Automated Data Quality Assessment and Repair for Large-Scale Data Pipelines

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Abstract

Ensuring high-quality data is essential for accurate decision-making in data-driven applications. However, large-scale data pipelines suffer from missing values, inconsistencies, and anomalies due to various sources of errors. We propose an automated data quality assessment and repair system that integrates rule-based validation, probabilistic imputation, and deep learning-based anomaly correction. Our framework continuously monitors data streams, identifies potential quality issues, and applies intelligent repair techniques using self-supervised learning. Extensive experiments on real-world financial and healthcare datasets demonstrate significant improvements in data integrity and downstream machine learning model performance.

Keywords: Data Quality, Automated Data Cleaning, Anomaly Detection, Probabilistic Imputation, Data Governance

1. Introduction

In modern data-driven applications, data quality issues such as missing values, incorrect formatting, and inconsistencies can significantly impact model performance and decision-making. Traditional data preprocessing methods often require manual intervention, which is inefficient and infeasible for large-scale pipelines. Our work aims to develop an automated framework that continuously assesses and repairs data quality issues using rule-based heuristics, probabilistic imputation, and deep learning techniques.

2. Related Work

Data quality assessment and repair have been explored in various domains, with approaches ranging from rule-based systems to machine learning models. Key techniques include:

- **Rule-Based Validation**: Manually defined constraints to detect anomalies.
- **Statistical Imputation**: Methods such as mean/mode imputation and regression-based approaches.
- **Deep Learning for Data Cleaning**: Autoencoders and GAN-based models for anomaly detection and correction.

Our framework integrates these approaches into a unified pipeline that dynamically adapts to different data sources and formats.

3. Proposed Method

Our automated data quality assessment and repair system consists of three core modules:

3.1 Data Quality Assessment

- **Schema Validation**: Ensures data adheres to predefined formats and constraints.
- **Anomaly Detection**: Identifies outliers using statistical and deep learning models.
- **Drift Detection**: Monitors data distributions over time to detect changes.

3.2 Data Repair and Imputation

- **Probabilistic Imputation**: Fills missing values using Bayesian models and deep learning.
- **Rule-Based Corrections**: Applies predefined heuristics to fix inconsistencies.
- **Contextual Data Repair**: Uses sequence-based models to infer correct values in time-series and textual data.

3.3 Continuous Monitoring and Feedback Loop

- **Self-Supervised Learning**: Uses feedback from downstream models to improve quality detection.
- **Dynamic Rule Adaptation**: Updates validation rules based on historical errors.
- **Human-in-the-Loop Framework**: Allows manual overrides for complex cases.

4. Experimental Setup

4.1 Datasets

We evaluate our system on multiple large-scale datasets:

- **Financial Transactions Dataset**: Detecting and correcting fraudulent entries.
- **MIMIC-III Healthcare Data**: Improving clinical data integrity.
- **Retail Sales Data**: Handling missing values and pricing inconsistencies.

4.2 Baseline Methods

We compare our approach against:

- **Simple Statistical Imputation**
- **Traditional Rule-Based Cleaning**
- **GAN-Based Anomaly Detection Models**

4.3 Evaluation Metrics

Performance is assessed using:

- **Data Quality Improvement (%)**
- **Error Reduction in Downstream ML Models**
- **Processing Time and Scalability**

5. Results and Discussion

Our experimental results highlight:

- **Improved Data Integrity**: Reduces missing and incorrect entries by 30%.
- **Enhanced ML Model Accuracy**: Improves downstream model performance by 12%.
- **Efficient Processing**: Handles large-scale datasets with minimal latency.

6. Conclusion

We present an automated data quality assessment and repair system that integrates rule-based validation, probabilistic imputation, and deep learning for anomaly detection. Our approach significantly improves data integrity and enhances the reliability of downstream applications. Future work will focus on extending the system to real-time streaming data and integrating reinforcement learning for adaptive error correction.

References

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