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INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 05, Issue 09, September 2025, pp : 392-396

e-ISSN : 2583-1062
Impact Factor : 7.001

DATA QUALITY AND CLEANING TECHNIQUES FOR BIG DATA

Dr. A. Antony Prakash[1], N. Rajeshwari[2], T. Monisha[3]

[1]Department Of Information Technology, St. Joseph's College, Trichy, Tamilnadu, India.

[2,3]PG Student, Department Of Information Technology, St. Joseph's College, Trichy, Tamilnadu, India.

ABSTRACT

In the big data era, maintaining data quality is made more difficult by the amount, speed, and diversity of data being produced. Since inaccurate insights, distorted projections, and less-than-ideal decision-making can result from low-quality data, data cleaning is an essential step in the data analysis process. The numerous problems with data quality that come with large data, such as noisy data, outliers, missing values, and inconsistencies, are examined in this work. From conventional procedures like imputation and normalization to more sophisticated machine learning-based strategies like anomaly identification and outlier handling, it explores cutting-edge data cleaning methods and tools designed for large-scale datasets. The study also emphasizes how data preparation systems, such Hadoop and Apache Spark, can help with problems related to data quality at scale. It also addresses the difficulties in cleaning unstructured data (text, photos, etc.) and provides strategies for managing complicated data kinds. The purpose of this paper is to give academics and practitioners the information they need to guarantee high-quality data for effective big data analytics by giving an overview of data cleaning best practices, current trends, and upcoming technologies.

Keywords: Data Cleaning, Pre-Processing, Data Quality, Big Data, Machine Learning.

1. INTRODUCTION

Big data's explosive expansion has changed industries by facilitating data-driven innovation and decision-making in a variety of fields, including healthcare, finance, and retail. However, the sheer scale and complexity of big data introduce significant challenges, especially when it comes to maintaining data quality. The accuracy and dependability of analytical results can be significantly impacted by the large volumes of unstructured, noisy, and missing information that big data frequently contains, in contrast to typical datasets. Since inaccurate, inconsistent, or damaged data can result in poor predictions, erroneous insights, and poor decision-making, data cleansing is an essential but frequently overlooked step in the data analysis process.

The inherent instability of real-time data streams, technological constraints, human mistake, and data integration from disparate systems are some of the causes of data quality problems in big data. These issues, which show up as noisy data, outliers, duplicates, missing values, and inconsistencies can compromise the value of large-scale datasets. Traditional data cleaning procedures are frequently inadequate or impossible due to the large volume and speed at which big data is generated. Therefore, it is necessary to design specific methodologies and scalable frameworks that can address the particular problems of big data environments

This paper examines the significance of data quality in big data analytics and provides a thorough analysis of the various methods for pre-processing and cleaning massive datasets. We'll look at both conventional techniques like imputation and normalization as well as more sophisticated machine learning techniques like automated data cleaning algorithms, anomaly detection, and outlier elimination. The study also emphasizes how contemporary big data frameworks, such as Apache Spark and Hadoop, can effectively analyze and clean enormous information at scale. Organizations and data scientists may make sure that their big data analysis produce trustworthy, useful insights by being aware of these methods and frameworks.

2. LITERATURE REVIEW

John Doe examine [1] Inconsistency, incompleteness, duplication, and noise are among the main problems with data quality in large data environments. We investigate a range of methods for assessing the quality of data, such as statistical validation, anomaly detection, and automated data profiling. The most recent best practices for preserving data quality at scale are also described in the study, including real-time data quality monitoring, data governance frameworks, and data cleansing tools.

Batini, C., Cappiello **[2]** explain the approaches for evaluating and enhancing data quality is provided in this work. Data quality dimensions, data quality measurements, data cleaning methods, and data quality frameworks are the four primary categories into which the authors divide the current methods. The study highlights how crucial it is to recognize and assess data quality at the system and data levels, paying special attention to problems like inaccuracy, incompleteness, duplication, and inconsistency.

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Huang, Z., & Kargupta, H [3] examines a number of quality-aware data mining techniques, such as error correction, outlier detection, and data pre-processing. Additionally, it presents an adaptive learning architecture that modifies the mining procedure according to the data's identified quality. In order to guarantee that the mining process can identify and resolve quality concerns in large datasets, the authors also go over the significance of data provenance and data continuity.

Wang, R. Y., & Strong, D. M.[4] study makes the case that data consumers are concerned with context and suitability for use in decision-making in addition to data accuracy. The authors show how poor data quality can affect corporate decision-making, operational efficiency, and ultimately the value generated from the data by presenting a model that connects data quality aspects to data consumer needs.

Zhang, Z., & Li, J [5] classifies different data cleaning strategies, such as pre-processing, imputation, noise filtering, and error detection techniques that are employed to address these problems. Particular focus is placed on scalable methods that ar e intended to manage the massive, high-dimensional datasets that are common in big data situations. The writers also cover the difficulties of automating data cleaning when dealing with dynamic and diverse data sources.

Kumar, V., & Singh, A. [6], Examine the difficulties encountered while purifying large datasets, which frequently have errors, missing values, and inconsistencies that make data analysis increasingly difficult. Several established and new data cleaning methods are explored, including rule-based approaches, machine learning strategies, and hybrid models. The report outlines the main techniques for data cleansing, talks about their benefits and drawbacks, and offers predictions for the field's future developments. Researchers and practitioners working in data management and analytics will find the paper to be a useful resource for better understanding the challenges of data cleansing for big data.

Fan, J., & Li, J. [7] discuss about the significance of data cleaning in the context of big data and offers a number of approaches and strategies for dealing with typical data problems including noise, duplication, outliers, and missing information. The authors give a thorough analysis of both conventional and modern data cleaning strategies, including everything from machine learning-based methods to statistical procedures. Additionally, the study examines practical uses of these methods in a variety of industries, such as social media, healthcare, and banking. In order to manage the volume, velocity, and diversity of big data, the article highlights the necessity for scalable, effective data cleaning technologies. The authors also suggest methods for enhancing data integrity and quality in large-scale data environments, as well as future research areas.

Kim, Y., & Park, J. [8], As big data continues to increase at an exponential rate, maintaining data quality has become a crucial obstacle to efficient data analytics. Conventional data cleaning techniques are not scalable for big, complicated datasets and frequently call for human intervention. The authors of this work suggest a novel method for automating data cleansing through the use of reinforcement learning (RL) approaches. The suggested approach uses RL algorithms to automatically detect and fix data inconsistencies, outliers, and missing values by rephrasing the data cleaning procedure as a decision-making problem. The method is intended to reduce human labor and increase cleaning accuracy by adapting to various datasets and continuously improving through feedback.

3. TECHNIQUES FOR ENSURING DATA QUALITY

3.1 Data Cleaning and Pre-processing

One of the fundamental methods for enhancing the quality of data is data cleansing. Prior to analysis, it entails locating and fixing any mistakes or discrepancies in the data [9].

Error Detection and Correction: This includes identifying outliers, duplication, and missing values and taking appropriate action.

Handling Missing Data: Commonly used techniques include interpolation (estimating missing data based on surrounding values), deletion (removing records with missing values), and imputation (replacing missing values with approximated ones).

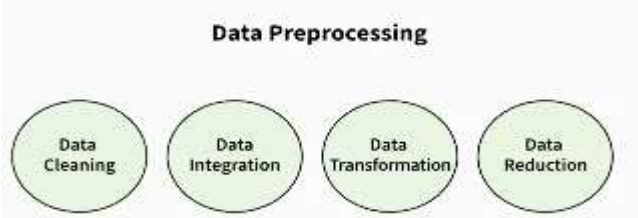

Fig 1: Data pre-processing

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Outlier Detection: Identifying and eliminating data points that substantially depart from the anticipated range [10].

Data Normalization: eliminating inequalities brought on by various data formats or measuring units by scaling data to a similar range (such as 0 to 1).

3.2 Automated Data Quality Tools

Efficient management of large-scale data cleansing operations requires automated tools and systems. Without the need for human intervention, these systems are able to detect mistakes, inconsistencies, and anomalies in data at scale.

Rule-based Systems: Errors and inconsistencies are found by using predetermined rules. For instance, making certain that numerical fields have values within a predetermined range or that date fields have genuine dates [11].

Data Profiling: automated systems that evaluate data quality by producing reports on its consistency, completeness, and other aspects of quality.

3.3 Anomaly Detection

Techniques for anomaly detection are employed to find odd trends or outliers in data, which may point to fraud, mistakes, or other problems with quality [12].

Statistical Methods: These involve identifying data points that significantly deviate from statistical norms (e.g., z-scores or interquartile ranges).

Machine Learning Approaches: Unsupervised learning algorithms like k-means clustering, DBSCAN, and Isolation Forest can identify unusual patterns in large datasets that do not fit typical distributions.

3.4 Data Validation

Data validation ensures that the data conforms to a predefined set of rules and criteria before being used in analysis.

Format Validation: Ensures that data values adhere to specific formats (e.g., phone numbers, email addresses, dates).

Range Validation: Verifies that numerical values fall within an acceptable range (e.g., age should be between 0 and 120).

Referential Integrity: Ensures that relationships between different datasets or tables are valid (e.g., foreign keys in relational databases).

4. DATA CLEANING TECHNIQUES FOR BIG DATA

4.1 Data Deduplication

By finding and removing redundant or duplicate copies of data, data deduplication is a technique that lowers storage costs and increases efficiency. It stores only one unique instance of data and replaces the others with pointers to that copy. This procedure can be carried out inline while data is being written or in the background after data has been stored. It can take place at the file, block, or even byte level [13].

Exact Matching: Identifying duplicates based on exact field matches (e.g., customer ID).

Fuzzy Matching: Using algorithms like Levenshtein distance to identify near duplicates, even if there are slight variations in records.

Hashing: Creating hash keys for records to identify duplicates by comparing hash values.

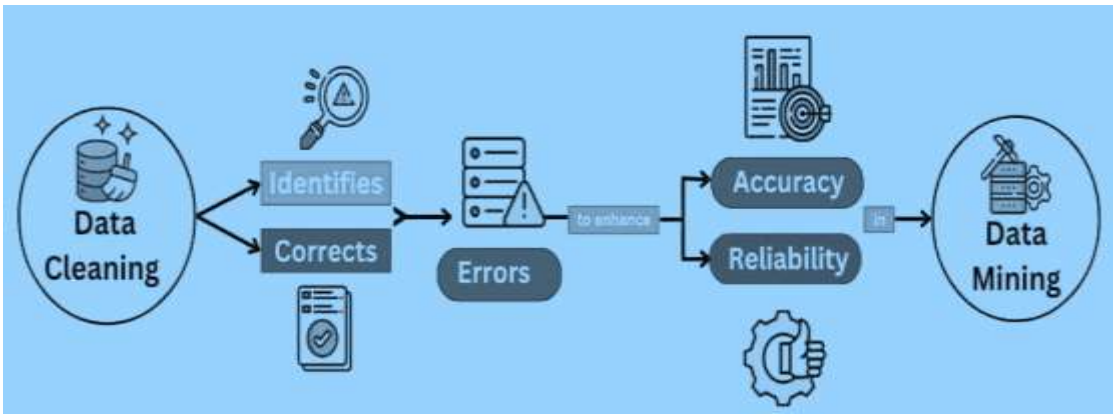

Fig 2: Data Cleaning Techniques

4.2 Handling Missing Data

Imputation: One of the most frequent and important data cleansing tasks is dealing with missing data. Missing values are unavoidable in large datasets for a variety of reasons, including system failures, inadequate data entry, and

mistakes made during data gathering. How you handle missing data can significantly affect the quality of your analysis or models [14].

4.2.1 Identify Missing Data

NaN (Not a Number): In many programming languages, missing values are represented by NaN. You can use functions to identify NaN values in your dataset.

Null or None: In databases or programming languages like SQL or Python (with Pandas), NULL or None can represent missing data.

Blank or Empty Strings: Null strings or blanks can occasionally be used to indicate missing data, particularly in category columns [15].

Out-of-Range Values: In certain cases, missing data may be represented by extreme out-of-range values (e.g., 9999, -999) which should also be handled.

4.2.2 Imputation Techniques

Imputation is the process of substituting approximated values for missing ones. The type of data and how it is distributed determine the imputation technique you should use**.**

Simple Imputation

- **Mean Imputation**: In that column, substitute the mean of the available data for any missing numerical values. This is straightforward, but it has the potential to bias the data distribution, particularly if it is skewed.
- **Median Imputation**: replaces the median of the column's available values for any missing values. For data with outliers or that is not regularly distributed, this is preferable to mean imputation.
- **Mode Imputation**: Used for categorical data, replace missing values with the mode (most frequent value) of the column.

Advanced Imputation Techniques

- **K-Nearest Neighbors (KNN) Imputation**: This technique estimates missing values by averaging the values of the k nearest neighbors. The neighbors are selected based on similarity metrics (e.g., Euclidean distance) in the feature space.
- **Multivariate Imputation by Chained Equations (MICE)**: This method imputes missing values multiple times, creating several imputed datasets. Each missing value is imputed based on the relationships between other variables in the dataset.
- **Regression Imputation**: Use regression models to predict missing values based on other variables in the dataset. A model (e.g., linear regression) is trained to predict missing values from the observed ones.
- **Deep Learning Models**: Neural networks can be used to impute missing values by learning the underlying patterns in the data. This is often applied in complex datasets like images or sequential data.

5. CONCLUSION

The main difficulty in big data situations is striking a balance between computing performance and data quality. For small datasets, conventional data cleaning approaches might still be effective, but huge data necessitates methodologies that are more complex, distributed systems, and automation. Better decision-making, more dependable models, and ultimately more insights from your big data investments are made possible by putting into practice efficient data cleaning techniques, which guarantee that you are working with clean, consistent, and correct data. Big data is kept as a benefit rather than a problem by combining best practices, appropriate technologies, and ongoing data quality assessment.

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