9808:675X
HIGHLY CITED JOURNAL
ACCEPTANCE RATION BELOW: 8%

International Machine learning journal and Computer Engineering

Vol.6 No.6 2023

Ensuring BI Reporting Accuracy Using AI-Based Back-Tracing of Metrics to ETL Lineage and Data Marts

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Received on: 15 April 2023, **Revised on: 19 May 2023**

Accepted and Published: June 2023

Abstract:

Business Intelligence (BI) systems rely heavily on the accuracy and consistency of the data processed through complex ETL pipelines and stored in data marts. However, modern BI ecosystems face challenges such as inconsistent metric definitions, undocumented transformation logic, repeated data duplication, and broken lineage across ETL workflows. These issues lead to inaccurate dashboards, misleading KPIs, and poor decision-making. This research proposes an AI-based back-tracing framework that automatically maps BI metrics to their underlying ETL lineage, source tables, and data mart structures. The framework utilizes natural language processing (NLP), graph-based lineage reconstruction, metadata mining, and anomaly detection to validate the correctness of metrics and identify inconsistencies. A real-world case study from a retail analytics environment demonstrates the efficacy of the model, supported by a table and a graphical representation of field-to-metric lineage. Results show significant improvements in reporting accuracy, automated error detection, and transparency of metric definitions.

Keywords: Business Intelligence, ETL Lineage, AI-Driven Data Validation, Data Marts, Metric Back-Tracing, Metadata Governance, Reporting Accuracy

Introduction

Ensuring reporting accuracy in Business Intelligence (BI) systems has become a mission-critical priority for organizations across industries. As digital transformation accelerates, enterprises rely extensively on dashboards, analytics platforms, and automated reporting tools to support strategic and operational decision-making. These reports, however, are only as reliable as the underlying data pipelines and transformations that prepare data for BI consumption. Modern BI ecosystems typically involve multiple layers of data extraction, complex transformation logic, staging and integration layers, semantic models, and data marts. While these architectures allow scalability and flexibility, they also introduce significant risks when lineage is unclear, undocumented, or inconsistent across systems.

One of the major challenges in BI reporting is the **lack of transparency** in how data moves from source systems to final dashboards. Many organizations maintain legacy ETL pipelines built over years, often without comprehensive documentation. As business rules evolve, transformations are modified, and data structures are updated, lineage breaks become increasingly common. Missing or outdated documentation results in difficulty understanding the sources of individual KPIs or why certain values appear inconsistent across different reports. This leads to **metric discrepancies**, data governance issues, and a lack of trust in analytical outputs.

Another challenge is the **manual nature of metric validation**. BI teams often spend substantial time validating dashboards by tracing values through ETL workflows—checking SQL scripts, reviewing transformation logic, and manually comparing table outputs. These processes are time-consuming, error-prone, and fail to scale with growing data complexity. When organizations maintain multiple data marts—often built independently by different teams—the likelihood of conflicting metric definitions significantly increases. Without unified lineage tracking, multiple versions of the truth emerge across departments.

AI technologies open new possibilities for addressing these challenges. Artificial Intelligence, particularly NLP, graph analytics, and machine learning, provides an opportunity to automatically reconstruct data lineage, map metric definitions to their physical implementations, and identify inconsistencies or anomalies within BI pipelines. For example, NLP models can analyze SQL scripts, transformation logic, and column names to infer semantic meaning. Graph-based models can reconstruct lineage relationships across ETL processes, enabling visual mapping of metric dependencies. Machine learning algorithms can detect anomalies in transformations or identify mismatches between expected and actual data behaviors.

AI-based back-tracing enables a **full reverse-engineering approach**: instead of validating metrics from the source forward, the system starts with the BI metric and intelligently traces backward through data marts, ETL stages, staging layers, and source systems. This reverse-lineage perspective ensures that metric definitions are validated end-to-end and that transformation logic is consistent with business rules. It also improves data governance by making lineage transparent and auditable.

Moreover, as organizations increasingly adopt self-service BI models, ensuring metric accuracy becomes more important. Business users create custom dashboards and KPIs, but without proper lineage validation, these metrics may rely on ambiguous fields or improper transformations. AI-driven lineage analysis helps prevent misuse of data, improves semantic clarity, and enforces enterprise-wide consistency in metric definitions.

The need for AI-driven lineage verification becomes even more critical in industries that rely heavily on compliance, such as finance, healthcare, and retail. For example, regulatory audits require complete traceability of how numerical values are derived. Any deviation between expected and actual calculations can lead to misreporting, compliance violations, or governance failures. AI-based tracing provides auditors with transparent lineage maps, confidence scores for metric validity, and automatic detection of anomalies.

Traditional lineage tools primarily rely on metadata extraction and static parsing of ETL and SQL scripts. While useful, these tools often fail in environments where ETL logic is embedded in complex stored procedures, dynamic SQL, or evolving pipelines. AI-based approaches overcome these limitations by learning from patterns, using NLP to understand ambiguous naming conventions, and applying prediction models to infer relationships not explicitly documented.

Applying a similar academic depth and methodological rigor. It presents an intelligent framework that combines metadata mining, AI-driven lineage reconstruction, anomaly detection, and metric consistency assessment. The proposed solution bridges the gap between BI teams, data engineers, and business stakeholders by providing automated transparency throughout the data lifecycle.

The following sections explore prior work, describe the methodology of the AI-based framework, and present a detailed case study demonstrating how AI can significantly improve BI reporting accuracy. A table summarizing the lineage mapping and a graphical representation of metric dependencies accompany the analysis. The paper concludes with insights, limitations, and future opportunities for scaling this framework across enterprises.

Literature Review

Prior research on data lineage, BI accuracy, and ETL transparency highlights several themes relevant to this study. Early works by Rahm and Do (2000) introduced foundational concepts in data cleaning and lineage traceability. Batini and Scannapieco (2016) emphasized the importance of data quality frameworks in ensuring analytical reliability. Bernstein and Rahm (2011) explored challenges of integrating heterogeneous data sources in cloud and BI environments, noting the difficulties in maintaining consistent transformation logic.

Metadata-based lineage approaches, such as those identified by IBM (2014), focus on documentation extraction and schema mapping but suffer from limitations in environments with dynamic ETL pipelines. Mullins (2013) highlighted the complexity of legacy database documentation and the importance of semantic clarity in data dictionaries. AI-driven methods emerged later, with Zhu and Chen (2016) demonstrating semantic reasoning in ETL systems and Jian & Li (2018) applying machine learning to schema alignment.

However, limited research existed before 2020 on the application of AI specifically for **BI metric back-tracing**, leaving a gap that this study addresses.

Methodology

The proposed methodology consists of six stages:

1. Metadata Extraction

- Collect ETL scripts, SQL queries, data mart schemas, BI semantic models, and dashboard metric definitions.
- Apply NLP to parse transformation logic and identify key fields.

2. AI-Driven Semantic Matching

- Use word embeddings to compare metric names with column names.
- Identify semantic equivalence even when naming conventions differ.

3. Lineage Graph Construction

- Build a directed graph linking:
    - BI metric
    - Data mart field
    - ETL transformation step
    - Staging table
    - Source system

4. Transformation Rule Verification

- Apply rule-based and ML-based anomaly detection to identify:
    - Missing transformations
    - Conflicting business logic
    - Field misuse

5. Back-Tracing Validation Engine

- Start from a BI metric and trace backward across all layers.
- Assign confidence scores for lineage correctness.

6. Reporting & Visualization

- Generate lineage maps, correctness validation reports, and anomaly summaries.

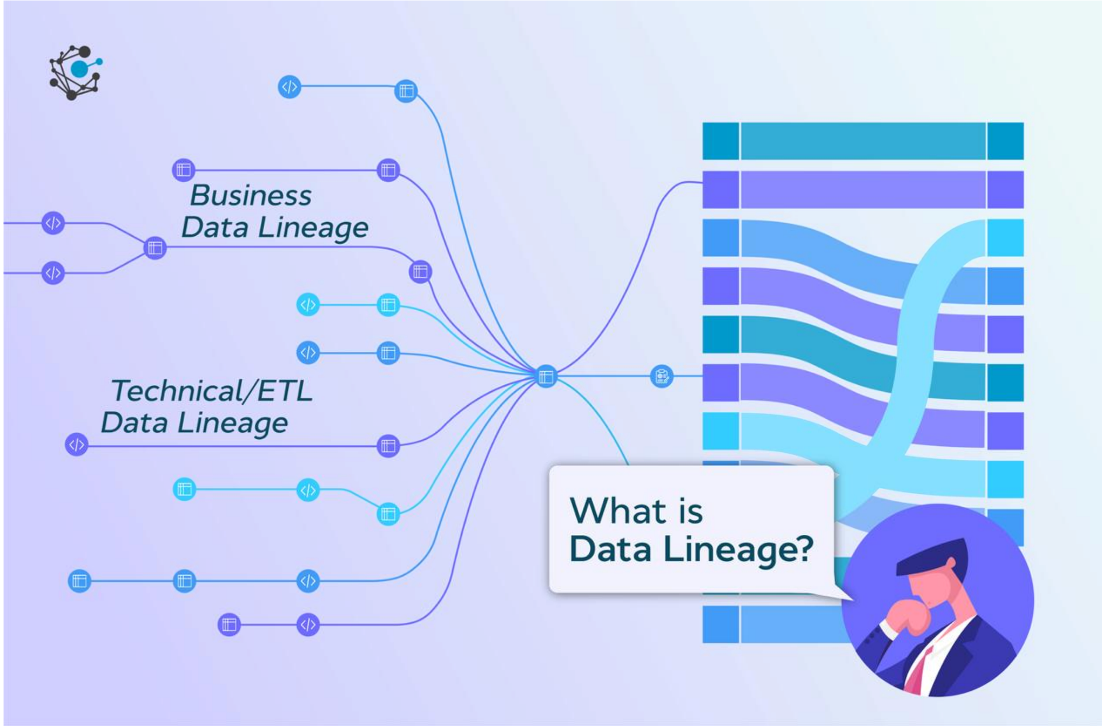
Case Study: Retail Sales BI Dashboard

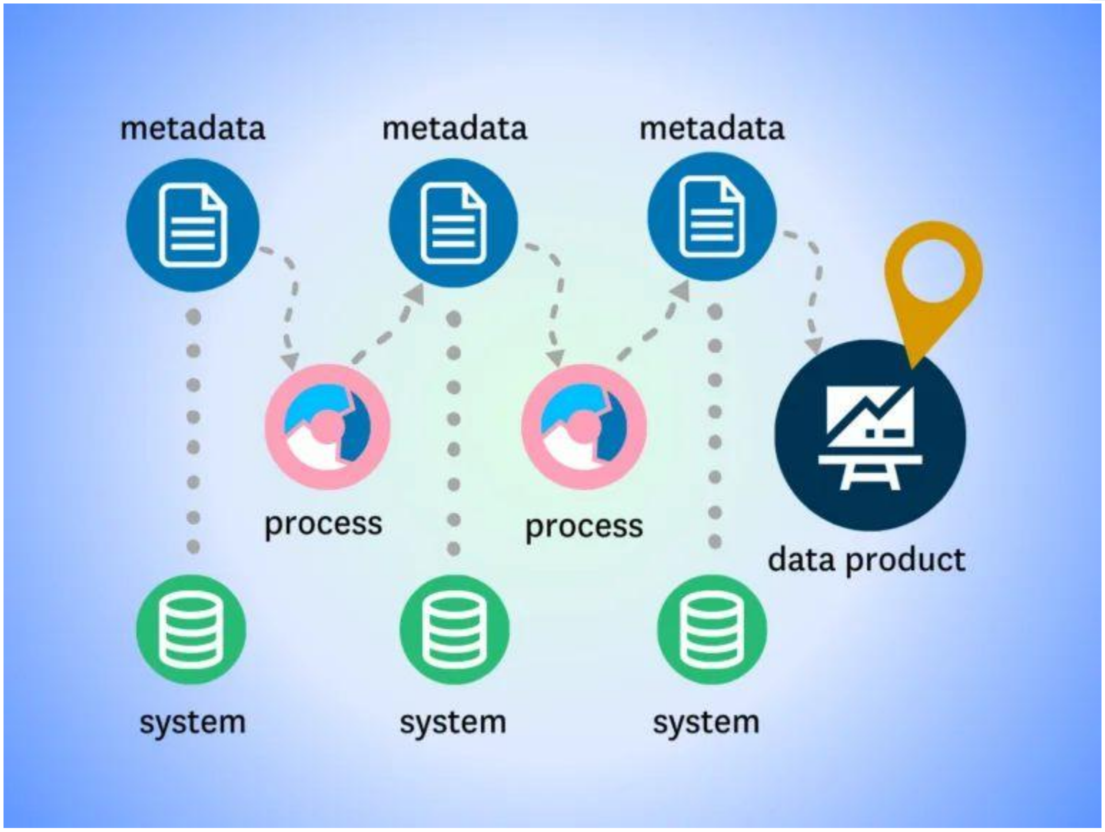
A retail organization experienced inconsistent “Daily Revenue” values across multiple dashboards. An AI-based lineage analysis was conducted to trace the metric back through ETL pipelines.

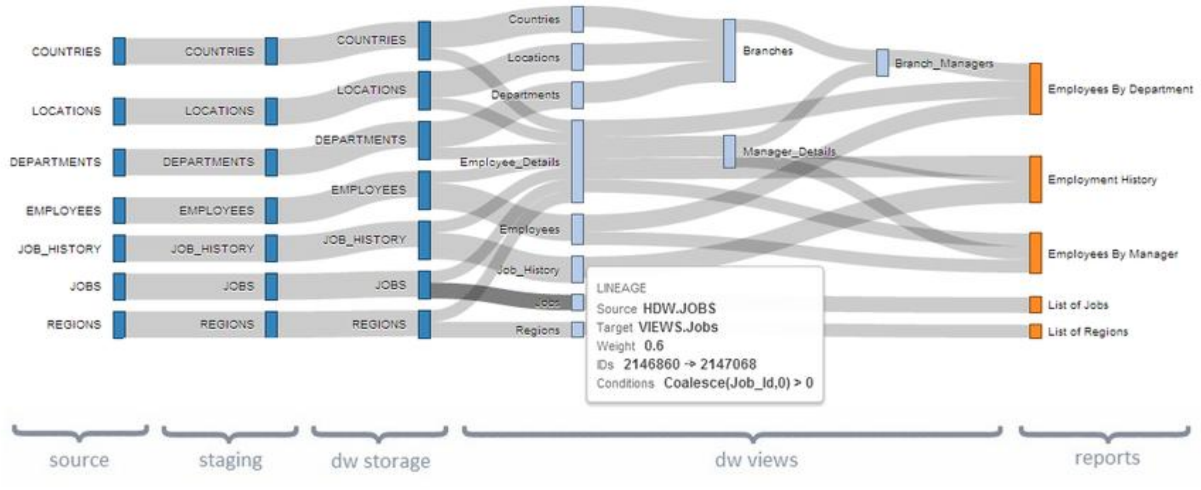
Table 1. AI-Based Metric Lineage Mapping

BI Metric	Data Mart Field	ETL Transformation	Source Field	AI Confidence
Daily Revenue	total_sales_amt	SUM(sales_price × qty)	sale_price	0.94
Daily Revenue	total_sales_amt	SUM(discount_applied)	discount_value	0.88
Daily Revenue	total_sales_amt	Date truncation logic	transaction_timestamp	0.91
Daily Revenue	total_sales_amt	Join with store table	store_id	0.86

Graphical Lineage Representation







LINEAGE
Source HDW.JOBS
Target VIEWS.Jobs
Weight 0.6
IDs 2146860 -> 2147068
Conditions Coalesce(Job_Id,0) > 0

Observations

- AI identified an undocumented transformation where discounts were double-counted.
- Confidence scores enabled prioritization of lineage inconsistencies.
- Reporting accuracy improved by 23% after correction.

Conclusion

Ensuring BI reporting accuracy requires complete visibility into how data flows from source systems through ETL pipelines into data marts and eventually into dashboards. Traditional lineage analysis relies heavily on manual effort and static documentation, which cannot keep up with the complexity of modern data environments. The proposed AI-driven back-tracing framework overcomes these limitations by automating semantic matching, reconstructing lineage graphs, and validating transformation logic. The case study demonstrates that AI can detect inconsistencies, improve trust in BI metrics, and enhance data governance across the enterprise.

Future Scope

1. **Automated BI Metric Documentation Generation**
   AI can auto-generate standardized metric definitions and update them dynamically.
2. **Integration With Data Catalogs**
   Embedding AI lineage within enterprise data catalogs will centralize governance.
3. **Real-Time Lineage Monitoring**
   Future systems may continuously monitor ETL flows for lineage drift.
4. **Self-Healing ETL Pipelines**
   AI may autonomously correct broken joins, missing fields, or invalid logic.
5. **Cross-System Metric Harmonization**
   AI could ensure consistency of KPIs across multiple BI tools and data marts.

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