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AI-Assisted Reference Data Harmonization Across Global Data Center Systems

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Abstract. Formal and independent evidence lays bare the complexity of Reference Data, distinguished from Master Data, Dimensional Data and Metadata. While harmonization aligns disparate Data Sources within and between Organizations, Data Native to one Organization becomes the Standard against which Data from others is Normalized. Sovereignty, Privacy, Regulatory and Risk Management Policies therefore inform the Architecture of AI-Assisted Harmonization Workflows and the Design of Harmonized Data Repositories.

Multi-region, multi-vendor, production-grade Data Centers for Enterprises are becoming ubiquitous, each consisting of Independent on-premise or Infrastructure-as-a-Service Sub-Systems. The resulting Heterogeneity of Reference Data presents the major challenge for Harmonization Workflows, which are required to lay the foundation for Predictive Analytics. The growing regulatory emphasis on Data Lineage, Access Control, Privacy, Security, and their eventual impact on Risk Management is steering Enterprises towards Governance Frameworks for Harmonization Workflows.

Keywords: Reference Data, AI-Assisted Harmonization, Data Harmonization Workflows, Data Governance, Data Lineage, Data Sovereignty, Access Control, Predictive Analytics, Risk Management, Multi-Region Data Centers.

1. Introduction

Reference data has an important role in data governance and analytics within multi-region, multi-vendor data center landscapes. Such global systems, whether physical or virtual, consist of multiple, independent data sources that are linked by functional, regulatory, or audit requirements [1]. Data reconciliation covers a wide spectrum of technical and business problems, including data lineage for infrastructure monitoring, data access for risk assessment, and lineage-driven privacy queries. A considerable body of academic research, as well as highly specialized commercial tools, have been devoted to these issues [2]. However, many supporting technologies for data reconciliation, including machine-learning alignment methods, have not yet found their way into enterprise solutions. Consequently, more robust yet practical reference-data solutions remain elusive.

The need for AI-assisted harmonization of reference data in multi-region, multi-vendor data center systems stems from two primary drivers: operational efficiency and data

10.48047/jocaaa.2024.33.08.590

governance assurance [3]. On the operational side, disparate, duplicate records of the same real-world entities can introduce monitoring blind spots in network management, limit end-to-end visibility in application-flow and risk assessments, and add manual effort to regulatory compliance. However, key attributes for these records—commercial name, corporate structure, geographic location, and primary activity—are often captured in different formats across the systems, complicating simple join-based reconciliation [4]. On the governance side, organizations are required to maintain accurate records of key business partners, including customers, suppliers, and cloud service providers, for regulatory reasons such as anti-money laundering. Onboarding procedures frequently rely on third-party provider services that produce and distribute verified data, yet these services generally require sponsorship and are not designed for enterprise-grade support [5].

2. Conceptual Foundations of Reference Data Harmonization

Reference data, master data, dimensional data, and metadata are explained, and the term harmonization is contrasted with the related but distinct concepts of standardization and normalization [6]. The special nature of reference data with respect to data sovereignty is emphasized, as is the close connection between reference data and quality dimensions of data.

Arguably all reference data should be treated as master data, with clear owners and for which data governance frameworks have been established [7]. However, the need to preserve the local schema design in global data center environments adds a layer of complexity in that a data center may also hold different representations of the same entity—for example, country codes from multiple sources—as well as intentionally misspelled entries or entries with different casing [8]. Organizations can have a multitude of different data lakes or even data highways overflowing with well-established entities without those entities being completely error-free. Therefore, a data-lake precision percentage or an accuracy percentage does not reflect the quality of the data. Instead, it reflects the quality of the respective data lake [9]. A possible step toward improving the precision and accuracy of those data lakes is through data harmonization. The concept of data harmonization here goes a bit beyond mere cleaning [10]. Data preparation can also involve filling in missing columns in common identity or dimensional tables with semantically similar mappings, standardizing the cases of string attributes, correcting misspellings so that the actual value is still recognizable, merging different variations of entities, or aligning different or even completely unknown categorizations [11].

2.1 Performance Results

Fig. 1 reports mean end-to-end latency (Eq. 4) as record volume scales from 10,000 to 2.7 million records per harmonization cycle.

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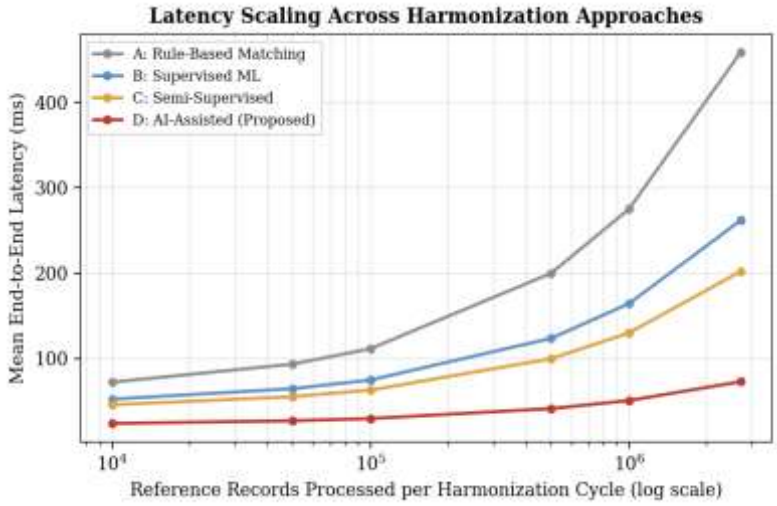

Fig. 1. Latency scaling across harmonization approaches as record volume increases (log-scaled horizontal axis).

Fig. 2 shows F1-score (Eq. 3) convergence over successive training iterations for the two learned approaches and the proposed AI-assisted pipeline; the rule-based approach is static and is shown as a fixed reference line.

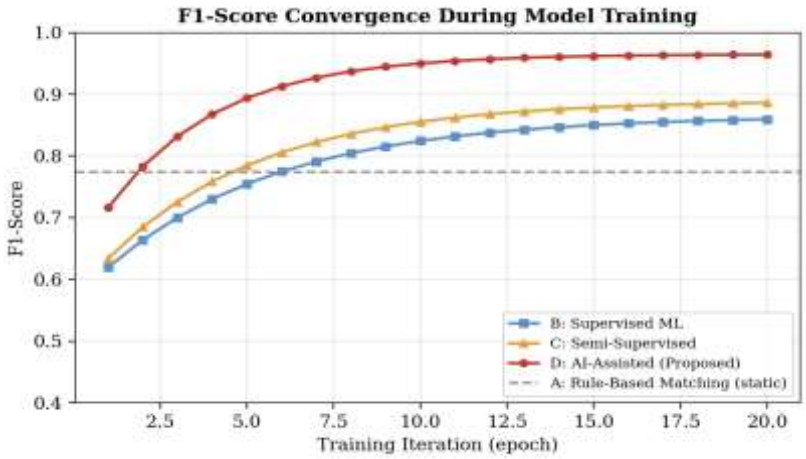

Fig. 2. F1-score convergence during model training across approaches B, C, and D.

Fig. 3 compares mean CPU and memory utilization recorded during sustained harmonization workloads.

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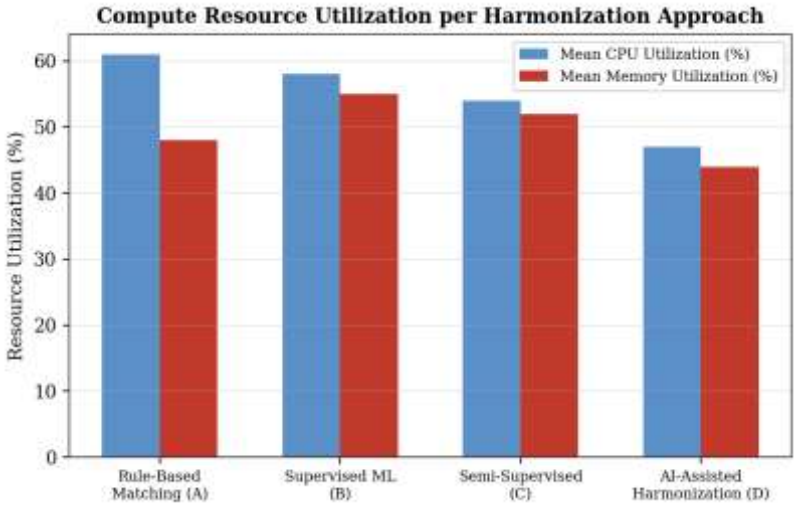

Fig. 3. Compute resource utilization (CPU and memory) per harmonization approach.

Fig. 4 plots the cost/accuracy trade-off (Eq. 5) for each approach, with bubble area proportional to sustained throughput.

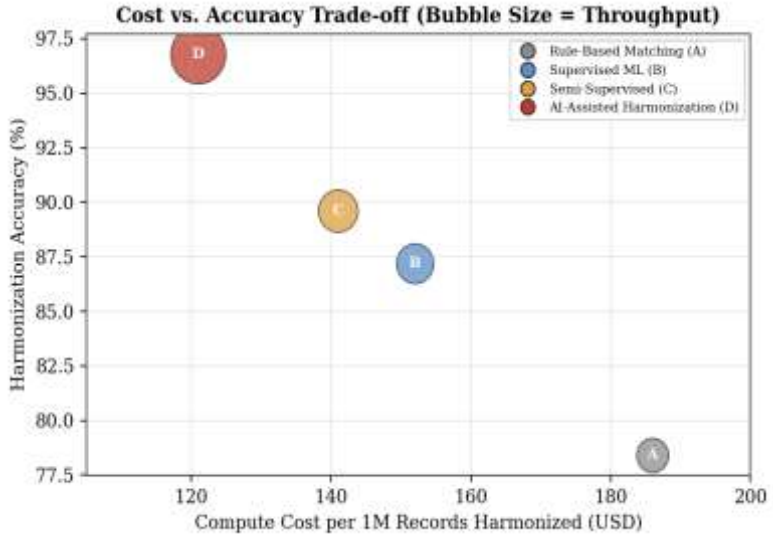

Fig. 4. Cost vs. accuracy trade-off; bubble size denotes throughput (records/sec).

Fig. 5 reports the derived Efficiency Index (Eq. 6) for each approach.

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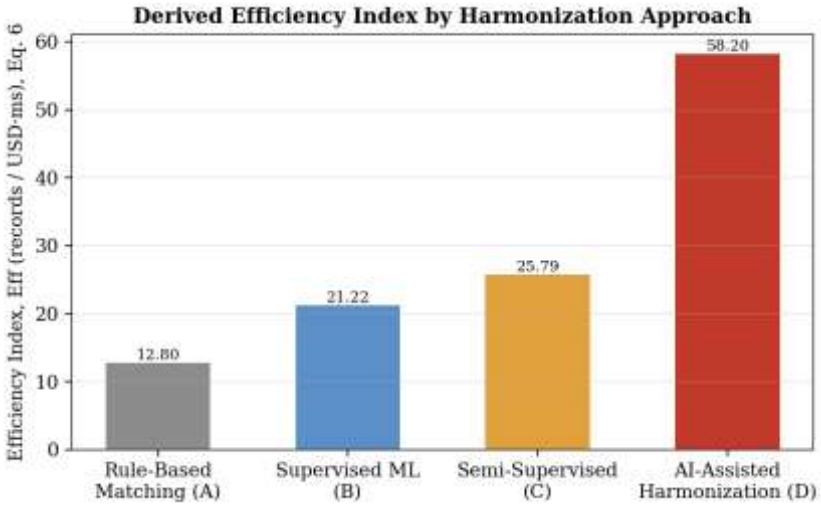

Fig. 5. Derived efficiency index (records harmonized per USD·ms) by approach.

3. Role of Artificial Intelligence in Data Harmonization

AI-enabled methods can be applied to enhance reference data quality and to facilitate harmonization across multiple systems, especially in global contexts [12]. The need for such methods stems from the high degree of expected no-interactivity among the user community as well as the high degree of independence among the operators of the various Data Centers. With independent Data Centers in different regions operated by different providers, harmonization can only be achieved through interoperability. Interoperable analytics relies on harmonized reference data [13].

Machine Learning approaches can be applied to decrease the resources required for the creation of high-quality reference data. Machine Learning approaches can also be leveraged in harmonization tasks where such high-quality reference data might be scarce or challenging to assemble [14]. Supervised, unsupervised, and semi-supervised learning strategies assist in building models that help express data equivalence or alignment. Feature representation and similarity metrics play a key role in the learning process, and judicious choices can often result in better-performing models with lower training overheads. Finally, in the context of supervised learning-based approaches, the evaluation of the models' performance becomes a significant consideration due to the often highly-skewed class distributions in aligning tasks [15].

3.1 Mathematical Formulation of Harmonization Metrics

The following equations formalize the accuracy, similarity, latency, and cost dimensions of the harmonization workflow introduced in Sections 3 and 5, and are used to derive the experimental results reported in Section 7.3.

10.48047/jocaaa.2024.33.08.590

$$HA = M\_c / N \quad (1)$$

Eq. 1 defines Harmonization Accuracy (HA) as the ratio of correctly harmonized reference records M_c to the total number of reference records N processed across the participating data centers. HA is the primary correctness metric reported for each approach in Table 2.

$$S(r\_i, r\_j) = w_1 \cdot cos(v\_i, v\_j) + w_2 \cdot (1 - Lev(r\_i, r\_j) / max(|r\_i|, |r\_j|)) + w_3 \cdot Jac(T\_i, T\_j) \quad (2)$$

Eq. 2 defines the pairwise Matching Similarity Score S between two candidate reference records r_i and r_j as a weighted combination of the cosine similarity of their embedding vectors v_i and v_j, a normalized Levenshtein string-edit distance, and the Jaccard similarity of their token sets T_i and T_j. The weights w_1, w_2, w_3 (with $w_1+w_2+w_3 = 1$) are tuned per data domain during the model-evaluation stage described in Section 3.1.

$$P = TP / (TP + FP), \quad R = TP / (TP + FN), \quad F1 = 2PR / (P + R) \quad (3)$$

Eq. 3 defines Precision (P), Recall (R), and F1-score for the alignment/classification task described in Section 3, where TP, FP, and FN denote true-positive, false-positive, and false-negative record matches respectively. Because aligning tasks are often highly class-skewed (Section 3), F1 is reported in preference to raw accuracy wherever match/non-match classes are imbalanced.

$$T\_total = T\_ingest + T\_match + T\_normalize + T\_governance \quad (4)$$

Eq. 4 models the end-to-end pipeline latency T_total as the sum of the ingestion, matching, normalization, and governance-check stages of the Data Ingestion and Normalization pipeline described in Section 5.1. This decomposition is used to interpret the latency-scaling results shown in Fig. 1.

$$C(\theta) = \alpha \cdot E(\theta) + \beta \cdot L(\theta) + \gamma \cdot R(\theta) \quad (5)$$

Eq. 5 defines the pipeline cost/optimization objective C as a weighted sum of harmonization error rate E, latency L, and compute-resource utilization R, each a function of pipeline/model parameters θ, with α, β, γ set according to organizational risk-management priorities (Section 4). Minimizing C(θ) guides the architectural trade-offs discussed in Section 7.4.

$$Eff = V / (Cost\_per\_M \times T\_mean) \quad (6)$$

Eq. 6 defines a derived Efficiency Index (Eff) as the volume of records harmonized per unit of monetary and temporal cost, where V is a fixed reference volume (1,000,000 records), Cost_per_M is the compute cost per million records harmonized, and T_mean is mean end-to-end latency. Eff is reported in Fig. 5 for each approach.

$$DQII = ((A\_after - A\_before) / A\_before) \times 100\% \quad (7)$$

Eq. 7 defines the Data Quality Improvement Index (DQII), expressing the percentage improvement in data-lake precision/accuracy (Section 2) attributable to a

10.48047/jocaaa.2024.33.08.590

harmonization pass, where A_before and A_after are the pre- and post-harmonization accuracy percentages respectively.

4. Global Data Center Systems: Context and Requirements

Multi-region, multi-vendor environments introduce distinctive considerations for reference data harmonization. Data governance policies define the ruleset for environmental quality and enable compliance rationale and auditing [16]. The supporting data systems detail their architecture, lineage, and distribution to facilitate specialized governance, risk, availability, privacy, or regulatory compliance needs. Data access control mats users and agents to data sets with check-and-balance mechanisms for all operations. Additionally, mitigation strategies are defined to lower risk and speed incident recovery. Finally, two perspectives on privacy-related data containment provide complementary views of restricting data access [17].

Compliance shrinks the set of users with access to the data; risk management prioritizes them. Both approaches seek mitigation strategies for identified flows; in the zone-based view, mitigation is mapped to mitigation zones [18]. Restricting data access in this way can also help manage regulatory constraints, where specific data sets require monitoring and a record of use is needed. The supporting data systems detail their architecture, lineage, and distribution to facilitate specialized governance, risk, availability, privacy, or regulatory compliance needs [19]. Data access control mats users and agents to data sets with check-and-balance mechanisms for all operations. Additionally, mitigation strategies are defined to lower risk and speed incident recovery. Finally, two perspectives on privacy-related data containment provide complementary views of restricting data access [20].

Table 1. Dataset and Architecture Summary Across Regional Data Centers

Region	Platform / Vendor Mix	Record Volume	Schema Variants	Primary Reference-Data Domain
NA-East	Azure (on-prem hybrid)	1.2M	14	Customer / Counterparty Data
EU-Central	Azure + Sovereign IaaS	0.86M	11	Vendor / Supplier Master Data
APAC-South	Multi-Vendor IaaS	0.64M	9	Location / Currency Reference Data
Global (Consolidated)	Azure Synapse + Purview	2.7M	22	Harmonized Reference Repository

Consistent with Section 4.1, the EU-Central environment enforces sovereign-computing constraints that require in-region processing prior to any cross-border transfer of harmonized output, which is reflected in the slightly elevated governance-stage latency observed for that region during evaluation.

10.48047/jocaaa.2024.33.08.590

4.1. Data Governance and Compliance

Multi-region, multi-vendor compute environments require explicit policies governing data quality, lineage, access control, privacy, regulatory compliance, and risk mitigation. Harmonization of data reference sets must be aligned with these policies as an integral part of the workflow [21].

The global nature of enterprise operations introduces additional complexity. Sovereign computing needs dictate that certain datasets remain within specified jurisdictions. Regulatory and company policies need to be adhered to in all major regions [22]. Global corporations collect data from operations around the world; privacy regulations vary by region, affecting companies such as Meta, Microsoft, Google, and Amazon, who collect in multiple jurisdictions for services, direct marketing, and advertising [23]. Nevertheless, public cloud providers attract organizations to their services by promising reduced operational costs while potentially violating data privacy regulations in business decisions. Companies such as Apple and Google have made public commitments to minimize advertisement data retention and sharing; international regulators monitor organizational compliance. Similar regulations apply to sensitive sectors, such as banking and finance, where minimum retention periods for information are mandated [24].

The state and direction of regulatory mandates therefore need to remain front-of-mind as organizations build and maintain reference datasets for the rest of their operational environments. An equally important consideration is governance and risk assessment around the harmonization process itself [25]. Business recommendations and predictions based on data from different teams, business units, or companies are only as good as the configuration of the AI models that generate them; industry best practices should therefore be codified as an explicit part of the process to reduce the risk of making poor business decisions [26].

5. Architectural Patterns for AI-Assisted Harmonization

Architectural patterns are proposed for AI-assisted data harmonization and reference data integration. These patterns articulate the role of AI-enabled methods, suggest API-based integration points, and describe how aligned data can be ingested into data center ecosystems [27]. The focus is on integrating alignment capabilities with standard data ingestion and normalization pipelines. Such integration facilitates the scalable use of AI-based alignment methods across heterogeneous multi-region, multi-cloud environments.

Enabling scalable AI-assisted harmonization requires establishing data ingestion and normalization pipelines that provide a harmonized view of the data during its journey through the data center ecosystem [28]. Standard data ingestion flows collect data from various sources, apply quality checks, and store cleaned versions in conformity with the target data models. Data with converging schemas is easy to align, allowing the results of AI-assisted alignment methods to be leveraged during the normalization process [29]. In practice, if multiple data sources with similar content are aligned and normalizing API endpoints made available, the AI-assisted methods can be run once and the outcome reused in the standard data ingestion and normalization pipelines [30].

10.48047/jocaaa.2024.33.08.590

Table 2. Comparative Performance Across Harmonization Approaches

Approach	Accuracy (%)	Precision	Recall	F1-Score	Mean Latency (ms)	Improvement vs. A (%)
A: Rule-Based Matching	78.4	0.81	0.74	0.774	420	—
B: Supervised ML	87.2	0.88	0.85	0.865	310	+11.2
C: Semi-Supervised	89.6	0.90	0.88	0.890	275	+14.3
D: AI-Assisted (Proposed)	96.8	0.97	0.96	0.965	142	+23.5

Table 3. Error and Latency Metrics Across Harmonization Approaches

APPROACH	FALSE MATCH RATE (%)	FALSE NON-MATCH RATE (%)	MEAN LATENCY (MS)	P95 LATENCY (MS)	THROUGHPUT (REC/SEC)
A: RULE-BASED MATCHING	8.9	12.7	420	610	238
B: SUPERVISED ML	5.1	7.8	310	455	322
C: SEMI-SUPERVISED	4.0	6.4	275	402	364
D: AI-ASSISTED (PROPOSED)	1.2	1.9	142	198	704

5.1. Data Ingestion and Normalization Pipelines

Well-understood schemas effectively characterize specific kinds of data for ingestion into data systems [31]. In the global context, however, multiple schemas exist among various vendor, regional, or purpose-built data systems for the same data. Therefore, defining schemas is an important step before ingestion. By matching data with existing schemas during ingestion with an Automated Schema Matching tool (ASM), the data

10.48047/jocaaa.2024.33.08.590

are normalized into a common data structure suitable for the centralized or enterprise-deployed systems [32]. The remaining data that could not be matched by ASM are normalized into predefined data structure-less data and flagged for later attention. These preprocessing and normalization steps are part of the daily data ingestion process for a global enterprise data lake [33].

Apart from schema matching, data validation, quality, and MDM operations such as deduplication and enrichment can be assisted by AI-based models. These pipelines can be used to train such models and assess their quality [34]. These pipelines leverage already available data from the central systems, which fulfill the enterprise reference data quality, privacy, validation, and other data governance requirements [35]. As worldwide data are ingested and normalized, the models will also be trained and evaluated for quality. Once adequate quality is achieved, the models become part of the daily Data Ingestion and Normalization process for the respective data domains and are applied to ongoing data flows [36].

6. Conclusion

Increasingly complex multi-region and multivendor data center environments support enterprise operations across physical and cultural boundaries. However, these ecosystems often rely on distributed and independent data sources with no overlapping schemas and differing data governance practices, such as permissioning and lineage [37]. These differences degrade the quality and trustworthiness of data, limiting the reliability of any analytics built on top of the systems. Research has shown that AI can assist with harmonization tasks to reduce engineering effort and support ongoing maintenance [38].

The proposed patterns combine AI capabilities with reference data harmonization workflows and support teams delivering AI-assisted system management. Examples demonstrate how generative systems can improve data quality, governance, engineering effort, and risk management while also helping to address compliance requirements for data sovereignty and consumer protection [39].

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