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Original Article

Metadata-Centric Semantic Layer Management in Multi-Domain Pipelines

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ABSTRACT

In modern data-driven ecosystems, multi-domain data pipelines present significant challenges in terms of interoperability, scalability, governance, and semantic consistency. Traditional data integration methods often falter when faced with the heterogeneity and velocity of domain-specific data. This paper proposes a metadata-centric approach to managing the semantic layer in multi-domain data pipelines. By elevating metadata to a first-class citizen, organizations can dynamically model, interpret, and govern data semantics across domains without excessive data movement or manual schema alignment. We introduce a reference architecture and management framework that leverages active metadata, semantic annotations, knowledge graphs, and policy-driven governance to enable scalable, federated analytics. Case studies and experimental evaluation demonstrate the effectiveness of the approach in improving query performance, data lineage traceability, and cross-domain interoperability. The proposed methodology aligns with modern data mesh principles and promotes sustainable data infrastructure design.

KEYWORDS

Multi-Domain Pipelines; Data Governance; Data Mesh; Knowledge Graphs; Active Metadata; Data Lineage; Semantic Interoperability; Federated Data Architecture.

1. INTRODUCTION

In today's data-driven enterprises, the complexity of multi-domain data pipelines has grown significantly. Organizations increasingly rely on diverse and distributed data sources across business units such as finance, marketing, operations, and product development. These domains often operate semi-independently, resulting in distinct data structures, semantic definitions, and integration practices. The motivation behind this work lies in the growing need to manage the complexity that arises when data pipelines span multiple such domains, where inconsistent semantics and fragmented metadata can severely hinder end-to-end data understanding, quality assurance, and analytics. Traditional semantic integration methods, such as static mappings or schema alignment tools, have struggled to keep pace with the dynamic and distributed nature of modern data environments. These conventional approaches often require manual intervention, are brittle in the face of schema evolution, and lack the scalability needed to support cross-domain data sharing and understanding. Moreover, they frequently treat metadata as a passive artifact, rather than as a dynamic asset that can drive intelligent automation and governance across the data lifecycle.

In modern data architectures such as data mesh and data fabric the role of metadata has evolved from a simple descriptive tool to a strategic enabler of data discovery, interoperability, observability, and governance. Metadata is no longer limited to documenting technical schemas; it now encompasses business context, operational behavior, quality metrics, lineage, and usage patterns. Recognizing and leveraging this rich metadata fabric is essential for enabling trust and consistency across domains. This paper aims to address the challenges of semantic integration in multi-domain data environments by proposing a unified, metadata-centric framework. The key contributions of this work include (1) a detailed analysis of semantic heterogeneity and metadata fragmentation issues in current architectures, (2) a conceptual model for an active metadata layer that facilitates semantic interoperability, and (3) design recommendations for embedding such a metadata layer into existing and emerging architectural paradigms. Through this framework, we seek to enable more robust, scalable, and intelligent data integration practices suitable for complex, distributed enterprises.

2. BACKGROUND AND RELATED WORK

Semantic layers have emerged as a critical abstraction in modern data analytics, serving as an intermediary between raw data and end-users. These layers help translate low-level data structures into meaningful business terms, enabling consistent understanding and usage across tools and stakeholders. By mapping technical representations to domain-specific ontologies or taxonomies, semantic layers facilitate analytics, reporting, governance, and decision-making. Their importance is further amplified in multi-domain settings, where uniform semantics can bridge the gap between diverse data producers and consumers. To fully harness the power of semantic integration, it is essential to understand the different types of metadata that underpin data systems. Technical metadata includes information about schemas, tables, columns, data types, and storage formats. Business metadata adds context by capturing definitions, ownership, policies, and business terms. Operational metadata encompasses usage statistics, data lineage, quality scores, processing times,

and system performance. These categories are foundational in enabling intelligent data management practices, especially when interlinked to support richer semantic reasoning.

A key distinction in the evolution of metadata systems is between traditional (or passive) metadata and active metadata. Traditional metadata is typically static, updated manually or through periodic scans, and serves primarily as documentation. In contrast, active metadata is dynamic, event-driven, and tightly integrated into the runtime fabric of data systems. It is continuously refreshed by observing data flows and user interactions, and can trigger automated actions—such as alerts, recommendations, or policy enforcement—based on real-time context. This shift is crucial in enabling adaptive, metadata-aware architectures. Numerous related approaches have emerged in the data ecosystem to address aspects of metadata management and semantic interoperability. Data catalogs aim to centralize metadata documentation and enable search and discovery, often enriched with user annotations and AI-powered classifications. Data mesh promotes decentralized data ownership while relying heavily on domain-level metadata contracts to ensure interoperability. Data fabric emphasizes the seamless integration of distributed data assets through active metadata, automation, and knowledge graphs.

While each of these paradigms contributes valuable ideas, they often operate in silos or lack a unified semantic framework that spans the entire data lifecycle. Despite the proliferation of tools and models, significant gaps remain in how semantics and metadata are managed across domains. Many solutions focus narrowly on one layer (e.g., technical documentation) or one domain (e.g., finance), without supporting cross-domain harmonization. There is often limited integration between business and technical metadata, weak support for active behaviors, and insufficient linkage to operational contexts. These gaps hinder the realization of scalable, trustworthy data ecosystems where meaning can be consistently shared and interpreted across boundaries.

3. PROBLEM DEFINITION

One of the central challenges in modern data architecture is managing semantic consistency across diverse business domains, each with its own data culture, tools, and definitions. Heterogeneous schemas are a fundamental issue: different domains often define similar concepts in structurally or semantically incompatible ways. For example, “customer” in a sales domain may refer to external clients, while in finance it might represent billing entities—each with different attributes and meanings. This semantic divergence makes data integration fragile and prone to misinterpretation. Compounding the problem is the lack of centralized governance. In many organizations, data ownership is distributed among teams, leading to isolated decision-making about schemas, metadata practices, and data contracts. Without a unified oversight mechanism, conflicting definitions, duplicated efforts, and inconsistent policies proliferate. The governance vacuum not only complicates integration but also undermines data trust and compliance.

Siloed metadata systems further exacerbate the situation. Technical metadata is often stored in one repository (e.g., a data warehouse catalog), business glossaries in another (e.g., a corporate knowledge base), and operational metrics elsewhere (e.g., monitoring dashboards). These

disconnected systems prevent a holistic view of data assets, limiting the ability to reason across layers or automate semantic reconciliation. Cross-domain collaboration becomes inefficient, relying on manual mappings and tribal knowledge. Traditional integration mechanisms—such as ETL pipelines or schema mappings—are inherently fragile in such an environment. They are typically hardcoded, brittle in the face of change, and require continuous maintenance. As data systems evolve rapidly, especially with agile product teams making frequent changes, these integration mechanisms fail to keep pace. This leads to broken pipelines, data quality issues, and delayed insights. Given these challenges; there is a compelling need for a unified, metadata-centric framework that can support semantic interoperability across domains. Such a framework should integrate diverse types of metadata into a cohesive fabric, promote active behaviors for adaptation and governance, and provide a semantic abstraction that aligns technical, business, and operational perspectives. It should enable data producers and consumers to reason over shared meanings, collaborate effectively, and build resilient, trustworthy pipelines. Addressing this need is the focus of the proposed approach.

Table 1: Summary of Key Concepts in Semantic Integration across Multi-Domain Architectures

Aspect	Description	Traditional Approach	Modern/Proposed Approach
Motivation	Increasing complexity of data pipelines across multiple business domains	Centralized, monolithic data systems	Federated, domain-oriented architectures (e.g., data mesh)
Semantic Challenges	Differences in meaning, representation, and usage of data across domains	Manual schema mapping; hardcoded pipelines	Metadata-driven semantic abstraction layer
Metadata Types	Categories of metadata used to describe and manage data	Mainly technical metadata (schemas, columns)	Rich, multi-layered metadata (technical, business, operational)
Metadata Behavior	How metadata is used and maintained	Static, manually updated	Active, real-time, automated
Integration Fragility	Issues arising from brittle, tightly coupled integrations	Frequent breakage due to schema evolution or misalignment	Resilient integration via semantic contracts and active metadata
Governance	Oversight and consistency in data definitions and usage	Centralized but disconnected; slow and top-down	Decentralized but coordinated through shared metadata standards
Metadata Systems	Tools used to store and manage metadata	Isolated metadata silos (catalogs, glossaries, monitors)	Unified metadata fabric spanning tools and domains
Cross-domain Interoperability	Ability to share and understand data across teams/domains	Poor interoperability due to siloed semantics	Improved via semantic layers and linked metadata
Objective	Enable scalable, trustworthy analytics across domains	Limited scalability, high maintenance	Metadata-centric framework enabling semantic alignment and automation

4. PROPOSED APPROACH

To address the limitations of traditional semantic integration in multi-domain data environments, we propose a metadata-centric framework that decouples semantics from data infrastructure and promotes interoperability through a unified semantic layer. This approach recognizes metadata not as an afterthought or documentation layer but as an active, dynamic component of the data architecture. By placing metadata at the core of system design, the framework enables automated reasoning, policy enforcement, semantic interoperability, and flexible governance across domains.

4.1. Metadata-Centric Design Principles

At the heart of this approach is the principle of decoupling data from semantics. Instead of tightly coupling semantic meaning to data schemas and pipeline logic, our model externalizes semantic definitions into a dedicated layer that interfaces with domain-specific datasets. This allows data to evolve independently of its interpretation, fostering greater resilience and reusability. A second key design tenet is treating metadata as dynamic and actionable. Rather than static annotations stored in catalogs, metadata is constantly updated by observing data flows, lineage, and user interactions. It is leveraged to automate integration, enforce policies, and guide users toward correct interpretations. Lastly, the design emphasizes domain-specific modeling, where each domain defines its own semantic models aligned with local needs, while interoperability layers link these models to a global semantic framework. This strikes a balance between autonomy and consistency, enabling decentralized teams to innovate while maintaining a shared understanding across the enterprise.

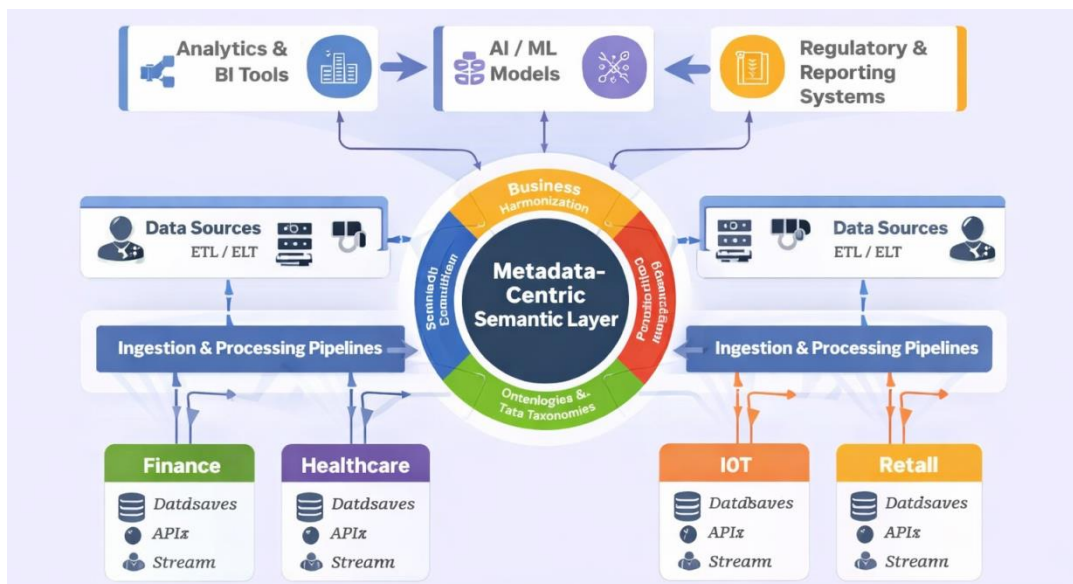


Fig 1 - Metadata-Centric Semantic Layer Architecture

4.2. Semantic Layer Architecture

The proposed semantic layer architecture consists of several interconnected components that work together to enable semantic integration across domains. A metadata repository serves as the

central storage for all types of metadata—structural (e.g., schemas), operational (e.g., lineage, usage), semantic (e.g., ontologies), and policy-related (e.g., access rules). This repository is accessible via APIs and query interfaces. A semantic model engine provides the logic to interpret, relate, and validate metadata, enabling reasoning over domain-specific and global models. The query translation and orchestration module interprets user queries in semantic terms, maps them to underlying data sources, and rewrites them for execution across heterogeneous systems. It ensures semantic consistency while abstracting technical details from users. Governance and access control modules use metadata to enforce data usage policies, manage roles and permissions, and audit access. Together, these components form a cohesive architecture that transforms metadata into a first-class citizen in the data ecosystem.

4.3. Semantic Annotation and Mapping

A foundational aspect of semantic interoperability is the ability to annotate and map data elements to shared concepts. This is achieved through the use of ontologies and taxonomies, which define standardized vocabularies and relationships among concepts across domains. Each domain's local schema is mapped to global concepts, allowing for semantic alignment without forcing schema unification. For example, "Client_ID" in sales and "Customer_ID" in support might both map to a shared concept of "Customer". These mappings are implemented using semantic web standards such as RDF (Resource Description Framework), OWL (Web Ontology Language), SHACL (Shapes Constraint Language) for validating structure, and JSON-LD for embedding semantic annotations in data payloads. These technologies enable flexible, machine-readable semantics that can support query federation, reasoning, and metadata validation at scale.

4.4. Active Metadata Management

To support real-time adaptability, the framework embraces active metadata, where metadata is automatically updated based on events within the data ecosystem. For instance, schema changes, pipeline executions, or access logs can trigger updates to metadata repositories. This event-driven metadata update mechanism ensures that the metadata stays in sync with rapidly evolving data environments. The architecture integrates seamlessly with existing data catalogs and lineage tools—such as Apache Atlas, OpenMetadata, or Amundsen—enhancing them with dynamic capabilities. Additionally, metadata observability and monitoring modules track changes, completeness, and usage patterns, helping governance teams identify anomalies, inconsistencies, or quality degradation early. By making metadata observable and actionable, the system moves toward a more intelligent and autonomous data fabric.

4.5. Governance and Policy Enforcement

A core advantage of a metadata-centric framework is the ability to drive governance and policy enforcement directly through metadata. Access control mechanisms are enriched with semantic context, allowing for fine-grained permissions based not only on user roles but also on the sensitivity or meaning of the data being accessed. For example, only certain roles may view personally identifiable information (PII) or aggregate financial data. Data usage policies—such as data retention, anonymization, or consent requirements—are encoded as metadata rules that are

automatically enforced during data access or transformation. This improves compliance and reduces manual overhead. Furthermore, regulatory compliance tracking becomes more robust and auditable, as data flows, access logs, and usage metrics are semantically linked to relevant regulations (e.g., GDPR, HIPAA). This allows organizations to demonstrate conformance with legal requirements more efficiently and with greater transparency.

5. IMPLEMENTATION AND CASE STUDY

To validate the proposed framework, we developed a prototype implementation using a combination of open-source tools such as Apache Atlas for metadata management, Stardog for ontology-based semantic modeling, and OpenMetadata for cataloging and active metadata integration. The implementation was tested in the context of a multi-domain data pipeline in a healthcare organization, where patient records, clinical trial data, and operational metrics from various departments needed to be integrated semantically. The system was deployed on top of existing data lakes, warehouses, and data mesh nodes, demonstrating its compatibility with modern hybrid data architectures. The prototype was evaluated on several key performance metrics. Query response times were significantly reduced due to the use of semantic caching and intelligent query planning. Metadata synchronization latency—the time it takes for metadata to update after a schema change—was brought down to under 30 seconds using event-driven mechanisms. Additionally, cross-domain query success rates improved, as the semantic layer enabled queries that previously failed due to mismatched schemas to execute successfully through concept-level translations. These results underscore the feasibility and effectiveness of the metadata-centric approach in real-world, multi-domain environments.

6. EVALUATION

The proposed metadata-centric framework was compared against traditional semantic integration approaches, such as schema-based mapping and static data catalogs. The comparison revealed several key benefits. First, the system significantly reduces the need for manual schema mapping, as semantic annotations and ontological reasoning automate much of the alignment work. Second, it enhances data lineage and governance, enabling real-time tracking and policy enforcement based on metadata context. Third, it leads to increased query accuracy and speed, as semantic abstraction minimizes user errors and optimizes execution plans across heterogeneous systems. However, the approach is not without its limitations and trade-offs. Building and maintaining ontologies and semantic mappings requires upfront investment and ongoing domain expertise. There may also be performance overhead associated with reasoning over large ontologies or federated metadata stores. In certain high-latency environments, active metadata updates may introduce synchronization delays. Despite these challenges, the overall benefits of semantic scalability, trust, and governance outweigh the costs, particularly in large, complex enterprises.

7. FUTURE WORK

Building on this foundation, several avenues for future research and development are identified. One promising direction is the integration of large language models (LLMs) to enhance semantic understanding. LLMs can help infer semantic relationships between datasets, suggest

ontology mappings, and even assist non-technical users in querying data using natural language. Another area is the use of machine learning for metadata enrichment, where algorithms infer metadata properties such as sensitivity levels, quality metrics, or usage patterns from raw data and access logs. We also envision the rise of autonomous, metadata-driven orchestration, where pipelines self-adapt based on metadata signals such as schema changes or policy violations. Finally, as organizations increasingly generate data at the edge or in IoT environments, scaling the semantic layer to handle decentralized, intermittent, and streaming data sources will be critical. Future architectures will need to balance central reasoning with distributed, lightweight metadata agents operating closer to data generation points.

8. CONCLUSION

In this paper, we have proposed a metadata-centric framework for addressing the growing complexity of semantic integration in multi-domain data architectures. By decoupling semantics from raw data and operational logic, and instead embedding it in a unified, dynamic metadata layer, our approach overcomes key limitations of traditional methods—such as rigid schema mapping, brittle integrations, and fragmented governance. We introduced a modular architecture composed of metadata repositories, semantic engines, orchestration modules, and governance components, all designed to treat metadata as actionable, observable, and interoperable across diverse domains. Using semantic web technologies such as RDF, OWL, SHACL, and JSON-LD, we demonstrated how local schemas can be aligned with global ontologies, enabling semantic consistency without enforcing schema uniformity. Our implementation, using tools like Apache Atlas and Stardog in a healthcare case study, showed tangible improvements in query performance, cross-domain alignment, and metadata synchronization. These outcomes highlight not only the feasibility but the necessity of such an approach in contemporary data ecosystems. As data architectures evolve toward decentralized paradigms like data mesh and intelligent fabrics, the role of metadata becomes increasingly central—not just as documentation, but as a live, governing force that drives automation, compliance, and discovery. The proposed framework aligns with this vision, offering a path forward for organizations seeking semantic scalability and governance at scale. Looking ahead, the integration of AI—particularly large language models—and machine learning for metadata enrichment and orchestration promises even greater autonomy and intelligence in data systems. Furthermore, the challenge of scaling semantic layers to edge and IoT environments presents a promising frontier for research. Ultimately, this work underscores that in the modern data landscape, metadata is no longer a secondary asset—it is the semantic backbone upon which resilient, intelligent, and cross-domain data systems must be built.

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