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How to Address the Data Quality Issues in Regression Models: A Guided Process for Data Cleaning

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Abstract: Today, data availability has gone from scarce to superabundant. Technologies like IoT, trends in social media and the capabilities of smart-phones are producing and digitizing lots of data that was previously unavailable. This massive increase of data creates opportunities to gain new business models, but also demands new techniques and methods of data quality in knowledge discovery, especially when the data comes from different sources (e.g., sensors, social networks, cameras, etc.). The data quality process of the data set proposes conclusions about the information they contain. This is increasingly done with the aid of data cleaning approaches. Therefore, guaranteeing a high data quality is considered as the primary goal of the data scientist. In this paper, we propose a process for data cleaning in regression models (DC-RM). The proposed data cleaning process is evaluated through a real datasets coming from the UCI Repository of Machine Learning Databases. With the aim of assessing the data cleaning process, the dataset that is cleaned by DC-RM was used to train the same regression models proposed by the authors of UCI datasets. The results achieved by the trained models with the dataset produced by DC-RM are better than or equal to that presented by the datasets' authors.

Keywords: data cleaning in regression models (DC-RM); data quality issue; data cleaning task; regression model

1. Introduction

The creation and consumption of data continue to grow by leaps and bounds. Due to advances in Information Technologies (IT), today the data explosion in the digital universe is a new trend [1,2]. The vast amount of data comes from different sources such as social networks, messenger applications for smart-phones, IoT, etc. The Forbes magazine reports an increase of data every second for every person in the world to 1.7 Megabytes from 2020 [3].

Thus, knowledge discovery and data mining gain importance due the abundance of data [4]. A successful process of knowledge discovery is necessary to undertake data treatment. For example, a preliminary step in the knowledge discovery tasks is the data preprocessing, where the main goal is the cleaning of raw data [5]. From data mining, recognized methodologies have been proposed: Knowledge Discovery in Databases (KDD) [6], Cross Industry Standard Process for Data Mining (CRISP-DM) [7], Sample, Explore, Modify, Model and Assess (SEMMA) [8]. Each of these describes a phase for data preprocessing. However, these methodologies do not explain how to address in detail the main issues in data cleaning, leaving out relevant analyses that may lead to problems related to poor data quality in data mining, machine learning, and data science projects [9].

To achieve a solution, the problems mentioned above, we propose a guided process for data cleaning in regression models (DC-RM). The procedure for building the process of data cleaning in regression models consist of identity, understand, organize and filter the data quality issues according to their meaning. After, for each data quality issues found in the datasets, a data cleaning task is suggested. Finally, we validate our approach applying the data cleaning process (DC-RM) to real datasets coming from UCI Repository of Machine Learning Databases [10], training the same algorithms used by the datasets authors with the dataset obtained by DC-RM, and comparing the precision achieved by these. The remainder of this paper is organized as follows: Section 2 discusses definitions of regression models, data quality and the related works. The process for data cleaning is explained in Section 3; Section 4 presents the results and Section 5 presents the conclusions and future works.

2. Materials and Methods

2.1. Background

This section exposes the concepts for building the process for data cleaning in regression models (DC-RM).

2.1.1. Regression Models

In knowledge discovery, regression models seek relations among a dependent variable (numeric) and a set of independent variables (numeric or nominal) through a learning proccess from a curated samples [11]. The main goal of the regression models is to obtain accurate predictions similarly to the values of the independent variable for new samples [12]. The Regression algorithms commonly used in the literature include multilayer perceptron [13], radial basis function network [14] and regression trees [15].

2.1.2. Data Quality

Data is affected by several processes, most of which affect its quality to a certain degree [16]. The authors in [17] define data quality as "*the degree of fulfilment of all those requirements defined for data, which is needed for a specific purpose*". On the other hand, according to the authors of [18], the data errors may affect the predictive accuracy of linear regression models in two ways. First, the training data used to build the model may contain errors. Second, even if the training data are free of errors, once a linear regression model is used for forecasting a user may input test data containing errors to the model. This study demonstrates that the outputs of one linear regression model are sensitive to data errors. From the two assumptions above, this research is focused on the first one, taking GIGO: "Garbage In Garbage Out" as principle.

2.2. Related Works

Several researchers have built mechanisms to address data quality issues. Table 1 presents a summary of the related works and the data quality issues addressed.

In Table 1, we observe a large diversity of approaches for addressing data quality issues designed for relational data bases, data warehouses, health systems, and other domain applications (wind energy, seismic waves, electricity consumption); however, the related works are not focused on regression tasks of knowledge discovery. Although the following works [19,20] are oriented for big data pre-processing, they lack a user-oriented process to address orderly many data quality issues (e.g., missing values, outliers, duplicate instances, high dimensionality).

Table 1. Related works.

Works	Domain	Data Quality Issues
[16,21–26]	Databases	Integrity constraints, validation of overloaded table, duplicate records, inconsistencies, missing values, data freshness.
[9,27–30]	Conceptual	Incomplete data, out-of-date data, lack of meta-data, high time to understand data
[31–38]	Health systems	Data heterogeneity, illegible handwriting, missing values, duplication of patient records, inconsistency, unsuitable data format, timeliness, inaccuracy.
[39–41]	Wind energy, seismic waves, electricity consumption	Data heterogeneity, missing values, out-of-date data, noise, outliers, inconsistency
[19,20]	Big data	Missing values, timeliness, contextual adequacy, operational adequacy, temporal adequacy

3. Process for Data Cleaning in Regression Models

This section presents the process to address poor quality data in regression tasks. The methodology "*Building a Conceptual Framework: Philosophy, Definitions, and Procedure*" [42] was adapted to build the proposed process. This offers an organized procedure of theorization for building conceptual process. The advantages of using this methodology proposed by [42] are the flexibility for make modifications, and the easy understanding. The procedure for building the process of data cleaning in regression models consists of the following phases:

3.1. Mapping the Selected Data Sources

The first phase identifies the data quality issues to regression tasks. Data sources as research papers and methodologies were reviewed:

- From data mining and machine learning four relevant methodologies, we found: Knowledge Discovery in Databases (KDD) [6], Cross Industry Standard Process for Data Mining (CRISP-DM) [7], Sample, Explore, Modify, Model and Assess (SEMMA) [8] and The Data Science Process [43]. These methodologies mention data quality issues such as: missing values, outliers, duplicate instances and high dimensionality.
- In [44] we present a literature review for data quality issues in knowledge discovery tasks. We reviewed research papers from IEEE Xplore, Science Direct, Springer Link, and Google Scholar. Based on the literature analysis, it can be stated that three quality issues were found: missing values, outliers, and redundancy (refers to duplicate instances). Also, the noise was identified as a data quality issue (see Figure 1).

Data quality issues such as missing values, outliers and redundancy have received greater attention from research community (papers found: 39, 47 and 55 respectively). Meanwhile noise (17 papers) has been paid less attention because it is defined as general consequence of the data measurement errors.

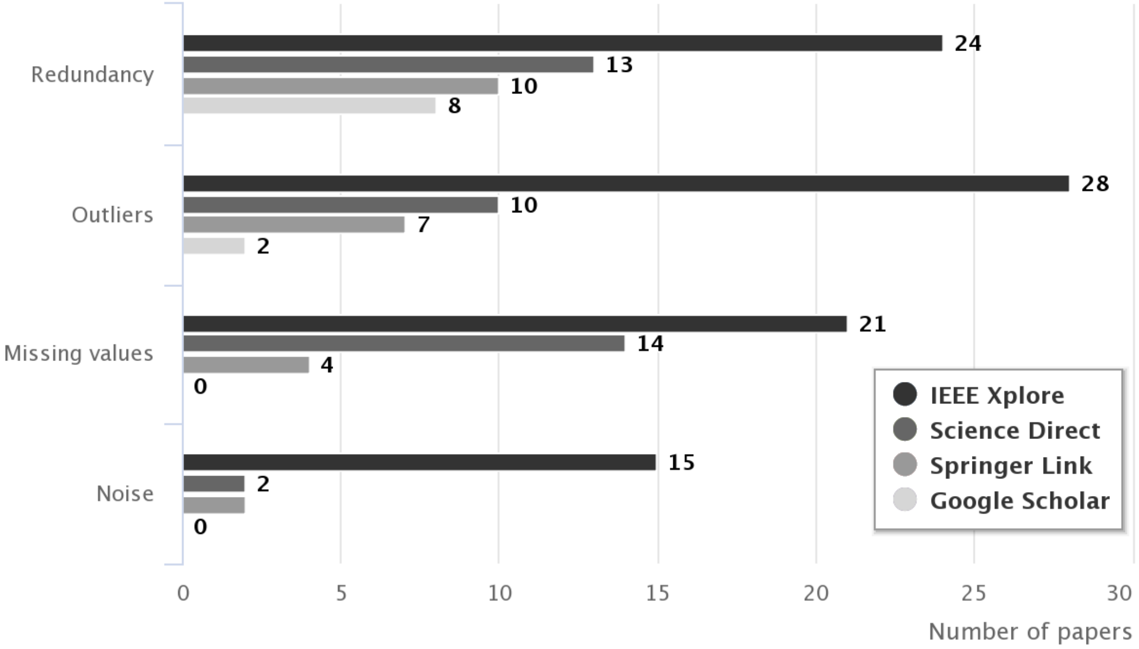


Figure 1. Number of papers found for each data quality issue [44].

3.2. Understanding the Selected Data

The aim in this phase is understand the data quality issues from regression task. Next a description of each data quality issue is presented:

- Missing values: refers when one variable or attribute does not contain any value. The missing values occur when the source of data has a problem, e.g., sensor faults, faulty measurements, data transfer problems or incomplete surveys [45].
- Outlier: can be an observation univariate or multivariate. An observation is denominated an outlier when it deviates markedly from other observations, in other words, when the observation appears to be inconsistent respect to the remainder of observations [46–48].
- High dimensionality: is referred to when dataset contains a large number of features [49]. In this case, the regression model tends to overfit, decreasing its performance [50].
- Redundancy: represents duplicate instances in data sets which might detrimentally affect the performance of classifiers [51].
- Noise: defined by [52] as irrelevant or meaningless data. The data noisy reduce the predictive ability in a regression model [53].

3.3. Identifying and Filtering Components

The aim in this phase is organize and filter the data quality issues according to their meaning. The following changes have been made:

- *Redundancy* were renamed as *Duplicate instances* to represent better the data quality issues in regression models.
- *Noise* is considered a general issue according it definition: "irrelevant or meaningless data". Thus *Missing values*, *Outliers*, *High dimensionality* and *Duplicate instances* are considered as a kind of *Noise*.

3.4. Integrating Components

In this phase, first, we define the data cleaning tasks. Subsequently, we propose a cleaning task as a solution for each noise issue (see Table 2).

Table 2. Data cleaning tasks in regression models.

Noise Issue	Data Cleaning Task
Missing values	Imputation
Outliers	Outlier detection
High dimensionality	Dimensionality reduction
Duplicate instances	Remove duplicate instances

- Imputation: replaces missing data with substituted values. In the literature we found four relevant approaches to imputing missing values:
  - *Deletion:* excludes instances if any value is missing [54].
  - *Hot deck:* missing items are replaced by using values from the same dataset [55].
  - *Imputation based on missing attribute:* assigns a representative value to a missing one based on measures of central tendency (e.g., mean, median, mode, trimmed mean) [56].
  - *Imputation based on non-missing attributes:* missing attributes are treated as dependent variables, and a regression or classification model is performed to impute missing values [57].
- Outlier detection: identifies candidate outliers through approaches based on *Clustering* (e.g., DBSCAN: Density-based spatial clustering of applications with noise) or *Distance* (e.g., LOF: Local Outlier Factor) [58–60].
- Dimensionality reduction: reduces the number of attributes finding useful features to represent the dataset [61]. A subset of features is selected for the learning process of the regression model [49]. The best subset of relevant features is the one with least number of dimensions that most contribute to learning accuracy [62]. Dimensionality reduction can take on four approaches:
  - *Filter:* selects features based on discriminating criteria that are relatively independent of the regression (e.g., correlation coefficients) [62].
  - *Wrapper:* based on the performance of regression models (e.g., error measures) are maintained or discarded features in each iteration [63].
  - *Embedded:* the features are selected when the regression model is trained. The embedded methods try to reduce the computation time of the wrapper methods [64].
  - *Projection:* looks for a projection of the original space to space with orthogonal dimensions (e.g., principal component analysis) [65].
- Remove duplicate instances: identifies and removes duplicate instances [66].

Several data cleaning tasks were identified for regression models. The integration of the data cleaning tasks is depicted in Figure 2:

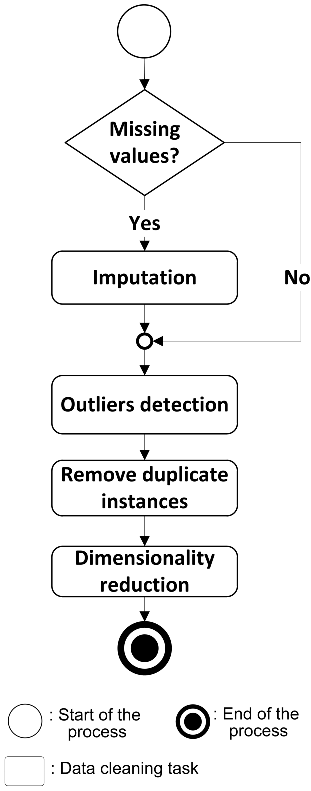


Figure 2. Process for data cleaning in regression models (DC-RM).

Below, we explain the step-step execution of data cleaning flow for the regression models.

1. *Verify if dataset contains missing values*: usually missing data are represented by special characters such as ?, *, blank spaces, specials words as NaN, null, etc. The first step is convert the missing values to format of the data cleaning algorithm.
2. *Apply imputation algorithms*: once the format of missing values is prepared, an imputation algorithm is used. The added values must be verified because the imputation algorithm often creates outliers.
3. *Apply outliers detection algorithm*: the outlier detection algorithm searches candidate outliers in the raw dataset or erroneous values generated by *Imputation* techniques.
4. *Apply algorithms to remove duplicate instances*: these algorithms search for duplicate instances in both the raw dataset or those generated by imputation algorithms.
5. *Apply algorithm for dimensionality reduction*: this kind of algorithms reduce the high dimensional in data sets by selecting a subset of most relevant features [67]. Different authors [68,69] assert that the feature selection methods have several advantages, such as: (i) improving the performance of the classifiers; (ii) better visualization and data understanding; and (iii) reducing time and computational cost

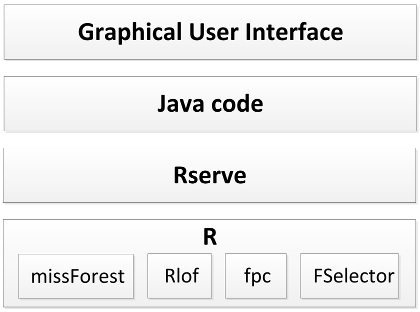
Once the phase of components integration is finished, we develop a software prototype of the guided process for data cleaning in regression models. Figure 3 presents the layer view of DC-RM.

DC-RM is composed by four layers:

- Graphical User Interface (GUI) enables an user of DC-RM interact with the algorithms of data cleaning through graphical elements, such as text, windows, icons, buttons, text fields, etc. We developed two main forms in NetBeans IDE 8.2. The first form presents statistic information related with the dataset (number of attributes and instances,percentage of missing values and duplicate instances) and its attributes (mean, median, skewness, kurtosis, etc.) as show Figure 4.

The second form (it appears when the button "Start cleaning" of the first form is pressed) presents the algorithms for each data cleaning task and the DC-RM process. In Figure 5 is depicted the second form when the chi–squared algorithm is applied in the dimensionality reduction phase.

- Java code establish a connection with R through Rserver, subsequently it invokes the data cleaning algorithms of the R packages, and finally, it sends the results of data cleaning algorithms to Graphical User Interface.
- Rserve acts as a socket server (TCP/IP or local sockets) which responds to requests from Java code. It listens for any incoming connections and processes incoming requests [70]. In other words, Rserve allows to embed R code within Java code.
- R is a system for statistical computation and graphics. It provides a programming language as dialect of S which was designed in the 1980s and has been in widespread use in the statistical community since [71]. R methods are based on packages, they are collections of functions and data sets developed by the community. We used R version 3.4.2 with missForest package [72] for imputation task, Rlof [73] and fpc [74] packages for outliers detection task, and Fselector [75] package for dimensionality reduction tasks. In case of remove duplicate instances, we used R function $duplicated()$.


Graphical User Interface

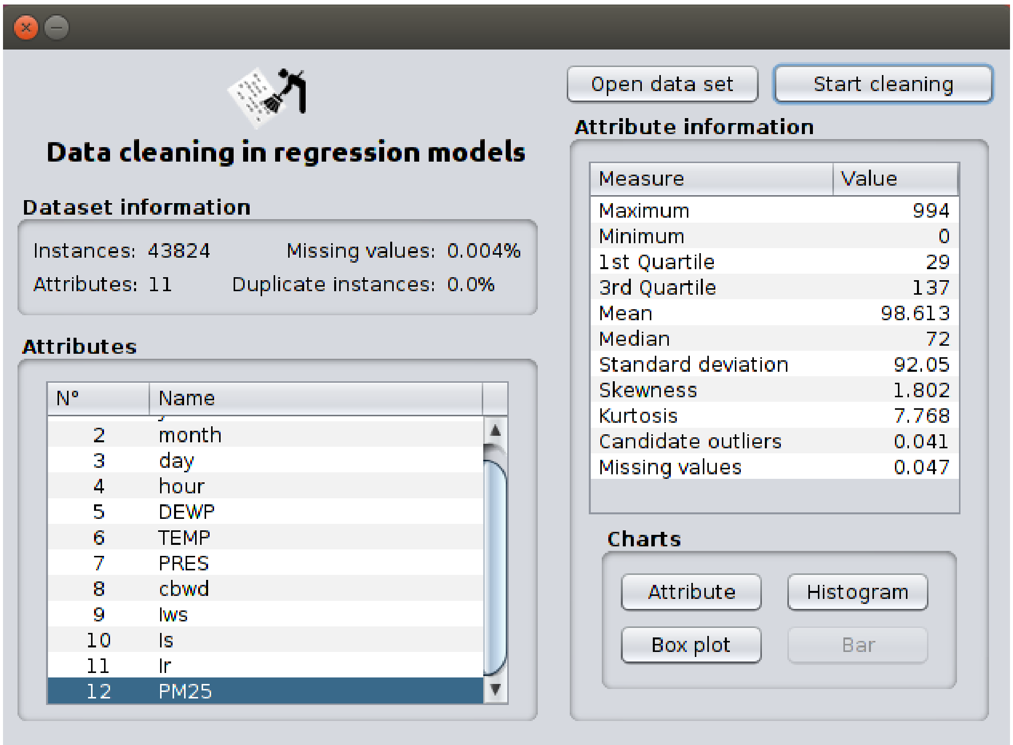
Java code

Rserve

R

missForest Rlof fpc FSelector

Figure 3. Layer view of DC-RM.



Data cleaning in regression models

Dataset information

Instances: 43824 Missing values: 0.004%

Attributes: 11 Duplicate instances: 0.0%

Attributes

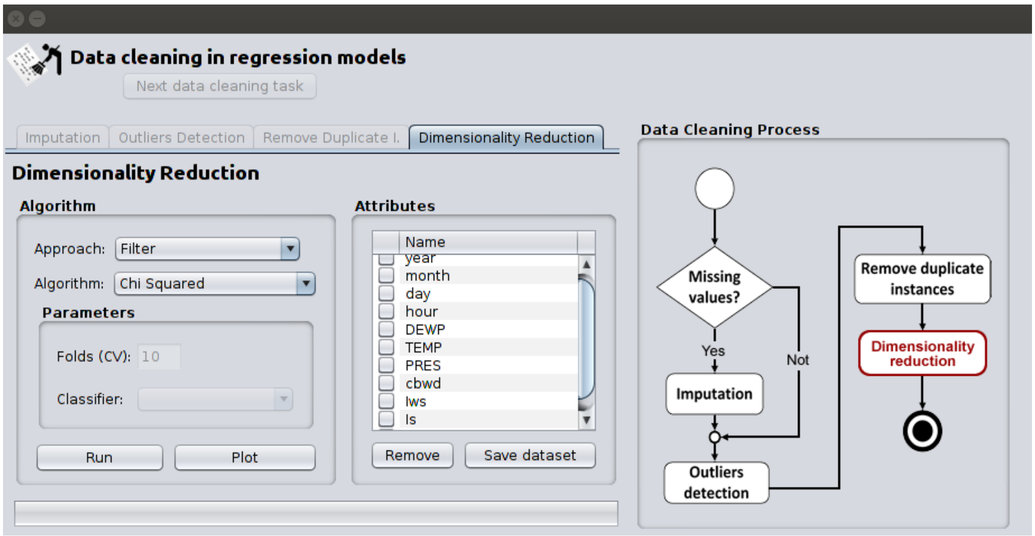
N°	Name
2	month
3	day
4	hour
5	DEWP
6	TEMP
7	PRES
8	cbwd
9	Iws
10	Is
11	Ir
12	PM25

Attribute information

Measure	Value
Maximum	994
Minimum	0
1st Quartile	29
3rd Quartile	137
Mean	98.613
Median	72
Standard deviation	92.05
Skewness	1.802
Kurtosis	7.768
Candidate outliers	0.041
Missing values	0.047

Charts

Figure 4. Form of the statistical information of the dataset.



Data cleaning in regression models

Dimensionality Reduction

Algorithm

Approach: Filter

Algorithm: Chi Squared

Parameters

Folds (CV): 10

Classifier:

Attributes

Name
year
month
day
hour
DEWP
TEMP
PRES
cbwd
Iws
Is

Figure 5. Form of the DC-RM process.

3.5. Validation

We evaluate the process for data cleaning in regression models (DC-RM) through real datasets coming from UCI Repository of Machine Learning Databases [10]. Section 4.2 explains in detail the validation of the proposed process for dataset: prediction of comments in Facebook post (cFp) [76].

4. Experimental Results

The DC-RM process was applied to real datasets of the UCI Repository of Machine Learning Databases [10]. Subsequently, the cleaned datasets by DC-RM are used to train the same algorithms proposed by authors of UCI datasets. Finally, we compare the Mean Absolute Errors (MAE) of the models trained with the datasets produced by the authors versus the models trained with the datasets processed by DC-RM.

The Mean Absolute Error (MAE) is defined by the next Equation:

$$\text{MAE} = \frac{\sum_{i=1}^{n} Y_i - \widehat{Y_i}}{n}$$

where Y_i is the actual measurement (comments in Facebook posts), $\widehat{Y_i}$ is the predicted value and n is the number of measurements.

We expose as case study the dataset for prediction of comments in Facebook posts (cFp) [76]. Thus, in Section 4.1 we presented the description of cFp dataset; in Section 4.2, we described the processing of the cFp dataset using DC-RM; Section 4.3 exposes the MAE achieved by the regression models (the trained by original cFp dataset versus the trained by DC-RM), finally Section 4.4 shows additional results of DC-RM with other datasets of UCI Repository [10].

4.1. Dataset Description

The dataset proposed in [76] is oriented towards the comments prediction in a Facebook post. The dataset is composed by a data test with 10.120 instances and five training sets as shown Table 3.

The dataset contains 53 attributes: 4 page features (page likes, page category, etc.), 30 essential features (comment count in last 24 and 48 h, etc.), 14 Weekday features (binary variables related with the date of Facebook post), and 5 other basic features (length of document, post share count, etc.).

Table 3. Instances of dataset for prediction of comments in Facebook posts.

Data Training	Instances
Variant 1	40.949
Variant 2	81.312
Variant 3	121.098
Variant 4	160.424
Variant 5	199.030

4.2. Evaluation Process

4.2.1. Imputation

After executing the first step in the execution flow, we conclude that the original dataset does not contain missing values. With the goal of testing the imputation step, we remove values randomly from the original dataset using R statistical software [71]. As a result of this operation, the dataset presents missing values in three attributes. Therefore, we test two imputation approaches.

- Global imputation based on non-missing attributes: the main idea is fill the missing values by regression models. Missing attributes are treated as dependent variables, and a regression is performed to impute missing values [57]. The random forest algorithm [77] was used to fill the missing values. This method builds a model for each variable. Then it uses the model to predict missing values in the variable with help of observed values.
- Global imputation based on missing attribute: assigns the most frequent value of the attribute to a missing values. Commonly, a measure of central tendency is used for filling the holes [57]. In this case, the mean imputation was used [78].

Table 4 presents the Mean Absolute Error of the imputation methods.

Random Forest reaches low MAEs in the imputations (MAE lowest: 0 in attribute 22 Variant 3, and MAE highest: 1.214 in attribute 31 of Variant 3). In contrast with Mean Imputation, the attributes 6, 15, 13, 29 shown in Table 4 have a MAE greater than 54.445. This happens because the imputation values were added on the center of the sample, diminishing the importance of values on the tails. Thus Random Forest was the algorithm used for impute the missing values. Figure 6 presents the imputed (red line) and original values (black line) for attribute 6 (comments average in last 24 h of the data training—variant 1).

Table 4. Mean absolute error for imputation methods.

Dataset	Attribute Index	Random Forest	Mean Imputation
Variant 1	6	0.011	97.749
	26	0.001	1.752
	44	0.017	0.237
Variant 2	15	0.009	287.652
	31	1.214	18.624
	8	5.86×10^{-4}	35.803
Variant 3	22	0	26.665
	48	0.004	0.203
	3	0.003	6.546
Variant 4	13	3.6×10^{-5}	126.782
	49	0.010	0.233
	17	2.47×10^{-13}	4.896
Variant 5	12	3.09×10^{-13}	7.172
	29	0.135	54.445
	52	0.006	0.223

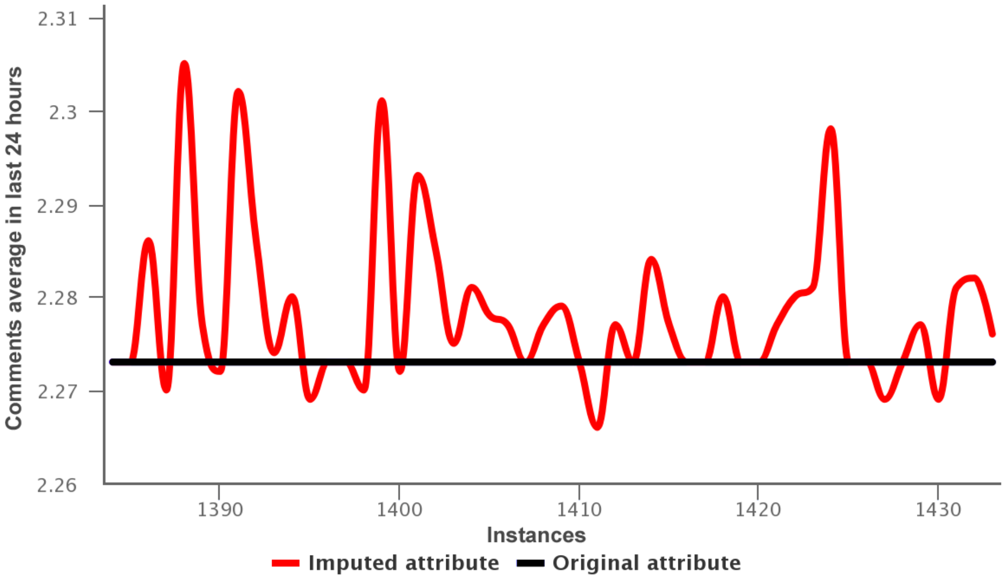


Figure 6. Data training—variant 1: imputed values for attribute 6.

In Figure 6, we observed the imputed values are around 2.225–2.305, while the original values are 2.273. Thus the imputation obtained by random forest reaches a mean absolute error 0.01. Other imputation for the attribute 31: comments in last 24 h of the data training—variant 2 is shown in Figure 7.

In this case the imputation method obtain a mean absolute error 1.21.

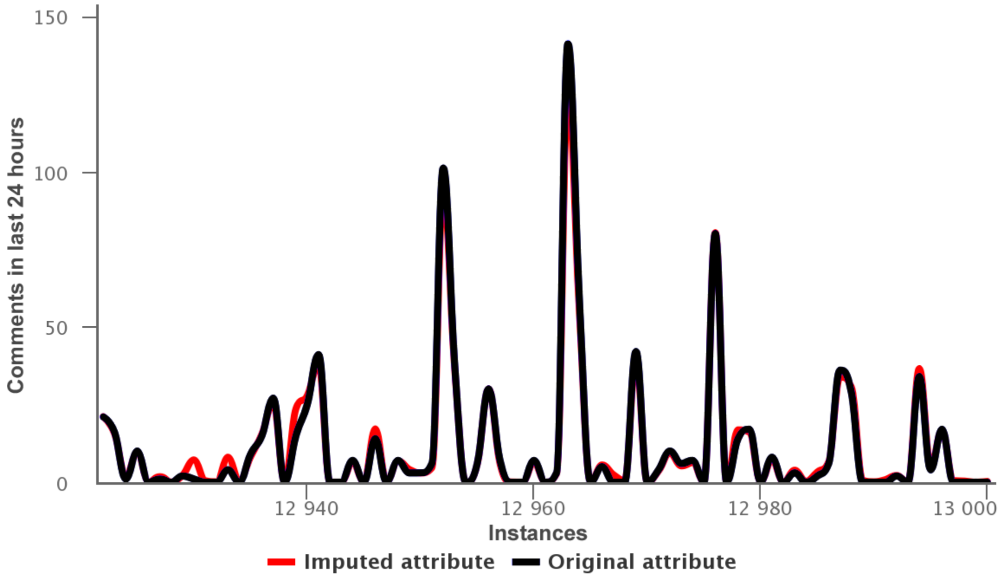


Figure 7. Data training—variant 2: imputed values for attribute 31.

4.2.2. Outliers Detection

After obtaining the imputed values, according to the execution flow presented in Figure 2, we applied the outliers detection task with the aim to find abnormal behavioral in the instances or erroneous imputations. In this case, we propose the use of outliers detection based on distance (Local Outlier Factor) and clustering (Density-Based Spatial Clustering of Applications with Noise) approaches.

- Local Outlier Factor (LOF): is an algorithm for identifying distance-based local outliers [58]. With LOF, the local density of a certain point is compared with its neighbors. If the former is significantly lower than the latter (with an LOF value greater than 1), the point can be in a sparser region than its neighbors, which suggests it be an outlier [79].

- Density-Based Spatial Clustering of Applications with Noise (DBSCAN): searches clusters with regions of high and low density [80]. DBSCAN chooses an arbitrary unassigned object p from the dataset. If p is a core object, DBSCAN finds all the connected objects and these objects are assigned to a new cluster. If p is not a core object, then p is considered outlier object and DBSCAN moves onto the next unassigned object. Once every object is assigned, the algorithm stops [81].

Table 5 shows the candidate outliers detected by LOF and DBSCAN.

The clusters of outliers created by DBSCAN reach among 97 and 219 instances (Table 5); however, 97.35% of the instances considered outliers are false positives. In case of Local Outlier Factor, the instances with LOF scores greater than 4.134 were analyzed (among 2 and 13 instances depending of dataset as shown Table 5), obtaining that 100% of the candidate outliers are true positives.

From the foregoing LOF was the algorithm used for outliers detection. To verify the candidate outliers obtained by LOF, the first two principal components for each training sets were plotted. Figure 8 presents principal components PC1 and PC2 for data training—variant 5; 99.99% of the information contained in the data training are retained by the first two components. The outliers are labeled with "+" in red.

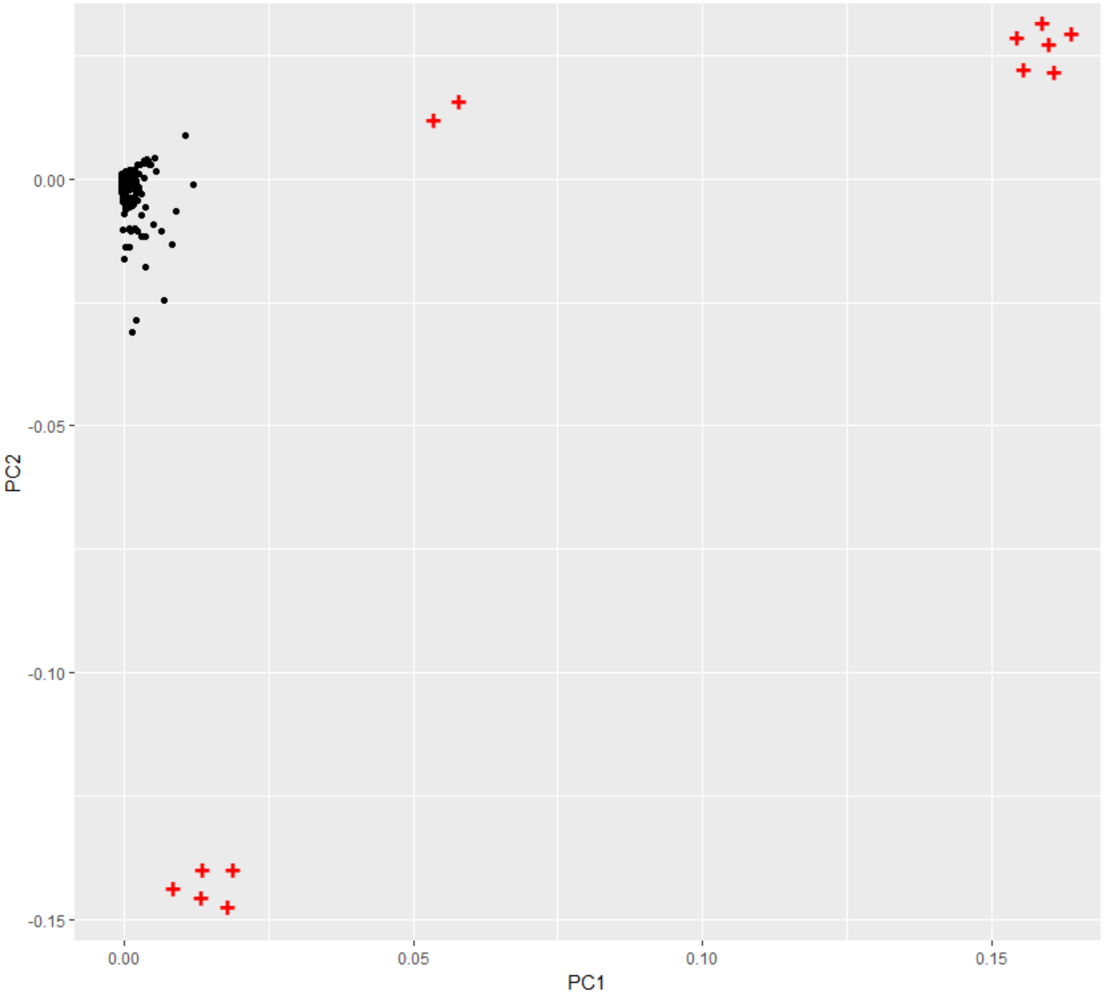


Figure 8. Outliers for data training—variant 5.

Table 5. Outliers detected by LOF and DBSCAN.

Data Training	LOF	DBSCAN
Variant 1	7	134
Variant 2	2	113
Variant 3	6	97
Variant 4	11	179
Variant 5	13	219

The candidate outliers detected by Local Outlier Factor (Table 5) were removed which can be erroneous observations generated in the imputation task.

4.2.3. Remove Duplicate Instances

We use the Standard Duplicate Elimination algorithm to detect duplicate instances [66]. They are removed by performing an external merge-sort and then scanning the sorted dataset. Similarly, we cluster and remove identical instances in a sequential scan of the sorted dataset [82]. Table 6 shows the number of duplicate instances for each data training set (remove 312 duplicate instances).

Table 6. Duplicate instances for each data training set.

Data Training	Duplicate Instances
Variant 1	8
Variant 2	21
Variant 3	59
Variant 4	88
Variant 5	136

4.2.4. Dimensionality Reduction

Considering that the datasets are large with respect to low computational resources, we recommend using two methods of filter approach based on the absolute correlation. This methods are considered faster and they have low computational cost [83]. The absolute values of pair-wise correlations are considered. If two attributes have a high correlation, the filter algorithm looks at the mean absolute correlation of each attribute and removes the variable with the largest mean absolute correlation [84]. Chi-squared and Information Gain were the methods used:

- Chi-Squared: is defined as sum of the squares of the differences of the independent and dependent variable divided by the dependent variable for every value [85]:

$$X^2 = \sum_{i=1}^{n} \frac{(I_i - D_i)^2}{D_i}$$

  where I is the independent variable, D is the dependent variable and i is the ith value of the dataset.
- Information Gain: measures the expected reduction in entropy (uncertainty associated with a random feature) [86,87]. Given S_x the set of training examples, x_i the vector of ith variables in this set, $|S_{x_{i=v}}|/|S_x|$ the fraction of examples of the ith variable having value v [88]:

$$IG(S_x, x_i) = H(S_x) - \sum_{v=values(x_i)}^{|S_{x_{i=v}}|/|S_x|} H(S_{x_{i=v}})$$

  with entropy:

$$H(S) = -p + (S)log_2 p + (S) - p - (S)log_2 p - (S)$$

$p \pm (S)$ is the probability of a training example in the set S to be close to the value of the class.

Figure 9 shows the absolute correlation for each attribute reached by Chi-squared and Information gain. The filter methods obtained a similar absolute correlation for the attributes of all datasets. The attributes with an absolute correlation of 0.2 or lower were removed (index of attributes removed: 4, 9, 14, 19, 35, 37–52).

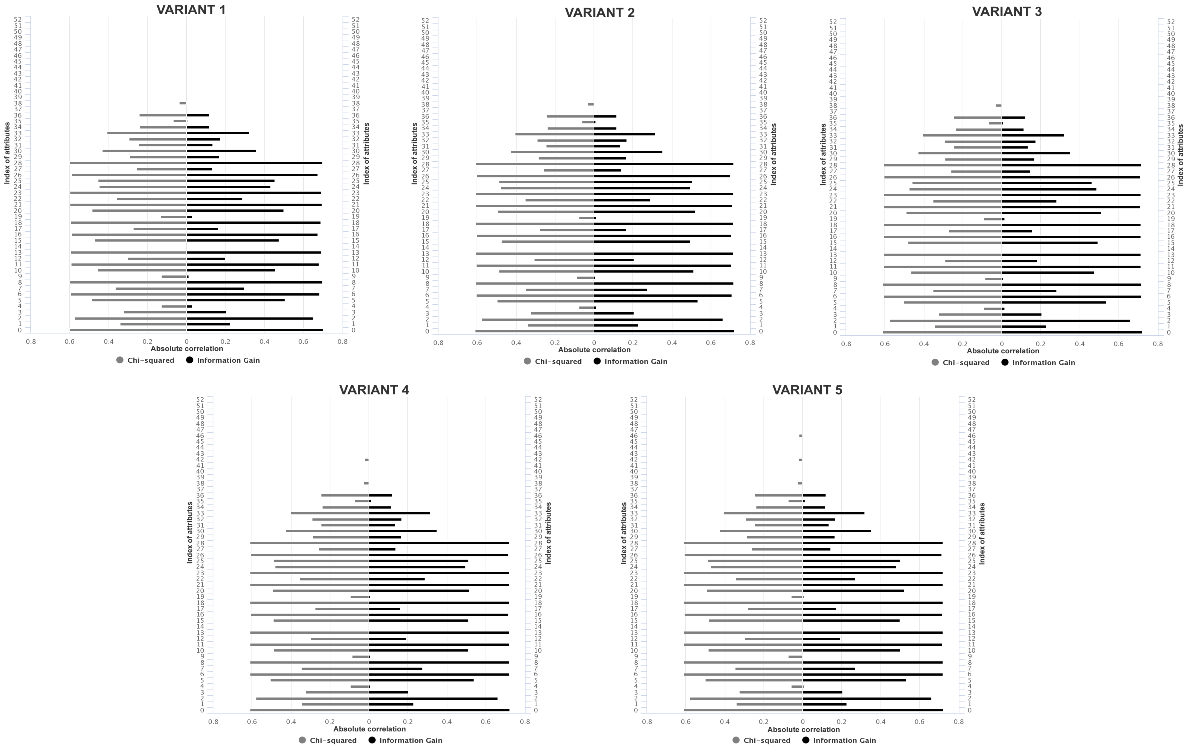


Figure 9. Absolute correlation obtained by Chi-squared and Information gain for datasets: Variant 1, 2, 3, 4 and 5.

4.3. Results

With the aim of assessing the data cleaning process, we use the dataset cleaned by DC-RM for training the same regression models proposed by the authors of cFp dataset [76]. Then, we compare the results of MAE obtained by the two approaches. The authors of [76] used four regression algorithms of the Weka toolkit:

- Multi Layer Perceptron (MLP): this neural network was designed with two hidden layers; the first hidden layer contains 20 neurons while the second hidden layer 4 neurons. The learning rate is adjusted to 0.1 and momentum to 0.01.
- Radial Basis Function Network (RBF): the number of clusters was modified to 90.
- In the models REP and M5P Tree were used the default parameters.

The regression models were evaluated with a data test set of 10.120 instances. Table 7 shows the mean absolute errors (MAE) of the models generated by dataset cleaned with DC-RM and the models proposed by the authors of cFp dataset [76]; the underlined values represent the best MAE overall achieved by the models using DC-RM and the authors proposal [76].

REP Tree was the model with the lowest MAE for DC-RM, as the authors proposed [76]. In contrast, the M5P tree of [76] (training with Variant 5) was the model with the highest MAE.

Overall, the training sets Variant 2, 3, 4, 5 cleaning by DC-RM achieve the best MAE in its models. In case of Variant 1, the authors' proposal [76] reaches a best measure with a difference of MAE overall 0.92 respect to DC-RM.

Table 7. Mean absolute error obtained by: DC-RM and [76].

Approach	Model	Var 1	Var 2	Var 3	Var 4	Var 5
DC-RM	MLP	34.55	31.31	35.19	38.59	55.17
	RBF	31.09	31.85	30.12	29.81	29.69
	REP	29.28	30.22	28.41	27.89	29.33
	M5P	35.53	30.32	32.68	50.77	32.59
	Overall	32.61	30.92	31.60	36.76	34.19
[76]	MLP	38.24	40.72	36.40	51.49	44.93
	RBF	31.38	30.08	30.22	32.67	31.37
	REP	27	28.67	27.92	27.47	27.72
	M5P	30.15	36.90	32.33	35.69	116.98
	Overall	31.69	34.09	31.71	41.33	55.25

4.4. Comparative Study

In order to demonstrate the performance of guided process for data cleaning in regression models, DC-RM also was validated with datasets coming from UCI Repository of Machine Learning Databases [10]. The models used were Support Vector Regression (SVR), Linear Regression (LR), Random Forest (RF), M5P Decision Tree, and Multi Layer Perceptron (MLP). Table 8 shows the MAE of models produced by the authors of UCI datasets compared with the same models trained with the datasets processed by DC-RM. The values underlined in Table 8 correspond to the MAE's lowest.

Once the UCI datasets are cleaned by DC-RM, 81.81% of the models reach a lower Mean Absolute Error than models proposed by the dataset's authors. For the remaining 8.19% of the models, the authors proposal of the datasets: "Turbine decay" and "Energy uses of appliances" achieve lowest MAE. However, the MAE's difference of the models generated by the authors with respect to models built with datasets processed by DC-RM is slight. In the case of "Turbine decay" dataset, the MAE's difference of SVR models is 0.002 and 0.06 for the "Energy uses of appliances" dataset, using the RF models.

Compared with effort in data preparation and previous domain knowledge by dataset authors, DC-RM offers a general data cleaning solution for any application domain. DC-RM reaches or overcomes the results proposed by the dataset's authors.

Table 8. Mean absolute errors of the models processed by DC-RM and datasets authors of UCI repository.

Dataset	Ref.	Approach	Model	MAE
Compressor decay	[89]	DC-RM	SVR	0.005
		Authors	SVR	0.17
Turbine decay	[89]	DC-RM	SVR	0.003
		Authors	SVR	0.001
Rental Bikes Hourly	[90]	DC-RM	LR	1×10^{-5}
		Authors	LR	0.017
Rental Bikes Daily	[90]	DC-RM	LR	5×10^{-5}
		Authors	LR	0.031
Energy use of appliances	[91]	DC-RM	RF	12.03
		Authors	RF	11.97

Table 8. *Cont.*

Dataset	Ref.	Approach	Model	MAE
Posts in Facebook pages	[92]	DC-RM	SVR	25.26
		Authors	SVR	26.9
Feedback Blogs Prediction	[93]	DC-RM	M5P	5.70
		Authors	M5P	6.06
I-Room temperature	[94]	DC-RM	MLP	0.47
		Authors	MLP	1.13
II-Room temperature	[94]	DC-RM	MLP	0.34
		Authors	MLP	0.88
I-Dinning room temperature	[94]	DC-RM	MLP	0.43
		Authors	MLP	0.89
II-Dinning room temperature	[94]	DC-RM	MLP	0.32
		Authors	MLP	0.78

5. Conclusions and Future Works

In this work, a process to address the data quality issues in regression models is proposed. From DC-RM, we conclude:

- DC-RM provides support to methodologies from data mining and machine learning. For instance, in Knowledge Discovery in Databases, DC-RM can support the Preprocessing and Data Cleaning, Data Reduction, and Projecton phases. In Cross Industry Standard Process for Data Mining, DC-RM gives support to Verify Data Quality and Clean Data steps. (especially: Sample, Explore, Modify, Model and Assess in Modify phase); and, in Data Science Process into the Clean Data phase. Finally, we would like to emphasize that none of the methodologies discussed above explain in detail how to address the data quality issues in regression models.
- The DC-RM approach reduces the time and effort invested by the user in pre-processing phase, since it detects the data quality issues and advises about the suitable approach and the execution order for data cleaning tasks.
- Once DC-RM has been used in the UCI datasets, the models reach or overcome the results compared by the models built for the dataset's authors [76,89–94]. DC-RM offers a general data cleaning solution for any application domain.
- The dimensionality reduction is an important task that must be applied in large feature space. Considering the high data dimensionality of the dataset proposed by [76], the filter methods were used in DC-RM (due their fast and low computational cost). However, several authors declare that other methods with high computational cost such as wrapper and embedded methods can obtain better results [49,64,95–97].

As future works, we propose:

- Building other processes for data cleaning in knowledge discovery tasks as classification and clustering.
- Including ontologies of specific domains to support some data quality issues; e.g, selection of relevant attributes based on expert knowledge. In the cancer domain, the ontology developed by [98] can be used for selecting the relevant attributes and avoid the use of algorithms with high computational complexity in dimensionality reduction tasks.
- Creating a case based reasoning (CBR) system for supporting the data cleaning process. The CBR will automatically recommend the suitable data cleaning algorithm (e.g., in outliers detection, the CBR suggests the local outlier factor algorithm to the user).

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Abbreviations

The following abbreviations are used in this manuscript:

DC-RM	Data Cleaning in Regression Models

References

1. Gantz, J.; Reinsel, D. *The Digital Universe in 2020: Big Data, Bigger Digital Shadows, and Biggest Growth in the Far East*; IDC: Framingham, MA, USA, 2012; pp. 1–16.
2. Hu, H.; Wen, Y.; Chua, T.S.; Li, X. Toward Scalable Systems for Big Data Analytics: A Technology Tutorial. *IEEE Access* **2014**, *2*, 652–687.
3. Marr, B. Big Data: 20 Mind-Boggling Facts Everyone Must Read, 2015. Available online: https://www.forbes.com/sites/bernardmarr/2015/09/30/big-data-20-mindbogglingfacts-everyone-must-read/ (accessed on 30 September 2015).
4. Maimon, O.; Rokach, L. Introduction to Knowledge Discovery in Databases. In *Data Mining and Knowledge Discovery Handbook*; Maimon, O., Rokach, L., Eds.; Springer: Boston, MA, USA, 2005; pp. 1–17.
5. Eyob, E. *Social Implications of Data Mining and Information Privacy: Interdisciplinary Frameworks and Solutions: Interdisciplinary Frameworks and Solutions*; Information Science Reference: Hershey, PA, USA, 2009.
6. Piateski, G.; Frawley, W. *Knowledge Discovery in Databases*; MIT Press: Cambridge, MA, USA, 1991.
7. Chapman, P. *CRISP-DM 1.0: Step-by-Step Data Mining Guide*; SPSS: Chicago, IL, USA, 2000.
8. Olson, D.L.; Delen, D. *Advanced Data Mining Techniques*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2008.
9. Corrales, D.C.; Ledezma, A.; Corrales, J.C. A Conceptual Framework for Data Quality in Knowledge Discovery Tasks (FDQ-KDT): A Proposal. *J. Comput.* **2015**, *10*, 396–405.
10. Asuncion, A.; Newman, D. *UCI Machine Learning Repository*. University of California, School of Information and Computer Science: Irvine, CA, USA, 2007. Available online: http://www.ics.uci.edu/~{}mlearn/MLRepository.html (accessed on 1 March 2018).
11. Sen, A.; Srivastava, M. *Regression Analysis: Theory, Methods, and Applications*; Springer Science & Business Media: New York, NY, USA, 2012.
12. Yang, L.; Liu, S.; Tsoka, S.; Papageorgiou, L.G. A regression tree approach using mathematical programming. *Expert Syst. Appl.* **2017**, *78*, 347–357.
13. Hill, T.; Marquez, L.; O'Connor, M.; Remus, W. Artificial neural network models for forecasting and decision making. *Int. J. Forecast.* **1994**, *10*, 5–15.
14. Chen, S.; Cowan, C.F.N.; Grant, P.M. Orthogonal least squares learning algorithm for radial basis function networks. *IEEE Trans. Neural Netw.* **1991**, *2*, 302–309.
15. Quinlan, J.R. *Learning With Continuous Classes*; World Scientific: Singapore, 1992; pp. 343–348.
16. Maydanchik, A. *Data Quality Assessment*; Technics Publications LLC: Madison, WI, USA, 2007.
17. Morbey, G. *Data Quality for Decision Makers: A Dialog between a Board Member and a DQ Expert*; Bücher, Springer Fachmedien: Wiesbaden, Germany, 2013.
18. Klein, B.D.; Rossin, D.F. Data Quality in Linear Regression Models: Effect of Errors in Test Data and Errors in Training Data on Predictive Accuracy. *Inf. Sci.* **1999**, *2*, 33–43.
19. Taleb, I.; Dssouli, R.; Serhani, M.A. Big Data Pre-processing: A Quality Framework. In Proceedings of the 2015 IEEE International Congress on Big Data, New York, NY, USA, 27 June–2 July 2015; pp. 191–198.
20. Merino, J.; Caballero, I.; Rivas, B.; Serrano, M.; Piattini, M. A Data Quality in Use model for Big Data. *Future Gener. Comput. Syst.* **2016**, *63*, 123–130.

21. Chiang, F.; Sitaramachandran, S. A Data Quality Framework for Customer Relationship Analytics. In Proceedingsof the 2015 16th International Conference on Web Information Systems Engineering (WISE), Miami, FL, USA, 1–3 November 2015; Wang, J., Cellary, W., Wang, D., Wang, H., Chen, S.C., Li, T., Zhang, Y., Eds.; Part II; Springer International Publishing: Cham, Switzerland, 2015; pp. 366–378.
22. Berti-Équille, L. Measuring and Modelling Data Quality for Quality-Awareness in Data Mining. In *Quality Measures in Data Mining*; Guillet, F.J., Hamilton, H.J., Eds.; Springer: Berlin/Heidelberg, Germany, 2007; pp. 101–126.
23. Galhard, H.; Florescu, D.; Shasha, D.; Simon, E. An extensible Framework for Data Cleaning. In Proceedings of the 2000 16th International Conference on Data Engineering, Washington, DC, USA, 28 February–3 March 2000; p. 312.
24. De F. Mendes Sampaio, S.; Dong, C.; Sampaio, P. DQ2S? A framework for data quality-aware information management. *Expert Syst. Appl.* **2015**, *42*, 8304–8326.
25. Li, W.; Lei, L. An Object-Oriented Framework for Data Quality Management of Enterprise Data Warehouse. In Proceedings of the PRICAI 2006 Trends in Artificial Intelligence 9th Pacific Rim International Conference on Artificial Intelligence Guilin, China, 7–11 August 2006; Yang, Q., Webb, G., Eds.; Springer: Berlin/Heidelberg, Germany, 2006; pp. 1125–1129.
26. Sebastian-Coleman, L. *Measuring Data Quality for Ongoing Improvement: A Data Quality Assessment Framework*; Newnes: Waltham, MA, USA, 2012.
27. Myrseth, P.; Stang, J.; Dalberg, V. A data quality framework applied to e-government metadata: A prerequsite to establish governance of interoperable e-services. In Proceedings of the 2011 International Conference on E-Business and E-Government (ICEE), Shanghai, China, 6–8 May 2011; pp. 1–4.
28. Vetro, A.; Canova, L.; Torchiano, M.; Minotas, C.O.; Iemma, R.; Morando, F. Open data quality measurement framework: Definition and application to Open Government Data. *Gov. Inf. Q.* **2016**, *33*, 325–337.
29. Panahy, P.H.S.; Sidi, F.; Affendey, L.S.; Jabar, M.A.; Ibrahim, H.; Mustapha, A. A Framework to Construct Data Quality Dimensions Relationships. *Indian J. Sci. Technol.* **2013**, *6*, 4421–4431.
30. Wang, R.Y.; Storey, V.C.; Firth, C.P. A framework for analysis of data quality research. *IEEE Trans. Knowl. Data Eng.* **1995**, *7*, 623–640.
31. Weiskopf, N.G.; Weng, C. Methods and dimensions of electronic health record data quality assessment: enabling reuse for clinical research. *J. Am. Med. Inform. Assoc.* **2013**, *20*, 144–151.
32. Reimer, A.P.; Milinovich, A.; Madigan, E.A. Data quality assessment framework to assess electronic medical record data for use in research. *Int. J. Med. Inform.* **2016**, *90*, 40–47.
33. Almutiry, O.; Wills, G.; Alwabel, A. Toward a framework for data quality in cloud-based health information system. In Proceedings of the 2013 International Conference on Information Society (i-Society), Toronto, ON, Canada, 24–26 June 2013; pp. 153–157.
34. Arts, D.G.; De Keizer, N.F.; Scheffer, G.J. Defining and improving data quality in medical registries: A literature review, case study, and generic framework. *J. Am. Med. Inform. Assoc.* **2002**, *9*, 600–611.
35. Taggart, J.; Liaw, S.T.; Yu, H. Structured data quality reports to improve EHR data quality. *Int. J. Med. Inform.* **2015**, *84*, 1094–1098.
36. Botsis, T.; Hartvigsen, G.; Chen, F.; Weng, C. Secondary use of EHR: Data quality issues and informatics opportunities. *Summit Transl. Bioinform.* **2010**, *2010*, 1–5.
37. Kahn, M.G.; Raebel, M.A.; Glanz, J.M.; Riedlinger, K.; Steiner, J.F. A pragmatic framework for single-site and multisite data quality assessment in electronic health record-based clinical research. *Med. Care* **2012**, *50*, S21–S29.
38. Ryzhov, A.; Bray, F.; Ferlay, J.; Fedorenko, Z.; Goulak, L.; Gorokh, Y.; Soumkina, O.; Znaor, A. Evaluation of data quality at the National Cancer Registry of Ukraine. *Cancer Epidemiol.* **2018**, *53*, 156–165.
39. Rasta, K.; Nguyen, T.H.; Prinz, A. A framework for data quality handling in enterprise service bus. In Proceedings of the 2013 Third International Conference on Innovative Computing Technology (INTECH), London, UK, 29–31 August 2013; pp. 491–497.
40. Ringler, A.; Hagerty, M.; Holland, J.; Gonzales, A.; Gee, L.; Edwards, J.; Wilson, D.; Baker, A. The data quality analyzer: A quality control program for seismic data. *Comput. Geosci.* **2015**, *76*, 96–111.
41. Chen, W.; Zhou, K.; Yang, S.; Wu, C. Data quality of electricity consumption data in a smart grid environment. *Renew. Sustain. Energy Rev.* **2017**, *75*, 98–105.

42. Jabareen, Y. Building a conceptual framework: philosophy, definitions, and procedure. *Int. J. Qual. Methods* **2009**, *8*, 49–62.
43. Schutt, R.; O'Neil, C. *Doing Data Science: Straight Talk from the Frontline*; O'Reilly Media, Inc.: Sevan Fort, CA, USA, 2013.
44. Corrales, D.; Ledezma, A.; Corrales, J. *A Systematic Review of Data Quality Issues in Knowledge Discovery Tasks*; Revista Ingenierias Universidad de Medellin: Medellin, Colombia, 2016; Volume 15.
45. Aydilek, I.B.; Arslan, A. A hybrid method for imputation of missing values using optimized fuzzy c-means with support vector regression and a genetic algorithm. *Inf. Sci.* **2013**, *233*, 25–35.
46. Hawkins, D.M. *Identification of Outliers*; Springer: London, UK, 1980; Volume 11,
47. Barnett, V.; Lewis, T. *Outliers in Statistical Data*; Wiley: New York, NY, USA, 1994; Volume 3.
48. Johnson, R.A.; Wichern, D.W. *Applied Multivariate Statistical Analysis*; Prentice-Hall: Upper Saddle River, NJ, USA, 2014; Volume 4.
49. Khalid, S.; Khalil, T.; Nasreen, S. A survey of feature selection and feature extraction techniques in machine learning. In Proceedings of the Science and Information Conference (SAI), London, UK, 27–29 August 2014; pp. 372–378.
50. Tang, J.; Alelyani, S.; Liu, H. Feature selection for classification: A review. In *Data Classification: Algorithms and Applications*; CRC Press: Boca Raton, FL, USA, 2014; p. 37.
51. Bosu, M.F.; MacDonell, S.G. A Taxonomy of Data Quality Challenges in Empirical Software Engineering. In Proceedings of the 2013 22nd Australian Software Engineering Conference, Melbourne, Australia, 4–7 June 2013; pp. 97–106.
52. Xiong, H.; Pandey, G.; Steinbach, M.; Kumar, V. Enhancing data analysis with noise removal. *IEEE Trans. Knowl. Data Eng.* **2006**, *18*, 304–319.
53. Chandola, V.; Banerjee, A.; Kumar, V. Anomaly Detection: A Survey. *ACM Comput. Surv.* **2009**, *41*, 15:1–15:58.
54. Aljuaid, T.; Sasi, S. Proper imputation techniques for missing values in data sets. In Proceedings of the 2016 International Conference on Data Science and Engineering (ICDSE), Cochin, India, 23–25 August 2016; pp. 1–5.
55. Strike, K.; Emam, K.E.; Madhavji, N. Software cost estimation with incomplete data. *IEEE Trans. Softw. Eng.* **2001**, *27*, 890–908.
56. Grzymala-Busse, J.W.; Hu, M. *A Comparison of Several Approaches to Missing Attribute Values in Data Mining*; Ziarko, W., Yao, Y., Eds.; Rough Sets and Current Trends in Computing; Springer: Berlin/Heidelberg, Germany, 2001; pp. 378–385.
57. Magnani, M. Techniques for Dealing With Missing Data in Knowledge Discovery Tasks. Available online: https://www.researchgate.net/profile/Matteo_Magnani/publication/228748415_Techniques_for_dealing_with_missing_data_in_knowledge_discovery_tasks/links/00b49521f12e9afa98000000.pdf (accessed on 1 March 2018).
58. Breunig, M.M.; Kriegel, H.P.; Ng, R.T.; Sander, J. LOF: Identifying density-based local outliers. In Proceedings of the ACM Sigmod Record, Dallas, TX, USA, 15–18 May 2000; Volume 29, pp. 93–104.
59. Ester, M.; Kriegel, H.P.; Sander, J.; Xu, X. A density-based algorithm for discovering clusters in large spatial databases with noise. In *KDD-96 Proceedings*; AAAI Press: Menlo Park, CA, USA, 1996; pp. 226–231.
60. Kriegel, H.P.; Zimek, A.; Hubert, M.S. Angle-based outlier detection in high-dimensional data. In Proceedings of the 14th ACM SIGKDD International Conference On Knowledge Discovery and Data Mining, Las Vegas, NV, USA, 24–27 August 2008; pp. 444–452.
61. Fayyad, U.M.; Piatetsky-Shapiro, G.; Smyth, P. *Advances in Knowledge Discovery and Data Mining*; Chapter from Data Mining to Knowledge Discovery: An Overview; American Association for Artificial Intelligence: Menlo Park, CA, USA, 1996; pp. 1–34.
62. Ladha, L.; Deepa, T. Feature Selection Methods And Algorithms. *Int. J. Comput. Sci. Eng.* **2011**, *3*, 1787–1797.
63. Chandrashekar, G.; Sahin, F. A survey on feature selection methods. *Comput. Electr. Eng.* **2014**, *40*, 16–28.
64. Blum, A.L.; Langley, P. Selection of relevant features and examples in machine learning. *Artif. Intell.* **1997**, *97*, 245–271.
65. Jolliffe, I. *Principal Component Analysis*; Wiley Online Library: New York, NY, USA, 2002.
66. Huang, L.; Jin, H.; Yuan, P.; Chu, F. Duplicate Records Cleansing with Length Filtering and Dynamic Weighting. In Proceedings of the 2008 Fourth International Conference on Semantics, Knowledge and Grid, Beijing, China, 3–5 December 2008; pp. 95–102.

67. John, G.H.; Kohavi, R.; Pfleger, K. Irrelevant Features and the Subset Selection Problem. In Proceedings of the Eleventh International Machine Learning, Morgan Kaufmann, New Brunswick, NJ, USA, 10–13 July 1994; pp. 121–129.
68. Guyon, I.; Gunn, S.; Nikravesh, M.; Zadeh, L.A. *Feature Extraction: Foundations and Applications (Studies in Fuzziness and Soft Computing)*; Springer: New York, NY, USA, 2008.
69. Sánchez-Maroño, N.; Alonso-Betanzos, A.; Tombilla-Sanromán, M., Filter Methods for Feature Selection—A Comparative Study. In *Intelligent Data Engineering and Automated Learning—IDEAL 2007 8th International Conference, Birmingham, UK, 16–19 December 2007*; Yin, H., Tino, P., Corchado, E., Byrne, W., Yao, X., Eds.; Springer: Berlin/Heidelberg, Germany, 2007; pp. 178–187.
70. Urbanek, S. Package 'Rserve' Manual. 2012. Available online: https://cran.r-project.org/web/packages/Rserve/Rserve.pdf (accessed on 1 March 2018).
71. Team, R.C. R: A Language and Environment for Statistical Computing. Available online: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.470.5851&rep=rep1&type=pdf (accessed on 1 March 2018).
72. Stekhoven, D. Package 'missForest' Manual. 2016. Available online: https://cran.r-project.org/web/packages/missForest/missForest.pdf (accessed on 1 March 2018).
73. Hu, Y.; Murray, W.; Shan, Y. Package 'Rlof' Manual. 2015. Available online: https://cran.r-project.org/web/packages/Rlof/Rlof.pdf (accessed on 1 March 2018).
74. Hennig, C. Package 'fpc' Manual. 2018. Available online: https://cran.r-project.org/web/packages/fpc/fpc.pdf (accessed on 1 March 2018).
75. Romanski, P.; Kotthoff, L. Package 'FSelector' Manual. 2016. Available online: https://cran.r-project.org/web/packages/FSelector/FSelector.pdf (accessed on 1 March 2018).
76. Singh, K.; Kaur, R.; Kumar, D. Comment Volume Prediction Using Neural Networks and Decision Trees. In Proceedings of the 2015 17th UKSIM'15 UKSIM-AMSS International Conference on Modelling and Simulation, IEEE Computer Society, Washington, DC, USA, 25–27 March 2015; pp. 15–20.
77. Ho, T.K. Random decision forests. In Proceedings of the IEEE Third International Conference on Document Analysis and Recognition, Montreal, QC, Canada, 14–16 August 1995; Volume 1, pp. 278–282.
78. Faubel, F.; McDonough, J.; Klakow, D. Bounded conditional mean imputation with Gaussian mixture models: A reconstruction approach to partly occluded features. In Proceedings of the ICASSP 2009 IEEE International Conference on Acoustics, Speech and Signal Processing, Taipei, Taiwan, 19–24 April 2009; pp. 3869–3872.
79. Zhao, Y. *R and Data Mining: Examples and Case Studies*; Academic Press: San Diego, CA, USA, 2012.
80. Castillo, E.F.; Gonzales, W.F.; Corrales, D.C.; Lopez, I.D.; Hoyos, M.G.; Figueroa, A.; Corrales, J.C. Water quality warnings based on cluster analysis in Colombian river basins. *Sist. Telemat.* **2015**, *13*, 9–26.
81. Erman, J.; Arlitt, M.; Mahanti, A. Traffic Classification Using Clustering Algorithms. In Proceedings of the 2006 MineNet'06 SIGCOMM Workshop on Mining Network Data, Pisa, Italy, 11–15 September 2006; ACM: New York, NY, USA, 2006; pp. 281–286.
82. Bitton, D.; DeWitt, D.J. Duplicate Record Elimination in Large Data Files. *ACM Trans. Database Syst.* **1983**, *8*, 255–265.
83. Corrales, D.C.; Lasso, E.; Ledezma, A.; Corrales, J.C. Feature selection for classification tasks: Expert knowledge or traditional methods? *J. Intell. Fuzzy Syst.* **2018**.
84. Kuhn, M. Caret package. *J. Stat. Softw.* **2008**, *28*, 1–26.
85. Plackett, R.L. Karl Pearson and the chi-squared test. *Int. Stat. Rev./Rev. Int. Stat.* **1983**, *51*, 59–72.
86. Kent, J.T. Information gain and a general measure of correlation. *Biometrika* **1983**, *70*, 163–173.
87. Mitchell, T.M. *Machine Learning*; McGraw Hill: Burr Ridge, IL, USA, 1997; Volume 45; pp. 870–877.
88. Roobaert, D.; Karakoulas, G.; Chawla, N.V. Information gain, correlation and support vector machines. *Stud. Fuzziness Soft Comput.* **2006**, *207*, 463–470.
89. Coraddu, A.; Oneto, L.; Ghio, A.; Savio, S.; Anguita, D.; Figari, M. Machine learning approaches for improving condition-based maintenance of naval propulsion plants. *Proc. Inst. Mech. Eng. Part M* **2016**, *230*, 136–153.
90. Fanaee-T, H.; Gama, J. Event labeling combining ensemble detectors and background knowledge. *Prog. Artif. Intell.* **2014**, *2*, 113–127.
91. Candanedo, L.M.; Feldheim, V.; Deramaix, D. Data driven prediction models of energy use of appliances in a low-energy house. *Energy Build.* **2017**, *140*, 81–97.

92. Moro, S.; Rita, P.; Vala, B. Predicting social media performance metrics and evaluation of the impact on brand building: A data mining approach. *J. Bus. Res.* **2016**, *69*, 3341–3351.
93. Buza, K. Feedback Prediction for Blogs. In *Data Analysis, Machine Learning and Knowledge Discovery*; Spiliopoulou, M., Schmidt-Thieme, L., Janning, R., Eds.; Springer International Publishing: Cham, Switzerland, 2014; pp. 145–152.
94. Zamora-Martinez, F.; Romeu, P.; Botella-Rocamora, P.; Pardo, J. On-line learning of indoor temperature forecasting models towards energy efficiency. *Energy Build.* **2014**, *83*, 162–172.
95. Langley, P.; Blum, A.L. Selection of relevant features in machine learning. *Proc. AAAI Fall Symp. Relev.* **1994**, *184*, 245–271.
96. Guyon, I.; Elisseeff, A. An introduction to variable and feature selection. *Introd. Var. Feature Sel.* **2003**, *3*, 1157–1182.
97. Saeys, Y.; Inza, I.; Larrañaga, P. A review of feature selection techniques in bioinformatics. *Bioinformatics* **2007**, *23*, 2507–2517.
98. Da Silva Jacinto, A.; da Silva Santos, R.; de Oliveira, J.M.P. Automatic and semantic pre-Selection of features using ontology for data mining on data sets related to cancer. In Proceedings of the International Conference on Information Society (i-Society 2014), London, UK, 10–12 November 2014; pp. 282–287.