribution of samples. We believe that the Bank dataset is drawn from a mixture of Gaussian distributions. Thus, the algorithm behaves better on the Covertype dataset and the best on the Letter dataset. A further analysis of the clustering results in terms of clusters number and density was moved for space reasons to our technical report.

**Consistent Representation.** We do not report on the Letter dataset as it has no categorical features. Figure 3a indicates that the performance of the k-Means / k-Prototypes and OPTICS algorithms is not affected by the degrading consistency of the Covertype dataset. The same observation applies to the Bank dataset. In contrast, the Agglomerative algorithm is strongly impaired even with only a small pollution degree. This susceptibility arises because the algorithm uses a Boolean distance matrix to represent differences between values for categorical columns rather than a distance matrix with actual distances like for numerical columns. This make it easy to disturb the bottom-up combination process by altering the representation of the values. For the Autoencoder approach, we suspect that its observed random behavior is due to the randomness of the neural network training and its dependence on the sampled data for each of the five runs, which is amplified in datasets with many features like the Covertype dataset. The Gaussian Mixture algorithm’s performance slightly decreases on average with decreasing dataset quality. We attribute the unexpected results (initial decrease, then increase in AMI) to the observation made at the beginning of this section.

**Completeness.** For all datasets, we notice a decline in average AMI for all algorithms as the completeness decreases. In Figure 3b, we can see that this decline is rapid and approaching zero in a negative exponential fashion. Yet, for the Covertype dataset, the Gaussian Mixture, k-Prototypes and Autoencoder algorithms performance degrades almost linearly and in a slightly slower fashion compared to other datasets. This is because of the high number of categorical features that are more resilient against the insertion of default values. As shown in Figure 3b, the Agglomerative algorithm drops almost to zero at a completeness of 0.9. The added placeholders are not values found in the Covertype dataset. This can create small clusters of outliers far away from the rest of the data points. This effect is exacerbated by the one-hot encoding, where new dimensions are created for the placeholders.

**Feature Accuracy.** For the Letter dataset, consisting of only numerical features, we observe a very uniform decrease in the AMI score when decreasing the dataset feature accuracy for almost all algorithms. This is due to the normally distributed noise we apply to numerical features. In Figure 3c, the Gaussian Mixture algorithm at the maximum pollution almost reaches the AMI score achieved on the clean dataset: the Covertype dataset consists mainly of binary features that have been completely inverted. The slight difference in performance comes from the ten remaining numerical features. The Agglomerative algorithm behaves similarly, but here the drop is again justified by the approach’s sensibility to outliers created in the high-dimensional space. Consequently, both the Gaussian Mixture and the Agglomerative algorithms cannot meaningfully interpret datasets that have mainly binary features and has low feature accuracy. OPTICS behaves similarly on the Covertype and the Letter datasets. The Autoencoder and k-Prototypes show an almost linear decrease in AMI score, which is not as rapid as the quality degradation is much less rapid for the Bank dataset than for the Letter dataset.

**Target Accuracy.** The pollution of the target accuracy should have no influence on any clustering algorithm, as they are unsupervised:
(a) Consistency with $k_\nu = 5$
(b) Completeness
(c) Feature Accuracy
(d) Target Accuracy
(e) Uniqueness dataset (normal distribution)
(f) Class Balance

Figure 3: Average AMI score of the clustering algorithms for the Covertype dataset.

a changed target class does not affect the clustering itself. However, the fact that we can still see a degrading curve in Figure 3d is due to us comparing the clustering result with the polluted target classes and not with the original target classes when calculating the AMI score.

**Uniqueness.** We used the polluter that inserts duplicates based on a normal distribution. The Gaussian Mixture, k-Means / k-Prototypes and Agglomerative clustering algorithms are not affected by the pollution on the Letter and Covertype datasets as shown in Figure 3e. Furthermore, the increase in duplicates helps the OPTICS approach to improve its performance: as a density-based clustering algorithm, it can benefit from somewhat evenly inserted duplicates as they increase the overall density of clusters and especially their cores without creating very dense cores consisting of only the same data point many times. The Autoencoder approach also enhances its performance above a certain number of duplicates for the Letter dataset. In contrast, we cannot see a clear behavior of the Autoencoder on the Covertype dataset, which is probably due to the generally random and sample-dependent nature of neural network training.

**Target Class Balance.** We observe a difference in behavior between the Letter dataset with numeric-only columns and high-class count and the Bank and Covertype datasets with fewer classes and features. In the Letter dataset, the imbalance in cluster sizes actually slightly improved the AMI score. For example, for OPTICS, we found that the number of clusters being identified on average increased as the dataset grew more imbalanced. For the Bank and Covertype datasets (Figure 3f), the k-Means / k-Prototypes algorithms’ AMI declines slightly and linearly, which can also be observed for the Agglomerative clustering on the Covertype dataset. This decline is caused by the inability of these algorithms to identify the shrunken clusters reliably. The irregular behavior of the Agglomerative clustering on the Bank dataset hints at this algorithm’s instability on this particular dataset.

OPTICS struggles with improving in contrast to the Autoencoder, as it is more susceptible to the high dimensionality and presence of categorical features in the Bank and Covertype datasets after one-hot Encoding. The Gaussian Mixture clustering shows a different behavior in the Bank and Covertype datasets, however, in both cases it does not behave in a clear way due to the assumption of a specific distribution. Therefore, we believe that altering the samples in the dataset provided to the Gaussian Mixture clustering can have positive or negative effects, depending on whether this new sampling more or less resembles the assumed distribution of data.

### 7 CONCLUSION AND FUTURE WORK

In this work, we experimentally studied the impact of six data quality dimensions on 15 algorithms from the three ML tasks: classification, regression and clustering. We ran a huge number of experiments using a quality degraded versions of nine real-world datasets. In addition, we distinguished between three scenarios that a data scientist could face while developing ML-pipelines: (1) polluted training set; (2) polluted test set; (3) polluted training and test sets. We summaries our findings and recommendations as follows.

**Classification.** We found that the quality dimensions with the least impact are uniqueness, consistent representation and target class balance with the condition that the balance is not shifted towards a very extreme imbalance. This suggests that when classifying tabular data, one can neglect pre-processing steps like exact de-duplication, unifying inconsistent representations and carefully balancing the target variable. However, the results of the target class balance dimension are incomplete as we did not investigate
a class balance shift in which the original minority class becomes the majority class, which could have a significant impact on the classifier’s performance.

For completeness, our findings suggest that missing values influence the performance of the classifiers the most if the classifier was not trained on data with missing values. The results also show that incorporating sensible amounts of missing values (less than 40%) in the training phase does not significantly decrease the model’s performance, which could be done to increase robustness if no information is provided on how to impute the serving data once the model reaches production. Reducing the target accuracy of the training data results in degradation of model performance to be below a majority classifier performance for training data with target accuracy lower than $\frac{1}{\text{classes}}$. However, this degradation requires large amounts of mislabeled data, so if you have an estimation of your target accuracy then our finding suggest that if 80% or more of your data is labeled correctly you can train classification models on that noisy data without significant losses in performance. Our findings also reinforce the importance of labeling the test data carefully as labeling errors could then lead to a significant underestimation of the model’s performance (e.g., with 40% label errors in the telco test data, the perceived performance of the classifier is below a baseline model). Very low feature accuracy in the training data can also lead to a strong degradation of model performance, but similar to the target accuracy, there is a certain robustness to that, especially for linear models. Though, the extent of this robustness is dataset-dependent. Reduced feature accuracy during serving time is also problematic but behaves more smoothly and in a linear trend, which makes performance estimation much easier if you can estimate the quality of the serving data. And even though the performance degrades constantly, it stays above baseline level most of the time and seldom dips below that. To further investigate the inner workings of this quality dimension, one could separate the categorical and numerical feature quality and analyze the behavior on a smaller dataset with only one type of data (e.g., classification with only numerical features).

Regression. We found that the quality dimensions with the largest impact are completeness, feature accuracy and target accuracy. A decrease of quality in one of those dimensions leads to worse than linear decrease in algorithm performance. Furthermore, the presence of missing values or inaccurate features in the test dataset without training the ML algorithm on such kind of data leads to even worse performance.

The dimensions uniqueness and target class balance show little impact. Still, we observed some degradation with small datasets and datasets with many columns. We recommend not to focus on these two dimensions, when using large training datasets with a few columns. Consistent representation has impact as soon as the new representations outweigh the old one. For linear regression-based algorithms, ridge regression performs better or equal to linear regression because the regularization helps to cope better with polluted data. For tree-based algorithms, random forest always outperforms decision trees. The multi layer perceptron’s performance highly depends on both the quality dimension and the dataset characteristics. Among all, random forest performs best across most cases, and thus seems to be the most robust algorithm. One exception is the target accuracy dimension.

Clustering. We found the quality dimensions of completeness and feature accuracy to be the most impactful. In both cases, a degradation of the dataset quality led to a decrease in clustering performance, which was linear for datasets with categorical features and approaching exponential concerning the Letter dataset containing only numerical features. The density-based OPTICS algorithm was most affected by changes in completeness and feature accuracy. The k-Means/k-Prototypes, Agglomerative clustering and Gaussian Mixture clustering generally behaved similarly to one another. The Autoencoder approach was least affected by changes in these two quality dimensions. An interesting observation is that the Gaussian Mixture benefited from the slight noise added to numerical features in the first step of feature accuracy pollution. Therefore, we recommend using this approach when dealing with datasets containing exclusively numerical features if one suspects inaccuracies in their feature values. In case of mixed-type datasets, we can recommend only the k-Prototypes algorithm, as its degradation to initial performance trade-off performs the best in our experiments.

Surprisingly, the consistent representation, target accuracy, target class balance and uniqueness dimensions had very low impact on the performance of the majority of the examined algorithms. In contrast, adding some duplicate values into a completely duplicate-free dataset, decreasing its uniqueness quality, improved the performance of OPTICS significantly. We recommend refraining from using Agglomerative clustering when dealing with a dataset with inconsistent representations for its categorical features, as it was unable to deal with this kind of pollution. Overall, the k-Means/k-Prototypes algorithms, i.e., the centroid-based family, showed the most robustness regarding the six data quality dimensions. Nevertheless, the Agglomerative and Gaussian Mixture clustering algorithms outperformed the k-Means/k-Prototypes approaches on clean data.

Limitations and Future Work. The lack of hyperparameter optimization in our work is intentional, as we are mainly interested in the impact of data quality on the algorithms’ performance; however, it also means that it is possible that the performance we reported is not the best for any algorithm. One minor drawback in the implementation of the completeness polluter is the choice of placeholder values. Comparing different values as placeholders is another potential area for future work.

In the clustering algorithms’ evaluation, we implemented the Autoencoder using a basic neural network, not yet optimized for its particular task. Improvements could include the usage of other network components than linear layers, or the incorporation of the clustering performance on the code space into the loss function. Additionally, we did not account for the information loss caused by encoding high-dimensional data into a two-dimensional embedded space. In future work, it is important to use not only AMI to evaluate the clustering algorithm, but to also consider metrics such as absolute size of overlap of the original and generated data clustering and average and variance of the cluster sizes in the algorithm output. We also plan to expand our evaluation in two directions: adding more data quality dimensions and conducting a deeper evaluation per ML-model.
