State of the Art on the Quality of Big Data: A Systematic Literature Review and Classification Framework

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Abstract
One of the most significant problems of Big Data is to extract knowledge through the huge amount of data. The usefulness of the extracted information depends strongly on data quality. In addition to the importance, data quality has recently been taken into consideration by the big data community and there is not any comprehensive review conducted in this area. Therefore, the purpose of this study is to review and present the state of the art on the quality of big data research through a hierarchical framework. The dimensions of the proposed framework cover various aspects in the quality assessment of Big Data including 1) the processing types of big data, i.e. stream, batch, and hybrid, 2) the main task, and 3) the method used to conduct the task. We compare and critically review all of the studies reported during the last ten years through our proposed framework to identify which of the available data quality assessment methods have been successfully adopted by the big data community. Finally, we provide a critical discussion on the limitations of existing methods and offer suggestions on potential valuable research directions that can be taken in future research in this domain.

Keywords
Big Data, Data Quality, Systematic Literature Review, Quality Assessment

1. Introduction
Recent developments in information and communication technology (ICT) have led to mass production of data by social networks, sensor networks, and other Internet-based applications of various domains like healthcare. The vast amount of data that is generated with high speed from various internet sources is called Big Data [1]. Recently, organizations have concluded that processing big data, especially the data coming from Twitter and Facebook can provide a significant impact on increasing the business's effectiveness and added values [2]–[6]. However, due to the exponential growth of the available data, traditional systems and methods are not able to meet the requirements for processing this data. In 2011, and in McKinney Global Institute report, three characteristics of data, i.e. Volume, Variety, and Velocity, which are called the 3 V’s, were introduced as the three major dimensions of big data [7]. In addition to these 3 V’s, two other dimensions are also introduced. These are Veracity and Value [8]–[10]. While it is clear that valuable information can be extracted through analysis of big data, the results of such an analysis are hardly reliable unless well-defined and proper verification and quality control mechanisms are applied on this data before it is used. As a result, the importance of data quality assessment in big data needs to be taken into consideration by both researchers and practitioners. For example, in the domain of Internet of things (IoT), which is an active area of big data production and consumption, the application scenarios include deployment of many sensors that should collect
the data. Quality aspects of the collected data in these networks should be at an appropriate level, but for different reasons, the data may have a low quality [11]. Since inadequate and inaccurate data creates serious problems, one of which is the incorrect decisions that organizations might make [12], big data quality assessment is one of the most critical challenges [13]. So without data quality assessment, organizations do not have a proper understanding of what happens on the market [14]. Figure 1 shows the significant problems caused by the poor quality of big data.

![Figure 1: Problems due to low quality (redrawn based on [14])](image)

As shown in Figure 1, low data quality may cause problems such as extra cost and allocating more time to reconcile data. California Independent System Operator (CAISO), which monitors the function of California's electric power system, stated that about 17% of the data received in 2011 had quality problems [15]. Also, IBM has reported that only one in three corporate executives trust their analytics results [16].

Moreover, a recent study has shown that low data quality costs the USA three trillion dollars per year [17]. It is also stated in [18] that two-thirds of European and American businesses are not able to unlock value from big data. All these reports emphasize the importance of assessing the data quality in the big data domain.

Data quality assessment is an essential prerequisite for data improvement, and the purpose of data quality evaluation is to determine the quality level of data [19]. Considering the importance of the data quality assessment in the big data era, we have decided to review the papers in this field to determine what methods have been proposed by different scholars and what challenges they encountered. For this purpose, we provided a Systematic Literature Review (SLR) to search and access high-quality papers in this era. Afterward, we have identified a research tree and various profiles that details of the methodology and results, which can provide useful information to other researchers interested in this field, are explained in the following sections.

The rest of the paper is organized as follows: motivation and research questions are mentioned in Section 2. In Section 3, related works has been explained and compared with the proposed method. Search methodology, which includes the planning and conducting phases, along with threats to validity is described in Section 4. In Section 5, the research tree obtained from the study of the papers is shown and explained. Studies related to stream processing in Section 6, batch processing in Section 7 and the hybrid methods in Section 8 are described. In Section 9, the results of the systematic review are presented and provide useful information to those researchers who are interested in the big data quality area. Challenges and future work in Section 10, and finally, Section 11 concludes the paper.

2. Motivation and Research questions

A systematic literature review (SLR) is a way to identify, interpret, and evaluate research topics related to particular research questions, phenomenon of interest or topic area. There are several reasons to conduct a SLR, most commonly are: 1- To collect comprehensive research topics in a specific field, 2-To summarize and review existing methods of a technology or concept, and 3- To express the gaps and challenges of a particular topic [20],[21]. The deficiency in
explored topics in the area of big data quality justifies a need to conduct a comprehensive systematic literature review. To our knowledge, there is no systematic literature reviews performed in the specific area of quality assessment methods in big data. Although some non-systematic review studies have been presented in this field, which we have compared them with the proposed method in Section 3.

One of the main parts of a systematic review is to identify the scope and the research questions. This study was conducted from April to September 2018, and papers that were available by September 2018 were reviewed. The primary purpose of the paper is to classify research topics, obtain information such as top authors, conferences and active countries on the subject of big data quality. Thus, the main research questions that we are trying to answer in this paper are the following:

**RQ1:** What are the main research topics in the area of Big Data Quality (BDQ)? Based on this research question, the following three sub-questions can be defined.

- What kind of methods, in terms of stream processing and batch processing, is used in the selected papers?
- What are the primary task of the proposed approach in the selected papers? For instance, is the paper intended only to detect poor quality data or it also tries to improve data quality by data cleaning techniques?
- What specific technique is used in each study to achieve the intended task?

This question will help future engagers to have a comprehensive picture of the categorization of BDQ methods and to easily examine existing techniques.

Section 5 will answer RQ1.

**RQ2:** Which researchers, research institutes and venues have been more active in publishing works related to the field of Big Data Quality? Are scholars still actively publishing papers in this area? What is the volume of studies presented each year on this topic?

This question will help researchers discover the most active venues and the most important topics in this field to do their future work.

RQ2 is answered in Section 9.

**RQ3:** What are the main open challenges in this field?

This question will help those who are willing to work in this area to identify and deal with the challenges and the existing gaps.

Section 10 will address challenges and future directions (i.e. RQ3).

### 3. Related Works

Prior to conducting this study, previous review papers were examined to ensure that the research questions defined are unique and have not been answered by previous studies. Given the fact that big data is a fairly new field, our analysis was performed on the scholarly papers published on this subject since 2007. Table 1 compares all review papers with the proposed systematic review.

| Ref   | Date  | Systematic | Number of studies | Number of citations* | Application Domain |
|-------|-------|------------|-------------------|----------------------|-------------------|
| [22]  | 2018  | No         | 26                | 2                    | General           |
| [23]  | 2018  | No         | 12                | 0                    | Temporal data    |
| [24]  | 2018  | No         | 14                | 1                    | General           |
| [25]  | 2017  | No         | 24                | 1                    | General           |
| [26]  | 2017  | No         | 17                | 9                    | WSN               |
| [27]  | 2016  | No         | 32                | 55                   | General           |
| [28]  | 2016  | No         | 21                | 4                    | General           |
| [29]  | 2016  | No         | 7                 | 1                    | General           |
| [30]  | 2016  | No         | 14                | 65                   | IoT               |
| [31]  | 2015  | No         | 6                 | 5                    | General           |
| [32]  | 2014  | No         | 125               | 363                  | Temporal data    |
| [33]  | 2013  | No         | 39                | 44                   | WSN               |
| [34]  | 2010  | No         | 16                | 630                  | WSN               |
| Our Method | 2019 | Yes     | 88                | N/A                  | General           |

* Conducted on Google Scholar on March 4, 2019

In [22], which is an unsystematic review paper, firstly, characteristics of big data and the relevant challenges are examined and then the recent methods for big data management are categorized and discussed from the perspective
of Big Data Value Chain, Big Data Management & Characteristics, Big Data Problems & Data Quality Issues, Data Quality, and Big Data Applications and Quality Improvements. Finally, solutions have been proposed, including fast, continuous, and online data quality assessment. The publication date is 2018 and the number of 26 papers are reviewed but none of the studies in 2018 have been covered.

In [23] outlier detection methods are divided into five categories: statistical, distance based, density based, sliding window based and clustering methods. In addition, some challenges in streaming outlier detection are mentioned which are: transient, notion of a timestamp, infinite, arrival rate, concept drift, and uncertainty. This article also did not have a systematic approach and reviewed the number of 12 papers, which the most recent published on 2013.

In [24] a review of outlier, anomaly and concept drift detection for data streams is presented. A different categorization is presented in [32], which is classified according to the type of data. Data types are time-series, stream, distributed, spatial-temporal and network. If the data type is a data stream, methods are classified into model-based, distance based and high-dimensional methods. The number of 14 studies that are published until 2016, are inspected.

The classification given in [25] has four categories and does not have a window-based category than the [23]. In [29], [31], the techniques in the data stream are divided into two groups based on clustering and outlier detection algorithms. Some available algorithms have been evaluated regarding the percentage of detection and the amount of memory usage and runtime. Challenges are divided into two groups of a single data stream and multiple data streams. In single data stream, all the challenges of [23] are mentioned and also multidimensional is added, then challenges in multiple data streams are cross-correlation, asynchronous data points, dynamic relationship, and heterogeneous schema.

Another similar classification is presented in [26], in which statistics, clustering, classification, artificial intelligence, and the nearest neighbor are in this classification. In this paper, there are some advantages and disadvantages of each category. It is said that statistical methods are efficient for single-variable data and cannot find the relationship between the multivariate data. The nearest neighbor based methods are simple, but it is costly to calculate the distance of multivariate data. Also, clustering algorithms are suitable for incremental environments and classification based methods are more expensive than other methods to calculate the corresponding criteria. The classification of outlier detection methods of the paper [34] is very similar to [26], there are spectral decomposition-based approaches instead of AI-based methods. In this category, normal data is obtained by the PCA algorithm.

The presence of preprocessing algorithms for data mining in big data are reviewed in this paper [27]. Definitions, characteristics, and categorization of big data methods are also outlined. The relationship between big data and preprocessing data is also investigated, including a review of the state-of-the-art.

In [30], first, the characteristics of data and data quality dimensions on the Internet of things are pointed out, then the impact of important factors in reducing the quality of data on these dimensions has been investigated and ultimately, data quality assessment methods are described from the perspective of the data cleaning and methods have been compared in terms of technique, scope, data stream type and data characteristics.

In [31], a hybrid method is also proposed. A different categorization is presented in [28]. In this paper, in addition to the statistical, clustering, classification and similarity-based methods, there are also soft computing, knowledge-based and combination learners.

In [33] first, the anomaly detection requirements in the sensor network are described, where data reduction, distributed detection, online detection, correlation exploitation, and adaptive detection are part of requirements. Then there are challenges to detect anomalies in the sensor network, such as resource constraints, communication overhead, dynamic network topology, and so forth. Besides, methods classification is provided for detecting anomalies in the sensor network, which includes statistics based, clustering based, nearest neighbor based, and classification based methods. The advantages and disadvantages of each one are mentioned, and they are the same as [26].

In addition to the above review papers, there are 11 studies that address the challenges and needs but have not reviewed any related papers that we will review them below.

There are various quality models available to assess the quality of the data. Researchers continue to suffer from the lack of a standardized model for the assessment of big data quality. So, in this paper [35], a quality model for big data that has been claimed to be integrated with any big data project is introduced. This model places the quality dimensions in three categories Contextual Adequacy, which is used in a specific area, Operational Adequacy, which means...
accessibility of data, and Temporal Adequacy. The appropriate time to analyze data. Accordingly, the 15 dimensions of quality referred to in ISO/IEC 25012 have been assigned in these three categories.

In this paper [36], first, big data characteristics and their definitions are expressed. Then the challenges associated with big data, especially data quality, have been reported. For example, challenges such as heterogeneity, incompleteness, incompatibility, diversity of data sources, lack of structure, lack of standardization in data quality, security, authenticity, etc., are mentioned.

In this paper [37], a preliminary study was initially presented to develop a conceptual model for describing the effects of data quality in the Big Data area. Also, the relationship between big data characteristics and data quality is discussed in the proposed model.

This paper [38] offers discussions for big data quality assurance. Some of these challenges are big data management and big data processing. Also, it provides a comparative on big data validation tools. Different tools are compared in terms of the function environment, supported data source and essential data validation functions.

This study [39] focuses on several factors that affect the quality of big data at various levels, including collection, processing, and storage. The purpose of these case studies is to provide information on issues related to the quality of the various data related to the design, implementation, and operation of large data plans.

The authors have identified data quality issues during data acquisition, storage, preprocessing, and analysis of big data processing in [40]. Some of these issues are noisy data, data sparseness, limitations of storage, timeliness, incomplete data, scalability and accuracy. In the end, there are also solutions to the challenges mentioned. For example, using clustering algorithms in order to complete data, Cloud Storage to deal with storage limitation and Spark platform to speed up the processing.

This paper [41] provides a perspective on data quality challenges in big data. Five quality dimensions that are mentioned are confidence, accuracy, completeness, timeliness and volume. In the following, some of the challenges in this area are mentioned.

The paper [42] describes the general description and some tutorials of how to handle data quality in big data as well as existing problems such as how to assess data quality in a distributed and real-time manner.

The authors of this paper [43] point to the development of data quality problems from small data to big data. Also examines the relationship between data quality and topics that are related to big data such as data type diversity, semi-structured data, data sources, linked open data and sensors.

Data quality management involves specifying dimensions, metrics, data quality rules, data profiling and, finally, data cleaning. This paper [44] discusses how data quality is managed, as well as the challenges in data quality associated with big data. These issues include computational complexity, volume, variety, and online cleaning.

This paper [45] analyzes the characteristics of big data, also examines the quality challenges such as volume, variety, and velocity. Ultimately, authors provide an abstract model for data quality assessment, which the goals and quality dimensions are first defined, then the indicators of each dimension are taken into account and when data comes, are cleaned, and the report is generated.

Finally, we find that the publication date of studies [22]–[24] is 2018, but these papers do not cover the studies of this year. Paper [23], mentions the researches until 2013, paper [24] discuss the studies published until 2016, and finally, paper [22] cover the publications until 2017, and the proposed method is the only paper that covers topics of 2018.

Paper [32] explains further studies than the proposed paper that in our method, each of the 88 studies is described individually, but in [32], sometimes more than ten references are included in a paragraph. Number of citations is another important criterion for recognizing the goodness of a study. By examining the values of this column, we find that papers [32], [34] have the highest number of citations, but none of them has covered the recent year studies.

Domain application is another factor, which means that if the domain of paper is not explicitly stated, it is General and otherwise, it is mentioned in the table. Most studies do not specify a domain, and therefore the "general" is added for them.

Therefore, the proposed method is the only systematic review study available on the subject of big data quality that reviews the most recent and most relevant papers. Also, we have identified a research tree and various profiles, which can provide useful information to other researchers interested in this field.
4. Search Methodology

The methods [46], [47] are employed in order to conduct the presented SLR. In addition to the research tree and the obtaining of information on various profiles, the papers of the big data quality domain have also been reviewed and compared. Our proposed process has two main steps: 1. Planning and 2. Conducting. Details of our method are discussed below.

4.1. Planning Phase

The first step in the systematic review is planning. In this phase, decisions and the requirements of the method that are relevant to the conducting phase are specified. Figure 2 shows the planning process of systematic review.

![Figure 2: Planning the Systematic Review](image)

As shown in Figure 2, this process has five steps: 1) specifying the scope and keywords, 2) specifying the search engines, 3) specifying related conferences and journals, 4) specifying inclusion and exclusion criteria, and 5) planning the data extraction. Next, we discuss each step separately.

4.1.1. Specifying the scope and keywords

One of the main parts of a systematic review is to identify the scope and the research questions. This study was conducted from April to September 2018, and papers that were available by September 2018 were reviewed. The primary purpose of the paper is to classify research topics, obtain information such as top authors, conferences and active countries on the subject of big data quality. After identifying the “Big Data Quality” as the target scope, and in order to answer the research questions, we have selected the following keywords, which is based on the experiences of the authors:

\((\text{Real-time OR distributed OR context-aware OR ‘’}) \text{ AND (streaming data OR Internet of things (IoT) OR Big data)} \text{ AND (quality OR assessment OR evaluation OR methodology OR improvement OR preprocessing OR cleaning OR outlier detection OR anomaly detection)})\)

4.1.2. Specifying the search engines
After selecting the search keywords, we need to select a list of search engines to access the papers by searching the keywords in them. These engines include Google Scholar\(^1\), ACM Digital Library\(^2\), IEEE Xplore Digital Library\(^3\), Springer Link\(^4\), Science Direct\(^5\), and DBLP\(^6\).

In order to find out more precisely the dissertations and theses, a number of relevant search engines are also listed which are: ProQuest\(^7\), OATD\(^8\), and California State University Library\(^9\).

### 4.1.3. Specifying related conferences and journals

To reduce the risk of missing some related works due to reliance on specified search engines, we have selected a list of related conferences and journals and have accessed their published papers through their web sites. In Table 2 the desired conferences and journals list is provided. The authors’ experience has been the main reason for choosing these conferences and journals.

| Conferences                                                                 |                                                                 |
|----------------------------------------------------------------------------|-----------------------------------------------------------------|
| International Conference on Information Quality (ICIQ)                     | CDOIQ Symposium                                                 |
| The Data Governance and Information Quality Conference                     | IEEE International Conference on Big Data                      |
| IEEE Big Data Congress                                                     | International Congress on Internet Of Things (ICIOT)           |
| ICDM 2018: IEEE International Conference on Data Mining                   | Quality of Information and Communications Technology (QUATIC)   |
| Quality Aspects in Big Data Systems (QABiD)                               | International Conference On Big Data, IoT And Data Science      |
| International Conference On Machine Learning and Big Data (ICMLB)         | Workshop on Quality of Open Data (QOD)                         |

| Journals                                                                  |                                                                 |
|--------------------------------------------------------------------------|-----------------------------------------------------------------|
| Journal of Healthcare Quality                                            | Journal of Data and Information Quality (JDIQ)                  |
| The International Journal on Very Large Data Bases (VLDB)               | The International Journal on Large Data Bases (LDB)            |
| International Journal of Sensor Networks                                  | International Journal of Information Quality                   |
| IEEE Sensors Journal                                                      | ACM Transactions on Sensor Networks                             |
| IEEE Transactions on Knowledge and Data Engineering                      | IEEE Transactions on Knowledge Discover from Data              |
| Data Mining and Knowledge Discovery                                       | ACM Transactions on Knowledge Discovery from Data              |
| IEEE Network                                                              | Computer Communications                                        |
| Advances in Data Analysis and Classification                              | Computer Networks                                             |
| ACM Transactions on Knowledge Discovery from Data                        | Wireless Networks                                             |
| Computer Communications                                                   | Wireless Personal Communications                               |
| Ad Hoc Networks                                                          | Journal of Network and Computer Applications                   |
| Journal of Network and Computer Applications                              | Big Data Research                                             |

### 4.1.4. Specifying inclusion and exclusion criteria

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\(^1\) https://scholar.google.com
\(^2\) https://dl.acm.org/
\(^3\) https://ieeexplore.ieee.org/Xplore/home.jsp
\(^4\) https://link.springer.com/
\(^5\) https://www.sciencedirect.com/
\(^6\) https://dblp.uni-trier.de/
\(^7\) https://pqdtopen.proquest.com/search.html
\(^8\) https://oatd.org/
\(^9\) https://csulb.libguides.com/dissertations
To determine which studies help answer our research questions, we need to define two categories of criteria. The first category is inclusion criteria, that is, the characteristics that the papers must have, and the second category is exclusion criteria, which denotes the characteristics that the papers must not have. If a study has at least one exclusion criterion, it will be removed from the list of appropriate studies. In Table 3 and Table 4 a list of inclusion and exclusion criteria is provided.

### Table 3: Inclusion criteria for determining the papers for the study.

| Inclusion criteria                                                                 | Rationale                                                                                   |
|----------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|
| Papers published between 2007 to 2018                                            | Because the scope has recently attracted the attention of researchers, only studies from a recent decade have been reviewed. |
| Either stream or batch processing                                                 | Since data can be generated in real time, in addition to batch (static) data, studies that use streaming data are also considered. |
| Papers where the search terms were found in the title and/or abstract             | Because the purpose of this paper is to assess quality of big data, the keywords should appear in the queried papers title or abstract. |
| Papers where the full text is available                                          | If the full text is not available, then there is no information to examine. |

### Table 4: Exclusion criteria for filtering out papers from the study.

| Exclusion criteria                                                                 | Rationale                                                                                   |
|----------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|
| Papers shorter than four pages                                                    | Since short papers do not provide useful, reliable, and accurate information, these types of studies, with less than four pages, have not been considered. |
| Papers having focused on unstructured data                                       | The focus of the method is on structured or semi-structured data, and studies that include un-structured data such as images, videos, etc. are deleted. |
| Studies outside the big data quality scope                                       | For example, in a paper, the data stream may be used as target data, but there is no focus on quality assessment, or in another study, the quality evaluation is considered, but no attention is paid to the big data. In this SLR, studies with the purpose of both big data and quality assessment, which is big data quality, are considered, and each one alone cannot help us to find the related and appropriate papers. |
| Papers that only aim to detect anomalies (the main purpose is not quality)       | Sometimes papers are presented that aim to find abnormal patterns that do not pay attention to clean, preprocess, or quality assessment, and only identify abnormal and possibly malicious patterns. These types of studies that do not focus on improving data quality are also excluded from the final papers pool. |

### 4.1.5. Planning the data extraction

To extract the data from the selected papers, we have prepared a list of required items. Table 5 lists these items and the reason for their selection. Regarding the systematic review, if there is a paper in the pool of studies, it should be thoroughly reviewed and, if confirmed, the required data is extracted based on the items mentioned in this table.

### Table 5: Extracted items and usages

| Item                                                                 | Usage                  |
|---------------------------------------------------------------------|------------------------|
| Paper Name, Doi, Volume, Number, Month, Pages, Publisher            | To describe the paper  |
| Processing type (Stream, Batch, Hybrid), Online or Offline, Task (detection, evaluation, cleaning), Quality dimensions (accuracy, completeness, etc) Technique (context-aware, learning based, etc) | To answer RQ1          |
| Authors name, Countries, Affiliation, Domain, Year, Paper type (conference, journal, theses, chapter) | To answer RQ2          |
| Challenges and needs                                                | To answer RQ3          |
| Keywords and Citations                                              | To do conducting phase |

In addition to the items mentioned in Table 5, after thoroughly studying the relevant papers, the challenges of each area are also extracted to answer the third research question. The next step of the systematic review is the conducting phase, which is explained in the next section.
4.2. Conducting Phase

After identifying the search strategy and related requirements, they must be applied to the conducting step. Conducting the presented systematic review has three phases that the number of papers obtained from each phase is shown in Figure 3.

In the first phase, the keywords defined in Section 4.1.1 are searched in both in the search engines defined in 4.1.2 and the related conferences and journals described in 4.1.3. Papers are filtered by year and those that are before the year 2007 not considered. Then the title of the paper is inspected and if the paper has a related title, it will be added to Mendeley software. Otherwise, it will not be considered. At this phase, 346 studies are obtained, of which 15 are theses.

In the second phase of conducting the systematic review, the studies are examined more precisely. In this phase, the abstract, the keywords, and the citations for each of the 346 papers are re-evaluated. If, after reviewing the abstract and the keywords as well as applying the inclusion and exclusion criteria, we conclude that the study is appropriate, it is selected for reviewing thoroughly. Also, the first conducting phase is applied to citations, and if the title of the paper is appropriate, the paper will be added to Mendeley in the current phase. A number of 58 studies were added to the Mendeley after inspecting the title of each citation, and finally, a number of 154 papers were included in the papers pool to be adequately studied.

The final phase of conducting the systematic review is the complete study of the papers. In this phase, all papers in the papers pool are thoroughly studied. If after a complete study of the paper and applying the inclusion and exclusion criteria, we conclude that the paper is appropriate, the items mentioned in Table 2 are extracted from the corresponding study. References and authors of the papers are also reviewed separately. If the reference is appropriate for study, it will be selected. Also, if other authors’ publications are on social networks like ResearchGate, Google Scholar and DBLP, their relevant papers are selected and reviewed, and if it is appropriate, it will be added to the final pool. Inspecting the authors on academic social pages is one of the innovations of the systematic review presented in this paper. The active authors of this field can also be accessed by this method. We can also access new papers if we have not already seen them. A number of 15 studies have been obtained by inspecting the references and authors. A total of 170 papers were thoroughly studied, and data from the number of 88 papers have been extracted, and the results are discussed in the next section.

4.3. Threats to Validity

There are some threats can affect the quality of this SLR, including review process, primary paper selection, and data extraction, which are addressed in this section.

4.3.1. Review process

The review process is the first threat, and one of the available guidelines should be used to deal with it. Various guidelines and references have been provided including the review and search process listed in [47]–[49], which [47] was selected as primary source of guidance.
4.3.2. Primary paper selection
To prevent selection bias, studies were searched in Google Scholar, ACM Digital Library, IEEE Xplore Digital Library, Springer Link, Science Direct, and DBLP. To reduce the risk of missing some related works due to reliance on specified search engines, we have selected a list of related conferences and journals (Table 2) and have accessed their published papers through their web sites. Also, in order to find out more precisely the dissertations and theses, a number of relevant search engines were listed which are: ProQuest, OATD, and California State University Library. Searching for studies in multiple databases can reduce the effect of paper selection threat.

4.3.3. Data extraction
In order to prevent data extraction bias, as stated in [47], different authors should conduct data extraction independently. The results from the researchers should be compared to reach a consensus. In this paper, the authors have also analyzed and compared the results in various sessions in order to reach the final conclusion and deal with the threat.

5. Research Tree
After studying all the selected papers, we have analyzed the data that has been extracted, and we have obtained the research tree shown in Figure 4. Through analysis of this research tree, it is possible to answer the first research question, i.e., RQ1.

Figure 4: Big Data Quality Research Tree
As it is shown in the research tree, at the first level, the studies are divided, based on their processing model, into three groups of Stream processing (Online), Batch processing (Offline), and Hybrid. Papers that assess big data quality only on streaming data have been considered in the first category. Moreover, papers that only use stored data for this purpose, are in the second group, and ultimately, the works which process both stored and streaming data are in the third category.

At the second level, the task of the selected papers has been examined. After scrutinizing the papers, we found that they all pursued one of the Outlier detection, Evaluation, and Cleaning, and provided an algorithm for achieving the desired task. The studies presented in the field of outlier detection tend to find abnormal data and further delete or modify it to clean up their datasets and enhance data quality. Also, papers presented with the aim of evaluating, assess their datasets using their quality dimensions and eventually report to the user. These type of papers do not change the datasets and merely examine the quality of the data. Finally, the papers that are in the area of cleaning have corrected dirty data, so that the decision-making process is done correctly.

At the last level of the research tree, the technique used in the paper is considered. The techniques that are used for the tasks of outlier detection and cleaning are very similar. These techniques include Learning-based, Rule-based, Context-aware, Model-based and Distance-based. Learning based methods use clustering or classification algorithms in order to enhance big data quality. Rule-based methods use a set of rules, for example, which strategy should be adopted when duplicate data is viewed, to achieve the desired goal. Generally, experts define these rules in order to increase the quality of data. Studies that use Context-aware technique, in addition to existing data, also use related and context data to detect and clean up data sets more accurately. Another existing technique is Model-based technique in which a model is first constructed from the previously observed data, and then this model is used to predict the new incoming data. Finally, the Distance-based methods use a distance measure such as Euclidian to measure the distance between different data with the purpose of identifying outlier data, i.e., data that its distance to other data distinguishes it from normal data. In these methods, after calculating the distance criterion, the density of data may be estimated for the detection of the outliers, which are also included in this classification.

In the Evaluation category, the papers are divided into the Schema based and Instance-based techniques. In Schema-based, methods use the constraints that are defined in the schema of data to evaluate the quality of data. For example, if there is a constraint stating that the value of the data should not be negative if negative data is observed, it will be considered as dirty data. On the other hand, since data schema may not be available, in Instance-based methods the constraints can be obtained by analyzing and examining the existing data and trying to identify the required constraints.

6. Stream Processing Methods

Stream processing methods are discussed in this section. As described in Figure 5, these methods are divided into three categories: outlier detection, evaluation, and cleaning.
Table 6 presents the list of selected papers, in terms of each technique in the stream processing.

| Model-based | Detection | Evaluation | Cleaning |
|--------------|-----------|------------|----------|
| Learning based | [50]–[55] | [56]–[61] |          |
| Distance-based | [11], [62]–[65] | [66] |          |
| Context aware | [74], [75] | [76]–[78] |          |
| Instance-based | | [79]–[84] |          |

In the following, the related papers are carefully examined, according to the technique used.

### 6.1. Outlier Detection Task

The papers in this category are divided into four sub-categories: Model-based, Learning-based, Distance based, and Context-aware.

#### 6.1.1. Model-based techniques

First, we explain the Model-based papers. There are six papers in this sub-category, which the common feature of all of them is to use data to build a model and predict future data based on the model to detect outliers. A spatial-temporal analysis based approach is presented in [50]. First, a temporal-based method (TOD) is proposed for detecting outliers. In this way, each sensor analyzes its data in terms of time and predicts the next value. Then, if the new data is far from the predicted value, it will be considered as an outlier. In the second method, data are analyzed for spatial analysis (SOD). In this way, the sensor data of the neighbors is examined and then the model is constructed and eventually the new value is predicted. In the third method, which combines the two previous methods (TSOD), the data in a sensor network is initially investigated by each sensor in terms of the temporal analysis. Subsequently, by receiving data from its neighbors, the spatial analysis is also done, and ultimately, the outlier is denoted. The evaluations are conducted in terms of accuracy, model complexity, and false positive rate. The results show that TOD, even though the communication complexity is low, obtains incorrect results. SOD, although predicting the correct results, but the communication complexity is exceptionally high, and in the TSOD, there is a right balance between these two criteria.

Another model-based method is presented in [51] to detect anomalies in the data stream. The proposed method has four main steps; in the first step, a predictive model predicts new data. The prediction algorithm can be the nearest cluster, single-layer linear network or multilayer perceptron. In these algorithms, there are some q data for constructing a model and predicting new data and specifying a range. When viewing new data, that data is compared with the predicted value and the allowed range. If it is outside of this range, data is anomalous. Otherwise, the data is normal.

In the following, the values of the q data must be updated to provide further data prediction. There are two strategies in this situation. If we add the new anomaly data to the data set, the strategy is AD, and if we add the predicted value to the data set, then we have adopted the ADAM. In order to evaluate, wind speed data has been used, and q is equal to 30, that is, from the last 30 data, the new data is predicted. The efficiency and accuracy of the mentioned algorithms have been evaluated. The ADAM strategy has been able to reduce the false positive rate of algorithms LN and MLP, but using this strategy has a negative impact on the performance of algorithms.

In [52], the method presented in [85] is developed. In [85], the IF (Iterative Filtering) algorithm is used to model data. This algorithm predicts new data, along with weight, based on a data model. Since IF-based algorithms use the entire data in order to improve the prediction accuracy, they are suitable for static data. This paper attempts to apply this method to streaming data. For this purpose, the first window data is used by the IF algorithm to construct the model. Then, if the new data differs from the measured variance, it is an outlier. In addition, it is said that if the number of outliers exceeds the normal data, the model is wrong and should be updated. The prediction accuracy, as well as the number of reconstruction of the model in the proposed model and the IF, have been evaluated. The results show that the proposed method has been able to have a better result in the streaming environment.

PCA based methods are presented in [53], [54], which have mutual authors, to detect the outliers of each sensor. In [53] first, each sensor builds its model with a PCA algorithm locally. Then the model is sent to cluster head, and the cluster head combines local models and builds a global model then sends it back to the sensors. Each sensor updates its model after receiving the global model, and when the new data comes, the data that is far from the threshold is considered as an outlier. In [54] only local model is provided, and there is no global and distributed model. The accuracy, the false positive rate, and the detection rate are used for evaluation, which results in many tests show an
accuracy of at least 97%. Paper [55], similar to [53], uses local and global models. In this paper, the model is based on the SVM algorithm, and, unlike [53], which transmits the model from the sensors to the cluster head, the model is sent from each sensor to its neighbors. The false positive rate are evaluated in this paper, which has a good false positive rate and a better detection rate than other methods. Next, we explain the Learning-based methods.

6.1.2. Learning based techniques
There are five papers in this sub-category, the first four papers are based on clustering, and the last one is based on classification.
A distributed clustering approach is presented in [62], which has six components. The first one is called System Adapter and is responsible for registering and executing the system. Event Extractor is the second component and is responsible for reading incoming events, setting a timestamp for each data and adding metadata to it. The third component, Central Splitter, distributes the data to existing nodes in order to make it scalable. Next, the k-means clustering algorithm is responsible for grouping the data and finding the cluster center. Then, the Markov model is used to detect outliers. This algorithm considers data outside of each cluster as an outlier. Finally, in Ordering Operator, the collected data is merged and then sent to the sink. Both parallel and sequential implementations are considered. Latency and throughput are evaluated, and the results indicate that the distributed algorithm has lower latency and higher efficiency.
The paper [63] also used the k-means clustering and Markov model to detect anomalies like [62]. The difference is that the input data is in triple format (RDF) and must first be parsed and then enter the window. In the end, the output must also be transformed into a triple form. The latency of the proposed method in multi-threaded mode has been evaluated that the system with four threads has been able to have good performance.
Another clustering-based approach is presented in [64]. First, the received signal is converted into a data format that can be preprocessed. Then the k-means algorithm groups data, moreover the HMM and PSO algorithms are used to optimize the parameters, and ultimately, new data is predicted. The average prediction rate is evaluated, and results show improvement of the proposed method in prediction accuracy.
The last clustering method, which has several innovations, is presented in [65]. First, an adaptive distance-based algorithm called SOStream is presented. Also, an online spatiotemporal clustering algorithm, called ASMM is proposed, which is capable of dynamically adjusting its clustering structure based on the incoming data. In this clustering, by observing the new data, its Euclidean distance is compared with the centroids of the existing cluster, and the closest one is chosen. If the distance of the selected centroids is less than the desired threshold, then the data is transferred to that cluster and otherwise returned to the input buffer. If the number of data transfers to the buffer exceeds the threshold, then that data is considered as an outlier. The algorithm is tested with different real-life datasets. The results show that ASMM outperformed both EMM and LOF regarding different confusion matrix measures.
In [11], which is a classification method, eigenvectors and eigenvalues are obtained by PCA, and data with a low eigenvalue is considered as an outlier. Then, the sensors that generate the outlier must be detected, which Bayesian Network is used for this purpose to identify the relationship between the sensors and find the corresponding sensors. The dependencies between sensors and anomaly detection rate are evaluated, and the results show that the proposed method can improve the precision of anomaly detection.

6.1.3. Distance-based techniques
There are seven papers that the first three papers are distance-based and the last four one is density-based. As previously mentioned, density based methods are also considered as distance-based methods because density-based methods use distance measures to determine the density and LOF.
In [67], a distance-based approach is presented in which the median of the data is calculated, and the new data is compared with the median. If it is higher than a threshold value, then new data is considered as an outlier. In this paper, two types of median are defined: one side and two sides. In two side, the 2k data is considered from the past data, and the median is selected, and in the one side, the median is calculated separately of each k data, and finally, the two medians are summed up, and the sum is considered as the final median. The reason for this is dealing with outliers in a row. The experiments are conducted for one side, and two side methods and the results show that one side method is better for detecting outliers in a row, but the complete improvement has not yet been achieved.
Another distance-based method is proposed in [68]. In this paper, there are two concepts of local deviation and global deviation. The purpose of the local deviation is to check the new data value with the average of the recent data. On the other hand, for global deviation, the new data value is compared with the average of the total data stored. If the new data value with local or global deviation exceeds more than three times the variance, then that data is an outlier. In this method, the concept of drift has also been solved with the help of global deviation. The run-time and predictive
accuracy of the proposed method is evaluated by three other methods, which the results show that, at a reasonable time, the accuracy of predictions was far more than the other methods.

In this dissertation [69], authors also propose a distance-based method to determine the outliers. Thus, By Euclidean distance, the number of nodes close to each data is determined. If this number is less than a certain threshold, then that data is known as an outlier. The proposed method is compared with several similar methods, and the results of the experiments show that the proposed method can efficiently detect and clean the outliers and free the data set of noise. In another work of the authors of [68], a density-based method is proposed [70]. An algorithm called Orion, which is first, calculates the similarity between new data and other data, then the stream density and k-distance criteria for each data are obtained. The stream density is the number of stream neighbors and the k-distance of a point is the least path that includes k nearest neighbors of that point. Then Orion uses a clustering algorithm to cluster the data. The clusters are divided into three groups: small, average, and large. Data that belongs to the small density and large k-distance clusters are considered as an outlier. The same method is presented in [71]. Also, this dissertation contains more details on the method and the proof of the lemmas. Several datasets have been used for evaluation. Precision, recall and the effect of the concept drift on the proposed method and other methods have been evaluated. The results show that in most of the datasets, the proposed method has a higher precision/recall and the concept drift does not affect the accuracy of Orion.

In [72], a density-based approach is presented in which the data space is split into several grids and according to the data entry, the information of each grid, including the number of data, the mean, the variance, and the time, is updated. After the updating process, the density of each grid is evaluated, and if the density is less than a threshold, then the grid is said to be an abnormal grid, and finally, the data that is contained in an abnormal grid is an outlier. The method is compared with the two algorithms STORM and LOF. The KDD-CUP99 dataset is considered as the actual dataset, and a synthetic data set of 400,000 records is also selected. The precision of the prediction and run-time has been compared, and the results indicate that the proposed method has been able to have lower execution time and more accurate prediction.

Another density-based method is presented in [73]. In this paper, after the data stored in the buffer, the Euclidean distance of the data is computed. Then, if the distance is greater than the desired threshold, it was checked as an outlier and went to the density calculation stage. At this stage, the data density is computed with the LOF formulas, and if it exceeds the threshold, it will be deleted from the buffer. The runtime of the algorithm is compared with another one, which the results indicate that the proposed method performed less time in processing and, thanks to the distributed platform, has approximately linear time complexity.

6.1.4. Context-aware techniques

The last sub-category of Outlier Detection is Context-aware. There are only two papers, which have the same authors, in this sub-category.

In [74] and [75], there are two main components: first Content Detection and second Context Detection. On Content Detection, each sensor uses its historical data to generate the corresponding regression model, then the data that is far from the model is considered as a content anomaly. Context Detection has two tasks: first, clustering and profiling the sensors, and the second, comparing the content anomaly with the average value of the sensor group. In order to cluster the sensors, the k-means algorithm is used, and the clustering parameters are location, time of year, time, date and weather phenomena. If the content anomaly is far from the average of each cluster, it is detected as a context anomaly. The difference between the two papers is that in the second paper map-reduce was used to allocate clusters. Evaluation is done on three datasets, and the results show that the proposed method has been able to detect both content and context anomalies in real time. The point is that any content anomaly cannot be a context anomaly.

6.2. Evaluation Task

The explanation of the papers with the task of evaluating the data stream is presented in this section.

6.2.1. Instance-based techniques

There are six papers in this category, which all of them are instance based, which means that in order to evaluate data stream, just the data record itself is used, not its schema.

In [79] for the first time, the concept of the quality window has been proposed. This implies that data quality evaluation should be done at the window level. Accuracy, completeness, and confidence are considered as data quality dimensions. At first, each data record in the window is evaluated in terms of three dimensions, and then all data results are aggregated based on the timestamp and data attributes. Finally, the measured values are used to analyze the data and compare it with the corresponding threshold whether the data is good enough.
The idea of the quality window is also used in [80]. The authors of the paper have argued that data analysis may not be sufficient only by the quality values of a window. Therefore, the data quality of more windows needs to be investigated. Therefore, it is suggested that not only stream data, but also quality values should be stored in relational tables. The authors have developed a database management system to store evaluated quality results. The results of data quality are calculated by the method [79] and are stored in a table. Finally, more data can be considered for data quality analysis.

If the data quality of a window is evaluated and it is determined that the corresponding value is less than the threshold, does all the window data have low quality or because of a particular data, the final result is lower than the threshold. In [81], the answer to this question is that, as soon as the data is of poor quality, the window size should be reduced. If the quality of the window data is low, then it can be easy to exclude all window data for analysis. In this paper, four functions are considered, by which they identify the suspicious data values and decide to reduce or increase the size of the window by comparing the amount of data with the given threshold.

In [82] and [83], which have the same authors, an ontology was used to evaluate the quality of data. In this architecture, three components of query, application, and content are defined. Data is first processed by the data processor. This component corrects the query using the Query-based Quality Service component. Then, the data quality evaluation is done by the Data Quality Processor and its interaction with the Application-based Quality Service and the Content-Based Quality Service. The Data Quality Monitor also analyzes the evaluated result. The information that enables this analysis is provided by the DQ Ontology component. In the Query-based Quality Service component, existing queries can also be rewritten. In the Application-based Quality Service, the user-defined quality dimensions (such as accuracy, etc.), can be defined and in the Content-based Quality Service component, there are some specific rules to evaluate the data values. For example, the maximum speed of a region is 280 km / h. The difference between the two papers is in the case study that authors have done. System performance and memory usage have been evaluated with and without data quality assessment. In the case of quality assessment, there is no significant difference in consumption.

A quality assessment architecture is presented in [84]. In this paper, there is a system by which the data consumer defines his requirements and the system automatically stores valid data in the database. In this system that is graphically available to the user, the data consumer can choose the quality dimensions and the specific data attributes. Finally, the system transforms the requirements to the executable code and executes it on the data.

6.3. Cleaning Task

The methods used to clean data stream are discussed in this section. Papers in this field are divided into three sub-categories: Learning-based, Context-aware, and Model-based.

6.3.1. Model-based techniques

The latest sub-category on cleaning is Model-based papers. There are six papers in this sub-category, which are explained below.

A method of tracking objects is presented in [56]. In this paper, one of the model-based methods is presented. First, a baseline algorithm is introduced, in which, according to the current position of the object, a model is constructed, and future locations are predicted. Then it is determined that if the data is corrupted, the prediction process will encounter an error. As a result, a solution to this problem is presented. In this method, in addition to the available information, a radius is considered for each object, depending on which radius of motion of each object is determined. As a result, the process of predicting the next location of each object can be done correctly. It is also said that the exact amount of radius is difficult to determine because if a large radius is selected, the prediction of the next location is difficult and if small, it may not be accurate to predict. Finally, this method is compared with the baseline algorithm. The effect of missing rate and moving speed on the accuracy of prediction and run-time are estimated. The results indicate that the proposed method has been able to control and reduce the impact of missing data in the prediction process.

In [57], another model-based approach is presented. First, the data value whose error is recognizable is determined. Then a statistical model of the existing data is created which is used to estimate the noisy data. In order to implement both R and Spark are used. Different algorithms are used to construct the model and the most accuracy one is chosen. In the evaluation section, the accuracy of the prediction has been measured, and the 87% prediction is obtained. Also, in [58], presented by the same authors, the model, in addition to the data that receives from each sensor, is made up of other information, such as wind speed and the distance of buses with specified locations, taken from external sources.

The reference [59] is also a model-based approach in which an abstract framework is provided to examine the quality of wireless sensor data as well as its cleaning. The authors say that the framework is part of a project that will be carried out later. In this framework, after collecting data from sensors, outliers are first detected, and then the new value is determined by the smoothing models. There is no description of what algorithms are used in each section.
In order to clean the data, a low-rank matrix used in [60] and [61]. The paper [60] presents a method for cleaning the missing data in air quality data sets. For this purpose, since the data is stored in the matrix, a mathematically based method called low-rank matrix is used. So the issue becomes an optimization problem. If the given and the optimal matrices are close together, the rank of the given matrix is less and, therefore, is complete. The SVT algorithm is used to recover the matrix. This algorithm continues until it reaches the optimal answer and finally delivers the complete matrix. The simulation results show that the proposed method can effectively recover and improve the missing data in the air quality data set.

6.3.2. Learning based techniques

There is one paper in this sub-category, which is [66]. In these papers, a learning-based cleaning framework is presented that has three primary modules: storage, computing, and data collection. In the storage module, MySQL is used to store structured data, HBase to store unstructured data and HDFS to store the data in Hadoop. The computing module is a combination of Yarn, Map Reduction and Spark for distributed computing. The collection module has been used to collect data from sensors, which consists of four components. Kafka is also used to transfer data from the collection module to the calculation module. The proposed cleaning method consists of three parts: k-means clustering, anomaly detection, and data alarm and cleaning. First, k-means clustering algorithm groups data in distinct clusters. In each cluster, the values of max and min are introduced as the cluster boundary. The data outside this range is called an outlier. Then the outlier data is replaced by the min or mean. In order to evaluate, recall, run-time, speed-up and scalability of the method has been evaluated. The results show that the proposed method has been able to increase the data quality by detecting and replacing most outliers.

6.3.3. Context-aware techniques

There are three papers in Context-aware, which are a manuscript and the last two are theses. In [76], a value is considered as a predicted value before the sensor generates the data. This value is derived from the mean of the data produced by the sensors correlated with the corresponding sensor. Then the newly generated data is compared to the value, if the difference is less than a threshold, the data is correct and, if more, the predicted value is considered to be the final value. Finally, the sensor's reliability level is also updated. Experiments have been conducted with artificial and real datasets, and also the precision of the method has been evaluated.

In this thesis [77], an introduction to data cleaning is first introduced. Then the data stream processing has been investigated. Also, stream processing problems are discussed. Then a cleaning algorithm is presented for the wireless sensor network. For this purpose, when viewing the corrupted and lost data, some k sensors that are associated with the corresponding sensor are chosen, and the final value is taken from the selected values from those sensors. Also, managing mobile trajectories and the effects of noise due to user mobility is considered.

In this dissertation [78], there is a method for cleaning the data stream of mobility sensors. In this method, a concept called the virtual sensor is used. Since sensors are moving and the location cannot be accurately predicted, virtual static sensors are used to clean the missing values generated by real sensors. To do this, the weighted average of actual sensor values is calculated, and the data value of each virtual sensor is updated so that the weight of the data produced is higher by the sensors near the virtual sensors. Then, with a predictive model, the next virtual sensor data is predicted. If the base station determines that the data produced by the real sensor has an error, refer to the timestamp and spatial range of that sensor, the predicted value of the corresponding virtual sensor is considered as the cleared data. The correct prediction rate and cleaning time are evaluated, and results showed that, when the location of a sensor is not missing, this algorithm cleans about 80% of missing data.

7. Batch Processing Methods

This section describes the papers that use batch processing model to improve the quality of big data. As indicated in Figure 6, based on the primary purpose of the proposed methods, we have divided these works into three categories: outlier detection, evaluation, and cleaning.
In Table 7 the list of selected papers, in terms of each technique in the batch processing category is provided.

| Technique        | Detection | Evaluation | Cleaning |
|------------------|-----------|------------|----------|
| Learning based   | [86], [87] |            |          |
| Rule-based       | [88]–[91] |            |          |
| Distance-based   | [92]–[94] | [95]–[98]  |          |
| Instance-based   |           |            | [99]–[104]|
| Schema-based     |           |            |          |

Next, we briefly review the papers in each category.

### 7.1. Outlier Detection Task

Papers that use static data in order to detect outliers are described in this section.

#### 7.1.1. Distance-based techniques

There are three papers in this category. Apart from the first method that uses the distance criterion, two other methods, after calculating the distance, use the density to detect the outliers. The explanation of each work is given below.

An important characteristic of a NoSQL data model, which is frequently used for storing big, is the lack of a fixed and predefined data schema. On the other hand, in order to evaluate data quality and identify quality issues, it is needed to analyze the schema. As a result, some researchers have worked on techniques for extracting schema from data instances. In [92] a method to extract the JSON files schema is presented in which, after selecting each JSON document, its structure is extracted, and a graph is made of the properties of each document. Then, by evaluating the new document and its properties, if the property is a duplicate, its count will be increased in the corresponding path, and if it is not, it will be added to the graph. After the graph is made, all properties are identified, but are all necessary? To understand, the count of repetitions of each property must be checked with the count of parent repeats. If this number is equal, then the property is necessary. Otherwise, it is optional. To determine duplicate properties, similarity and distance measures are used. After creating the graph and specifying a threshold for each property, it is possible to create a list of properties that are less than the threshold in the relevant document. This approach is useful for determining optional properties. The algorithm is provided on the Wendelstein project database. The database has been recording plasma experiments for several years. There are now over 120 different documents. Until today, this data set has no explicit schema. The execution time of the algorithm is evaluated with documents of varying size, which is almost linear and the algorithm can generate a JSON document schema at the right time.

Paper [93], which is a density-based approach, data is first mapped to a grid space. Then, in each grid, density (LOF) is calculated in parallel. If the density is less than the threshold, then the grid data is considered as an outlier. When splitting data, it may be placed on the boundary of the two grids. In this case, the proposed method calculates the distance of that data with two grids, and if it is closer to the second grid, it will be transferred to that grid. The runtime and the number of transmissions are evaluated in the proposed method and in another method, and the experiments have stated that the method has a better performance.
Another distributed density-based approach is presented in [94]. To reduce computations, after partitioning data, partitions whose data count exceeds the threshold value are removed from the next calculation. Then, in partitions with less data, the LOF is calculated, and the outlier is detected. The proposed method is evaluated in terms of execution cost, and the results have demonstrated that it has a higher speed in comparison to related works.

### 7.2. Evaluation Task

The big data evaluation methods are mentioned in this section. These methods are divided into two categories: schema and instance based. In six papers, the schema has been used to evaluate big data, and in four papers, authors have used the data itself for this purpose. First, we explain the instance-based papers.

#### 7.2.1. Instance-based techniques

In the following, we explain the instance based methods. A model for improving the quality of open data is presented in [95]. In the first step, the data quality dimensions are evaluated, then the data quality criteria are defined, how each quality dimension is calculated. In the third step, each quality dimension is weighed to define the data quality index. In order to select a dataset, the popularity index is defined by the number of downloads, number of uses, and so on. Then the evaluations carried out by the end users are measured, and their comments are collected to be analyzed, and the quality level evaluated.

A model for assessing the quality of health data is presented in [96]. After data collection, data quality is evaluated before and after the preprocessing stage. The quality dimensions such as accuracy, correctness and completeness are evaluated before the pre-processing, then the transformation, filtering, and other pre-processing techniques are performed, and after this stage, again the accuracy, correctness, and completeness of the data are evaluated to determine the degree of quality improvement. In order to evaluate the method, the data quality improvement has been conducted, and the results indicate that data quality has increased in big health data.

In [97], the number of six quality dimensions are specified for the evaluation of electrical data. These dimensions include accuracy, consistency, integrity, redundancy, timeliness, and intelligence. The data are evaluated by the specified dimensions, and the following results are obtained: 1. the number of duplicate data is very high and can affect the results, and 2- In the conversion process, there is an inconsistency.

The thesis [98] first addresses the big data quality problems such as big data management and big data processing. Then it goes into the big data validation process. This process involves the following steps: data cleaning, data collection, data loading, data transformation, and data analysis. Also, the data quality assessment tools are discussed like MS-Excel, Zoho Reports, DataCleaner, Tableau, etc. Then some quality evaluation frameworks are also mentioned. In this thesis, eight data quality dimensions have been proposed, including the accuracy, completeness, uniqueness, timeliness, consistency, validity, usability and the reliability of sensor. Each of these dimensions is evaluated in a dataset, and the output results are examined, and it is said that the results can be extended in the future.

#### 7.2.2. Schema-based techniques

A data quality evaluation architecture is presented in [99], [100], which has several modules. The profiling module profiles data based on its features and gains statistical data. The results of this step are stored in the Quality Metadata module. On the other hand, the user specifies his requirements through the user interface, for example, confidence level and so on. The data are evaluated by the data quality assessment module in terms of quality dimensions, and if the data volume and a large number of computations are time-consuming, the Adapter module will sample the data and perform the evaluation on fewer data to spend less time. In experiments, the impact of confidence has been evaluated on quality dimensions as well as on runtime. The presented architecture has been able to evaluate the quality of the data by the defined requirements by optimizing the user's parameters.

Data extraction, data preprocessing, data processing, data analysis, data transformation, and visualization are big data management steps. In [101], [102], authors have tried to evaluate the quality of data by metadata in each of these steps. Metadata is obtained after extracting data and analyzing its attributes. Then the quality of the data is evaluated by calculating the quality dimensions and with metadata assistance. Extracting metadata in the processing, analyzing and deciding making phases are also performed. In each of these steps, after data selecting, the metadata is obtained by examining the attributes of the data, then quality evaluation takes place as long as the decision-making step is complete. The quality evaluation of Twitter data is presented in [102]. The manager first lists the required quality dimensions. Then the data expert identifies the criteria for evaluating these dimensions and also specifies the metadata for the tweets. The manager in the final step considers a threshold for each quality dimension. When a data is taken from Twitter, its schema first is examined by the metadata, and if it is within the range, its quality dimensions are evaluated. In the end, only good enough data is sent to the analytic process.
The paper [103] presents a framework for finding data quality rules. In the first step, and from a huge amount of data, data sampling and profiling are performed. After profiling and reviewing data features, quality dimensions are identified, and sampled data are evaluated using quality dimensions. Then the score for each feature is calculated. By analyzing the quality score, a set of rules is generated — for example, a rule to delete incomplete data and so on. Then the rules apply to the sampled data, and the changes are inspected. If the rules need to be changed, they will be updated. This thesis [104] presents a tool for evaluating big data quality. In this tool, data is first loaded from the storage location, and then, after profiling the data, the system evaluates them based on four data quality dimensions, such as timeliness, completeness, accuracy, and reputation. The reason for choosing these four dimensions is their applicability in some domains, such as e-Business, e-Science and Information Systems. The focus of this research is on the scalability and cost-effectively of the tool, so the tool has been developed on Apache Spark in order to be more effective. The performance of the tool has been evaluated on different dataset sizes, and the results demonstrate that big data framework can be used to make better performance and scalability of a data quality query system on small, medium, and large workloads.

7.3. Cleaning Task

In this section, papers that focus on the cleaning task are presented, which are divided into two sub-categories: Learning-based and Rule-based.

7.3.1. Learning based techniques

In this section, we briefly review two papers that employ clustering to develop a learning technique for the task of big data cleaning.

In [86], a fuzzy-based clustering algorithm is proposed to clean the incomplete data. After normalization, the data is divided into two categories, complete and incomplete data. A fuzzy clustering algorithm is executed on complete data, and cluster heads are identified. Then, the membership degree of all data to all clusters is computed. Subsequently, the fuzzy algorithm is executed on incomplete data to determine the appropriate values to reduce data incompleteness based on membership degrees. The performance, the proper number of clusters and the runtime of the proposed method are compared with five other methods, and the experimental results indicate that the proposed method outperforms the other five techniques.

Another clustering based method is presented in [87]. In the proposed method, by the Cure clustering, the center of the clusters as well as the borderline data are detected. In order to determine the cluster boundary points, the center of each cluster is first defined, and the distance of each data with the center is determined, then the farthest data is a border point. When analyzing the new data, the data is examined by the cluster boundary, and if exceeded, it is considered as an outlier. Since big electrical data is being generated over time, it changes slowly. Therefore, in order to handle the outliers, we can use the centroid of the cluster for corresponding outliers. In order to evaluate, the authors use Spark, six Ubuntu servers, one for master and others for slave servers. In this paper wind power data is used for examination. The detection rate, the false positive rate, and the performance of the proposed method are evaluated with three other methods, which the results indicate that the proposed method has a higher detection rate and a lower false positive rate compared to other methods.

7.3.2. Rule-based techniques

A rule-based methodology for detecting and cleaning inconsistency in triple data is presented in [88]. Inconsistency rules and logic are used to detect inconsistencies in knowledge bases. Then, the degree of inconsistency of each triple is determined by the definitions given in the paper, and finally, the data whose degree of inconsistency exceeds the desired threshold is eliminated. There is no evaluation section in this paper.

In [89], a big data preprocessing framework is provided. In this framework, the activity and the technique is selected first by the Data Quality Class Selection module. In activity, data integration or data cleaning is selected, and in the technique, one of the domain related, auto-discovery and user-defined can be selected. In domain related, predefined rules, in auto-discovery, heuristics algorithms, and in the user-defined, some rules that are defined by users are applied to the data. Further, in the Data Quality module, quality dimensions and quality rules are determined. Then the activity is performed on a small volume of data, and if the evaluation results are approved, it runs on the entire data source. It is said that the framework is still not complete and is in development, so the evaluation of work has not been done.

In [90], a data cleaning scenario is proposed. Data volume, correctness, timeliness, and completeness are selected as quality dimensions. After examining the correlation between dimensions, the result is that there is a positive correlation between volume and completeness, as well as when the received signal is continuous, there is also a positive correlation between timeliness and accuracy. Then six scenarios have been introduced to clean the data. By examining the correlation between dimensions, one of them is selected as the best scenario. In this scenario, firstly,
the data completeness must be evaluated. Secondly, the data are analyzed in terms of the timeliness dimension, and finally, data correction must be verified. In the evaluation, the results of the dimensions correlation are specified, and the scenario is also compared with another scenario, which results show that the selected scenario has been able to clean the data better.

A data cleaning framework for big batch data is presented in this dissertation [91]. This framework consists of identification and linking steps, recovering and association process, ranking system, and cleaning process. Identifying data from other resources that are related to an entity is done by identification component. The linking component is responsible for linking identified objects. Prioritizing the cleaning process based on data quality issues is the duty of ranking system. The metadata generator is responsible for providing additional information such as data items, types and uniqueness for the data. When data issues are identified and reported, the data quality administrator must determine the appropriate actions to be taken based on their severity. Data repairing is carried out based on obtained metadata. The results of the experiments have shown that the data quality has been improved using the proposed method.

8. Hybrid Approach

Some methods work both on batch and stream data, which usually use static data to build a model and apply the model to the data stream. Sometimes authors implement a specific algorithm on both types of data. As shown in Figure 7, these methods are divided into three categories: Outlier Detection, Evaluation, and Cleaning. Since the number of papers in hybrid methods is limited, there is no other classification on each category.

![Figure 7: Research Tree of Hybrid Methods](image)

The list of the papers based on the technique in hybrid methods is determined in Table 8.

| Detection     | Evaluation | Cleaning |
|---------------|------------|----------|
| Learning based|            | [105]    |
| Rule-based    | [106], [107]| [108]    |
| Model-based   | [109]      | [110], [111] |
| Schema based  | [112]      | [113]    |

The methods of each category are explained in the following sub-sections.

8.1. Outlier Detection Task

There is only one paper in this category that we explain below. A big data processing platform is implemented in [112] which is based on the Lambda architecture and is intended to improve it. In lambda architecture, there are three main layers: batch, speed and serving. In the batch layer, a copy of the input data is taken, and then the data is processed in batch, in the speed layer, the data stream is entered and processed in real-time and the results are stored and in the serving layer, the results have been delivered to the user. In the proposed method, it is claimed that the lambda architecture can handle the volume and velocity characteristics of big data, but not variety. So a layer called the metadata management system (MDM) is added to the Lambda architecture and called the new architecture Bolster. In MDM, there is a metadata repository in which all the relevant metadata are stored in an ontology. In this ontology, there are features of the input data, where they come from and what attributes they should have. When data is ingested, they are first validated by the MDM in terms of their attributes, and if they have the desired features, the processing phase begins. Otherwise, they will either be deleted or stored in the data storage. The architecture has been used in

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1 Big Data, book by Nathan Marz and James Warren
several use cases such as BDAL\textsuperscript{1}, SUPERSEDE\textsuperscript{1}, and WISCC\textsuperscript{1}. In each use case, several roles have been participated to test the method. Authors asked a number of questions and participants evaluated the system based on their factors.

8.2. Evaluation Task

There are four papers in this section that assess data quality on both batch and streaming data. The interpretation of each method is as follows.

A data quality assessment tool for power supply sources is presented in [106]. In the tool provided, streaming data from the XML format is taken from the smart meter and evaluated online and stored for later analysis in the Oracle database. Given the fact that the power data feature is already specified, for each feature, some indicators and quality rules are defined. After calculating quality indicators, whether online or offline, the results are presented in real time and graphically. The most important quality indicators are checking missing values, duplicated data and comparing the value with a threshold. The framework has been implemented, and there are screenshots of the tool in the paper, but the accuracy and runtime of the tool have not been evaluated.

As the processing of a large amount of data is complicated, most of the methods for assessing the quality of big data use sampling. In [107], after data sampling, the data quality, in particular, the completeness, is evaluated for a small amount of data. As the data is likely to be updated, their quality may also change. For example, due to updating, the data that was complete is now null, and vice versa, the data that did not have any values is now a complete record. Two approaches are presented here. First, by observing any updates, all selected data are reevaluated. It is clear that this method can be both time-consuming and resource-intensive. However, the proposed method reevaluates only the records that have been changed. The runtime and efficiency of the method have been evaluated, which results show a 78% efficiency of the proposed method.

To control the patient's health, his condition is monitored by checking the patient's data generated by sensors that are connected to the patient. In [109], the information is received from the body sensors and sensors in the patient's house, and after assessing the quality of the data, if it is at risk level, an alarm is generated. The proposed architecture has three main components. The first component is monitoring in which the requirements and quality parameters are defined, and these requirements are sent to the Middleware component. After receiving data from different sensors, this component manages and executes requirements for data. The Middleware component interacts with the Data Quality Manager component. The Data Quality Manager is responsible for assessing data quality and also analyzes the measured values by examining relevant historical data. If the measured values do not match with the minimum and maximum historical values, the alarms are generated. The proposed method is part of the thesis and implementation, and evaluation has not been presented in the paper.

It can be said that in this thesis [113] statistical information, metadata, etc. from the static data is obtained from a database and then the quality assessment is applied to streaming data. Firstly, the author uses three algorithms such as reference algorithm, a frequency algorithm, and an entropy algorithm to identify essential data in the database. Secondly, there is a model for quality assessment that has five layers and can support the evaluation of data steam quality. Finally, a distributed platform is developed with Python language, and the author compares the results in terms of the algorithm's performance in a machine and parallel and the results show that the higher the number of threads, the less time it takes to process.

8.3. Cleaning Task

Hybrid cleaning is also presented in four papers, each of which is described in detail below.

In [105], a hybrid method for data preprocessing is presented. The k-nearest neighbor algorithm runs on historical data and is applied to a window of a data stream. After cleaning the data stream by MSSA algorithm, the model, adaptively, is updated with cleaned data in order to make the next prediction more accurate. The prediction accuracy of the proposed method is evaluated, and the results indicate a precise prediction of the algorithm when the method uses an adaptive algorithm for predictive purposes.

In [108] a distributed rule-based method is presented to clean streaming data. The proposed method has two basic modules. First, the detection module and the second, the cleaning module. A set of rules is defined in the data. The number of detect workers is defined by the number of rules. The input data is entered by the router to the corresponding

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\textsuperscript{1} This project takes place in a multinational company in Barcelona

\textsuperscript{1} https://www.supersede.eu

\textsuperscript{2} This project funded by the World Health Organization which is part of the Programme on Control of the Chagas disease
detect worker. Each detect worker is responsible for investigating the violation of the corresponding rule. In each worker, historical data is also available to compare the new data with them, and if there is a violation, it will be announced. Then the noisy data will enter to the cleaning module. In this module, the equivalence class algorithm is used, in order to clean data. In this algorithm, the same data is placed in a group, and the majority value is introduced as new data. The throughput and time delay of the method is one of the experiments that the authors of this paper have done and the results show that the method has been able to provide a little delay, in addition to the accuracy of the results.

Paper [110] also provides a framework for assessing and cleaning Chinese electricity data. This framework has three main modules. First is a data collection module where data is accumulated from sensors, power grids, and databases. Second, the storage module, this module is designed to store different types of data. The third is the calculation module in which historical and real-time data are processed. In addition to data processing, this module also assesses the quality of the data as well as its cleaning. The proposed framework has been implemented, but its evaluation results are not presented in the paper.

Another hybrid method for detecting and cleaning sensor data is presented in [111]. At first, each sensor individually analyzes time series data, and those who are not similar to the majority are marked as an outlier. These data may be identified as normal data when compared with other sensor data. So in the second step, each sensor compares its neighbors' data with its own data to detect the event outliers, and if a conflict is observed, the data is tagged. Thirdly, the data is sent to the sink, and in the sink, after analyzing the correlation between all sensor data, the smoothing process is done. Moreover, the cleaned data is transmitted to the server for processing phase. The proposed method is compared with other methods, and the results indicate that the algorithm is more accurate and more efficient.

9. Results

In this section, we refer to the results of the systematic review in order to answer the second research question, i.e. RQ2. Through analysis of the title and keywords of the papers, a tag cloud is produced which is presented in Figure 8.

![Word Tag Cloud on Big Data Quality](image)

(a) With 50 words  
(b) With 3 words

**Figure 8: Word Tag Cloud on Big Data Quality**

The top 50 words, which are depicted in Figure 8(a), are data, quality, big, detection, stream, online, and so on. The tag cloud with the number of three words is also given in Figure 8 (b). As indicated in Figure 8 (b), the most three frequent words in the titles and keywords of the studies are big, data and quality. The result shows that the keywords defined in 4.1.1 are correctly selected and the search methodology has been able to obtain related papers based on the scope mentioned in 4.1.1.

Figure 9 illustrates the number of papers on Big Data Quality during the last decade (from 2007 to 2018), based on processing type. According to this figure, it can be seen that the overall number of studies in this area is increasing. Since 2015, there has been a significant increase in the number of studies in this field. The number of papers that use streaming data has generally risen, while batch papers have been falling since 2016. If we do not consider the number of studies in 2018 (due to lack of completeness), we see a continuous increase in the number of papers in the hybrid methods. This means that the research in the hybrid methods has begun since 2015 and it continues to attract the attention of the researchers.
In Table 9, some statistics about the type of the studies is presented that the abundance of the number of journals as well as Ph.D. dissertations emphasized the importance of the topic. Additionally, the number of papers in terms of processing type is shown in Figure 10. Due to the expansion of the use of social networks and the increasing use of the Internet of things, the data stream has been used in many papers, and this is illustrated in Figure 10. A smaller number of studies is associated with batch and hybrid processing.

Table 9: Research study type

| No. | research study type           | Number of studies |
|-----|-------------------------------|-------------------|
| 1   | Books/Book Chapters           | 3                 |
| 2   | Conference Papers             | 41                |
| 3   | Journal Papers                | 35                |
| 4   | Ph.D. Dissertations           | 6                 |
| 5   | MS Theses                     | 3                 |

Figure 9: Frequency of publications per year

Figure 10: Number of studies in terms of processing type
In Figure 11, the number of papers is displayed in terms of both the processing type and the task. Given this figure, we find that most papers that use streaming data have focused on the task of detecting outliers. Since data evaluation and cleaning spend more time than detection and given the importance of real-time data processing, the most number of studies in detection task are related to stream processing type. In the evaluation, the most significant number of papers is related to batch data. As stated above, and given the fact that more time is needed in the evaluation, most researchers use static data and offline processing than other types of processing. Finally, more data stream processing has been used for cleaning. The need to correct the data and achieve high-quality data set in real-time leads to the use of streaming data for the cleaning task. Most hybrid papers are presented to evaluate and clean the data. Generally, static data is used when researchers want to increase the accuracy of cleaning and evaluating streaming data. To this end, the application of hybrid processing is carried out more precisely with the task of evaluation and cleaning.

The number of papers published in big data quality era is presented in terms of the technique used and the type of processing in Figure 12. Each of the five context-aware papers has used data stream, while hybrid methods can be used to increase the accuracy of the algorithm. Distance-based methods that have been used to detect outliers, use data streams more than static data. Since calculating the distance criterion for data in a window is less cost-effective than big data, researchers are more willing to use distance-based methods in the data stream. Instance-based methods are used to assess data quality, which results indicate that streaming data has the largest share. Since the schema constraints are usually not specified in the data stream, instance-based methods are usually used to evaluate this type of data. In learning-based methods, most papers have also used data stream compared to other types of processing. Learning methods, which include clustering and classification algorithms, are more suitable for batch data than for data stream, because of large computations. These techniques can be more accurate if they use a hybrid method. The most significant number of stream processing papers use a model-based technique. As previously mentioned, constructing the model has the least time compared to other techniques, and researchers employ this technique more in stream processing. Since defining the appropriate rules require static data, rule-based methods either work on batch or hybrid. If these rules are defined by an expert, it can also be applied to streaming data. Because the schema constraints can be obtained in batch data, schema-based evaluation algorithms use batch or hybrid processing type to assess big data quality.

Figure 11: Number of studies in terms of processing type and task
The distribution of the studies from the point of view of their application domain is shown in Figure 13. As indicated in the figure, in 44% of the papers, no domain is specified, and the domain is general. In other studies, the most commonly used is the Internet of things. Due to the high usage of the Internet of things and the abundance of papers in the field of the data stream, the largest share of the domain specific is the Internet of things with 37%. 10% of the papers are related to the weather, 5% to health, 2% to the social network, and finally 2% to the linked open data.

Further, we have analyzed the affiliation of the authors of the studies. We have found that the maximum number of the papers of an author is four. We also searched the author's name on related sources such as Google Scholar, Research Gate, and DBLP, and found that the author has not published any papers since 2010. Therefore, it can be said that this area still does not have any active authors who have a large number of publications. Table 10 refers to the top 5 affiliations that have published studies in big data quality scope.

| Affiliation Title     | Number of Studies |
|-----------------------|-------------------|
| University of Twente  | 12                |
The distribution of the affiliations based on countries with at least four papers is shown in Figure 14.

Figure 14: Active countries in big data quality scope

The active conferences and journals is also listed in Table 11. The most number of studies in the field of big data quality are accepted at the two IEEE conferences, which indicates that these two conferences are of particular importance to the topic. Then, the ICIQ conference, which specializes in (small) data quality, than big data quality. Then the name of the five journals and one conference in which the papers in this field have been accepted are given. The list helps scholars interested in this field to submit their manuscript to these conferences and journals.

Table 11: Top conferences and journals with at least two papers

| Name                                                      | Type                     | Rank*            | Number of studies |
|-----------------------------------------------------------|--------------------------|------------------|-------------------|
| IEEE International Conference on Big Data                 | Conference               | N/A              | 6                 |
| IEEE International Congress on Big Data                   | Conference               | N/A              | 6                 |
| International Conference on Information Quality (ICIQ)    | Conference               | B1               | 3                 |
| Future Generation Computer Systems                        | Journal                  | JCR Q1 (IF: 4.639) | 2                 |
| Knowledge and Information Systems                         | Journal                  | JCR Q1 (IF: 2.247) | 2                 |
| Journal of Big Data                                       | Journal                  | Q1               | 2                 |
| Journal of Data and Information Quality                   | Journal                  | Q2               | 2                 |
| International Journal of Computers and Applications       | Journal                  | Q4               | 2                 |
| ACM International Conference on Distributed and Event-based Systems | Conference | N/A | 2 |

* Taken from “http://www.conferenceranks.com” for conferences and “https://www.scimagojr.com” for journals

10. Challenges and Future Works

In this section, we intend to answer the third research question, i.e. “What are the main open challenges in this field?” Generally, the challenges and limitations of big data quality can be classified into three main categories, including source dependent limitations, inherent challenges of data streams, and technique related challenges. In the following, we explain each of these categories.

10.1. Source dependent limitations
Some limitations depend on the sources that generate the data. For example, if data is generated by a sensor, any equipment malfunction of the sensor, can affect the data quality. Regarding the source-dependent limitations, we have identified the following groups:

- **Resource constraints**: The process of quality assessment requires computational capacity and enough time in order to have better quality data, which is mentioned in [52], [53], [55], [56], [77], [79]-[81], [84], [110], [111]. In some data production environments such as the sensor networks and the Internet of things that the sensors are responsible for generating data, there are computational, communication and memory limitations that do not allow a powerful evaluation process to be performed.

- **Source heterogeneity**: Source heterogeneity is another challenge to achieving the assessment goal [11], [54], [99], [100]. On the social networks, the heterogeneity challenge of the network structure is a serious problem. The difference in structure may lead to unusual behaviors, and this creates different data distributions. As a result of the different distributions, there is a severe problem of detecting and cleaning data.

### 10.2. Inherent challenges of Data Streams

Some challenges are inherent to the nature of data streams, and the quality evaluation algorithm has to face these constraints. Some of the problems are related to the nature of the big data, such as data volume, velocity, and variety. In this section, we have tried to highlight the challenges of big data quality assessment, so we have avoided describing such problems and only explains the inherent problems in big data quality:

- **Variety of arrival rate**: Data values arrives at the different rate, so the evaluation algorithm should provide a mechanism for processing existing data before the arrival of the new incoming data. Studies [23], [29], [31] discuss this problem.

- **Infinite**: As in [23], [29] explained, in streaming data, data is continuously being received, and the evaluation process must be done online and without interruption of the main retrieval process.

- **Transient**: In data stream, transient data is a significant challenge that is mentioned in [23], [29], [31]. Data expires after a while and lose credibility, so data processing should be done before it expires.

- **Concept drift**: Data distribution may change after some time, and if the evaluation algorithm fails to find the new distribution, it will not be adequately performed. One of the significant challenges in designing the algorithm is attention to the distribution of data which is considered in [57], [68], [70].

- **Heterogeneous schema**: In some cases [11], [71], [89], [92], [107], [112], we face the heterogeneity problem of the data schema. One of the complexities of data preprocessing is to provide the right solution to deal with this issue.

- **Lack of suitable tools**: Another problem that has not been solved yet is providing a proper tool for assessing the big data quality. As indicated in [38], most commonly used tools only assess the quality of batch data and do not focus on the data stream, while real-time data evaluation is one of the severe needs of this area. Also, these tools after profiling the data only consider the accuracy and completeness dimensions and have no idea to evaluate other quality dimensions, such as timeliness, consistency and so on.

### 10.3. Technique related challenges

Some challenges are related to the technique used in the quality evaluation algorithm, since any technique with its advantages has some limitations. As briefly explained in Figure 4, the advantages and disadvantages of each technique are presented below:

- **Learning based**: Clustering and classification algorithms challenges are discussed in [23], [25], [28], [33], [34], [40]. Clustering algorithms can be adapted to complex data types and can be used to obtain context information. However, in most clustering algorithms, the number of clusters is one of the crucial parameters to be defined. Since there is no access to all data in the data stream, it is impossible to specify the number of clusters. Not specifying the number of clusters leads to the production of arbitrary shapes, and ultimately it will be difficult to analyze these clusters. Classification algorithms do not need to set the parameter. In these algorithms, the existence of a label in a dataset is necessary. In the batch, we can test and classify the data with reasonable accuracy by constructing the model, but in the streaming data, specifying the size of test data and updating the model are major challenges. Also, the computational complexity of this kind of methods is higher than clustering algorithms.

- **Model-based**: In some studies [23], [25], [26], [28], [32], [34] model-based methods (also known as statistical-based technique) are explained. These methods use temporal correlation in order to build the model, and the least change in data distribution results in the detection of poor quality data. The simplicity
of this method makes it more used in streaming data than batch. On the other hand, updating the model is one of the challenges of this technique, mainly when the concept drift occurs; this method cannot adapt itself to the new data distribution. These methods are suitable for univariate data and cannot find the interactions between attributes in multivariate data.

- **Distance-based**: As in [23], [25], [26], [28], [31]–[34] explained, these methods (also known as nearest neighbor based) do not assume any data distribution. Applying this technique for different types of data is simple because it only needs to define the appropriate distance criterion. However, it is difficult to define the distance criterion for complex data. The computation cost in multivariate data is prohibitive, and they are not suitable for high dimensional data. Also, the scalability of these methods is a significant concern. Typically, in these methods, a threshold value is used to detect outliers; the inappropriate threshold setting results in a lot of false positives.

- **Rule-based**: The rules are identified by the expert, so the precision of evaluation is more than other methods. Since these rules are obtained by examining historical data, the corresponding algorithm can be performed in batch or hybrid processing. One of the disadvantages of this approach is human intervention which is discussed in [30], [33], [87], which may take much time to define the rules. Also, since the results are obtained by the rules, the learning process, as well as the proper approach to changing the distribution of data, is not achieved.

- **Context-aware**: Context information can improve the quality of the results [75] and is useful for identifying low-quality data whose pattern is not obtained locally [74]. However, it is difficult to adapt to the local pattern with global patterns, especially when other data sources have different structures and schemas. Also, data integration in this situation is arduous.

- **Instance and Schema-based**: In these methods, if the schema is available, then constraints of each attribute are obtained by profiling [3], [99], [100], [102], [103]. Otherwise, it is done by analyzing and inspecting data values [79]–[81]. The presence of the schema, which often exists in batch data, can help with the accuracy of profiling results. On the other hand, and in streaming data with no data schema, the evaluation process becomes onerous, and generally with scholars evaluate the data by identifying a series of quality dimensions and defining their measures [79]–[84]. Finding the appropriate data quality dimensions that are suitable for the target data is another challenge of data assessment.

### 11. Conclusion and Future Research Directions

In this paper, a systematic literature review in the area of big data quality was conducted to investigate three main topics, including (a) type of processing, tasks and the techniques used, (b) Active researchers, research institutes, countries and venues, and (c) Challenges and unsolved problems. The main contribution of this study was to present a classification framework in the field of big data quality which has classified the state of the art methods according to the type of data processing, task, and the technique applied. To this end, a total of 419 studies were identified, and 170 papers were thoroughly studied, and finally, 88 research papers were included in the final paper pool. Also, the information necessary to answer the specified research questions were extracted from these studies, and the results demonstrated that the quality of big data is an active and also attractive subject in the last decade. Given the geographical distribution of studies, China and the USA had the most frequent papers in this field. Moreover, concerning the active venues, IEEE International Conference on Big Data (Big Data) and IEEE International Congress on Big Data devoted the most publications. Among all universities and research, University of Twente and Politecnico di Milano had the highest number of published papers in this area.

Along with all of the works done in the context of big data quality, there are some areas that have not been investigated well and it is required further efforts to address identified challenges. Here, we summarize future research directions.

- **Using hybrid methods, achieving higher accuracy**: Due to the popularity of social networks and similar data sources that generate data continuously, quality assessment should be done in an online manner to allow the analyst to make the right decision in real time. On the other hand, in the batch processing, due to the large amount of stored data, the focus of the most methods is to use the common tools, such as Hadoop, Spark and etc. to perform their processing at the right time. Therefore, in these methods, the technique used does not have much innovation. Furthermore, if in hybrid methods, loading data and constructing the model have been done at the right time, these type of processing can be an appropriate option for evaluating data in real time because as indicated in [105], [108], they are more accurate than other methods.
• **Context awareness, capable of detecting global deviations instead of local:** In order to increase the accuracy of the assessment, relying on local data is not enough, and global data should be considered in addition to the local data. For example, if in a sensor network, the data produced by a specific sensor is poor quality, it may be due to the failure of that sensor. In this situation, if assessment algorithm only considers the data of each sensor individually, we will never reach the correct result, while comparing the sensor's data with other sensors, we can understand the environment events and evaluate more accurately. Due to the small number of context aware studies [74]–[78], [99] and the importance of this topic as well as its higher accuracy, it is recommended that researchers use this technique to evaluate the big data.

• **Distributed architecture, more efficient but less used:** In many studies, centralized architecture is used, while due to the high volume of data and also considering the computational constraints and providing an appropriate solution to the fault tolerant problem, researchers should use a distributed architecture. It is stated in [54], [63], [89], [111] that distributed architecture can be a good solution to the high communication cost, moreover, studies [55], [57], [58], [66], [73]–[75], [93], [94], [108], [110] use distributed architecture in order to face this problem. However, distributed architecture also has challenges such as node failure, network interruption, and so forth, which should be an excellent solution to these problems.

• **Self-adaptive method, a way to recognize the concept of drift:** Some papers [54]–[56], [68], [99], [100], [105] presented an adaptive solution for assessing big data quality and [33] has emphasized on the presentation of an adaptive algorithm. As discussed earlier, data distribution may change over time; in this situation, the algorithm should adapt itself to the changes in the distribution of data. If the proposed method fails to predict the data distribution and do not consider the adaptation, it is difficult to detect outliers or evaluate the data, so the proposed method should be adaptable.

• **Human intervention, better accuracy in batch, less velocity in stream:** In some papers, the expert intervenes to adjust some of the parameters to improve the accuracy of the method. In some studies [30], [33], [87] this problem has been mentioned, in addition, the intervention of the expert for the type of batch processing in which real-time processing is not critical is appropriate, but this is a severe concern for real-time processing. The proposed method should either adopt a mechanism to minimize this intervention or take this process in the shortest possible time so as not to impede the fast processing.

Based on the identified research challenges, we are going to continue our research by focusing on the first two areas, including hybrid methods and context awareness in the quality assessment of big data. In other words, we intend to propose a hybrid context-aware method for fast quality evaluation of data streams.

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