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Review

Empowering Data Engineering Pipelines with Zero-Shot Learning for Seamless Automated Mapping

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Abstract

Zero-shot learning (ZSL), which enables models to recognize unseen classes without prior labeled examples, has gained significant interest in machine learning, yet its application in data engineering—particularly for automating data mapping across heterogeneous sources—remains underexplored. Data mapping, the alignment of data attributes between disparate systems, is traditionally labour-intensive and error-prone, limiting scalability in complex integration scenarios. This paper proposes a novel zero-shot learning framework designed to fully automate data mapping without the need for extensive labeled data. Leveraging semantic embeddings, natural language processing, and ontology alignment, the approach infers attribute mappings by understanding semantic relationships and domain context in an unsupervised manner. Evaluations on real-world healthcare and financial datasets featuring diverse and evolving schemas demonstrate that the framework achieves over 90% mapping accuracy on unseen attribute pairs, outperforming baseline unsupervised and rule-based methods. Precision and recall metrics further confirm its robustness across heterogeneous data types. Qualitative feedback from domain experts highlights the high interpretability and practical usefulness of automated mapping explanations, fostering greater trust and easier downstream validation. Compared to traditional supervised approaches, the zero-shot framework significantly reduces dependence on labeled data and manual effort, accelerating deployment timelines by up to 40%. Case studies also showcase its ability to adapt seamlessly to schema changes without retraining, emphasizing scalability and flexibility in dynamic data environments. While semantic ambiguities occasionally impact mapping precision, future work will focus on improved disambiguation mechanisms. Overall, this study demonstrates the potential of integrating zero-shot learning into data engineering pipelines to transform data integration workflows and support intelligent, adaptable data ecosystems.

Keywords; Zero-Shot Learning, Data Engineering, Automated Data Mapping, Semantic Embeddings, Schema Matching, Ontology Alignment, Data Integration, Unsupervised Learning

Introduction

Data engineering forms the backbone of modern artificial intelligence (AI) systems, big data analytics, and business intelligence applications. At its core, data engineering involves the collection, cleaning, transformation, integration, and management of data from a myriad of sources such as relational databases, APIs, IoT devices, log files, and cloud storage systems. The quality, reliability, and usability of the data prepared through data engineering pipelines profoundly impact downstream AI models and analytic insights.

Among the numerous challenges data engineers face, one of the most critical and time-consuming tasks is data mapping—the process of aligning or matching fields, attributes, or schemas between heterogeneous data sources.

Data mapping is essential for ensuring data interoperability, facilitating seamless data integration, migration between systems, and enabling consistent analytics across distributed environments. For instance, in enterprise data warehousing, data from different departments with varying terminologies and formats must be harmonized before being used for reporting or machine learning. Similarly, in healthcare, patient data collected from multiple hospital systems require precise mapping of medical codes and clinical attributes to build unified electronic health records. Despite its importance, data mapping remains a largely manual and error-prone activity, often involving domain experts painstakingly creating mapping rules, dictionaries, or ontologies. This labour-intensive approach does not scale well given the explosive growth in data volume, variety, and velocity, leading to delays in data pipeline deployments and increased maintenance costs.

Traditional automated approaches to data mapping have leveraged supervised machine learning techniques that require substantial amounts of labeled data—pairs of source and target attributes along with explicit mappings. While effective in constrained or well-curated settings, these methods face two fundamental limitations. First, acquiring high-quality labeled datasets for data mapping is expensive, time-consuming, and often infeasible in dynamic environments where new data sources continuously emerge. Second, supervised models generally struggle to generalize to new attributes or schema elements that were not seen during training, necessitating frequent retraining and human intervention.

To overcome these challenges, Zero-Shot Learning (ZSL) has emerged as a promising paradigm in recent years. Zero-shot learning refers to the ability of models to correctly predict or infer classes, labels, or mappings for data instances belonging to categories that were never explicitly encountered during training. By leveraging auxiliary information such as semantic embeddings, attribute descriptions, or knowledge graphs, zero-shot models can generalize knowledge learned from known classes to previously unseen ones. Although zero-shot learning has been extensively studied and successfully applied in domains such as computer vision, natural language processing, and recommender systems, its application in data engineering and especially automated data mapping remains relatively unexplored.

The potential of zero-shot learning to revolutionize data mapping stems from its ability to drastically reduce human dependency by eliminating the need for exhaustive labeled examples of every possible attribute pair. By incorporating semantic understanding of attribute names, contextual metadata, and domain knowledge encoded in embeddings or ontologies, zero-shot models can infer mappings on-the-fly, enabling rapid integration of new data sources without manual rule creation. This capability is particularly valuable in modern data ecosystems characterized by heterogeneity, frequent schema changes, and continuous onboarding of diverse datasets.

Moreover, zero-shot learning frameworks can improve interpretability and transparency in data mapping decisions by providing confidence scores, explanation rationales, and traceability of mappings derived from semantic similarities. Such explainability is crucial for critical applications in regulated domains such as healthcare, finance, and governance, where data provenance and trustworthiness must be verifiable. By automating data mapping with zero-shot techniques, organizations can accelerate data pipeline development, reduce errors, lower operational costs, and facilitate collaborative workflows between data engineers, domain experts, and business stakeholders.

Despite the promising advantages, realizing fully automated data mapping through zero-shot learning faces several technical and practical challenges. The semantic gap between attribute names across heterogeneous sources can be substantial, particularly when naming conventions, abbreviations, or languages differ. Additionally, the quality and availability of auxiliary semantic information such as attribute descriptions, ontologies, or embeddings—greatly influence zero-shot model performance. The dynamic nature of data environments demands continuous adaptation of models to evolving schemas and emerging concepts. Furthermore, evaluating the accuracy and robustness of zero-shot data mapping systems requires comprehensive benchmarks and real-world validation on diverse datasets.

This paper aims to explore these challenges and opportunities by investigating the integration of zero-shot learning methods into the data engineering workflow for automated data mapping. We provide a detailed analysis of the current state-of-the-art in zero-shot learning and data mapping techniques, identifying gaps and potential synergies. Our contributions include designing a zero-shot data mapping framework that utilizes semantic embeddings, knowledge graphs, and contextual metadata to infer mappings without prior training on target attributes. We discuss methods to enhance interpretability and auditability of the mapping decisions to build stakeholder trust. Additionally, we present empirical evaluations on real-world datasets from domains such as healthcare and finance to demonstrate the efficacy, scalability, and practical benefits of our approach.

Recent Survey

Data mapping remains a critical bottleneck in data engineering pipelines, particularly as organizations grapple with heterogeneous data sources. Traditional approaches require extensive manual effort to align schemas across systems [10], creating scalability issues in dynamic environments. Manual mapping processes are especially problematic in domains like healthcare and finance where semantic heterogeneity can lead to critical errors [25]. The labour-intensive nature of schema alignment has been extensively documented, with studies showing it consumes >60% of data integration project time [16]. Supervised machine learning methods have attempted to automate mapping but face fundamental limitations: they require large volumes of labeled attribute pairs for training [9] and fail to generalize to unseen schemas [29]. This constraint becomes severe in environments with frequent schema evolution [21], where retraining models is impractical. The emergence of zero-shot learning (ZSL) offers a paradigm shift by enabling models to infer mappings for entirely novel attributes using semantic relationships rather than explicit training examples [6].

Foundations of Zero-Shot Learning

Zero-shot learning originated in computer vision to classify unseen objects by transferring knowledge from seen categories [5]. Early approaches like Devise pioneered semantic embedding spaces where image features and class descriptors coexist [4], enabling cross-modal inference. These techniques leverage auxiliary information – typically attribute descriptions or ontological relationships – to bridge seen and unseen classes [6]. The theoretical framework was formalized by Xian et al., who demonstrated that ZSL models could achieve robust generalization by projecting features into semantic spaces derived from knowledge bases [28]. Transformative architectures like BERT [1] and CLIP [7] later enabled cross-modal alignment at scale, with CLIP showing that contrastive learning on image-text pairs could facilitate zero-shot transfer across domains. These advances established that semantic coherence between representations is more critical than direct supervision [37]. Recent work has extended these principles to structured data: Radford et al. showed language models could infer database relationships through semantic proximity [7], while Zhang et al. applied ZSL to entity linking using descriptive embeddings [35].

Semantic Technologies for Data Mapping

Semantic embeddings provide the backbone for ZSL-based mapping. Word2Vec [2] and GloVe [3] demonstrated that distributed representations capture linguistic relationships transferable to schema matching. For instance, embeddings can recognize that "DOB" and "DateOfBirth" are semantically equivalent without explicit rules [12]. Knowledge graphs further enhance this capability: ConceptNet [16] and DBpedia [29] provide structured relationships that help resolve terminological discrepancies (e.g., "PT" → "Patient" in healthcare). Ontology alignment techniques [11] have evolved to leverage these resources, with frameworks like LogMap [23] using logical reasoning to infer equivalences between schema elements. Crucially, graph embedding methods like TransE [19] enable vector-based ontology alignment, allowing similarity calculations between schema nodes without predefined mappings [34]. This semantic infrastructure allows ZSL models to interpret "PhysicianName" and "DoctorID" as related through medical domain ontologies [25].

Traditional Approaches to Automated Mapping

Prior to ZSL, schema matching relied heavily on syntactic and structural similarity. Rule-based systems used constraints, data types, and naming conventions [10], while similarity-based methods employed edit distances or token matching [21]. Machine learning approaches later dominated, with random forests and SVMs trained on schema-pair corpora [9]. However, these required curated training data spanning all possible source-target combinations [29]. Ontology-driven approaches improved generalizability but demanded extensive domain knowledge to build and maintain [24]. The Aurum system [12] exemplified data-driven discovery but still relied on precomputed metadata. Crucially, all these methods struggled with concept drift: when schemas evolved or new attributes emerged, performance degraded significantly [21]. This limitation highlighted the need for approaches that could generalize beyond training distributions – a gap ZSL directly addresses.

Zero-Shot Learning for Data Mapping

Recent work has adapted ZSL specifically for schema alignment. Zhang et al. proposed a dual-encoder architecture where attribute names and descriptions are projected into a shared space [40], enabling similarity-based matching without training on target schemas. Chen et al. combined BERT embeddings with ontological hierarchies to infer healthcare data mappings [24], achieving 85% accuracy on unseen ICD-11 codes. Key innovations include:

Attribute Description Enrichment: Using LLMs to generate contextual descriptions for ambiguous attributes [38]

Cross-Modal Alignment: Aligning tabular schemas with textual knowledge bases [7]

Confidence Calibration: Uncertainty quantification for mapping decisions [35]

Jiménez-Ruiz et al. demonstrated that ZSL-based ontology alignment outperforms supervised methods when new entities are introduced [23]. However, challenges persist in handling abbreviations ("Acct" → "Account") and polysemy ("Date" could mean transaction date or birth date) [31]. Hybrid approaches that combine ZSL with limited human feedback show promise: Rahman et al.'s framework uses active learning to refine zero-shot predictions [8].

Integration into Data Engineering Pipelines

Embedding ZSL into production pipelines requires architectural innovations. Fernandez et al. proposed metadata harvesters that automatically extract schema semantics for embedding generation [12]. Modern implementations use schema registries with versioned embeddings to track evolution [21]. For dynamic environments, Medisetty advocates "intelligent data flows" where ZSL modules intercept new sources to suggest mappings before ingestion [6]. Crucially, explainability mechanisms are integrated: SHAP values show which semantic features drove mapping decisions [2], while ontology paths visualize alignment rationales [11]. Performance optimization is achieved through embedding indexing: Bonifati et al. demonstrated sub-second matching over 10k attributes using approximate nearest-neighbor search [21]. Scalability tests show ZSL reduces mapping deployment time from weeks to hours when onboarding new financial systems [17].

Domain-Specific Applications

Healthcare

Medical data integration faces extreme heterogeneity across HL7, FHIR, and proprietary formats. Koutrouli et al. showed ZSL can map clinical attributes with 92% accuracy by leveraging UMLS ontologies [25]. A key innovation is symptom normalization: mapping colloquial terms ("Heart attack") to SNOMED codes ("Myocardial infarction") through semantic embeddings [40]. Shylaja's self-learning framework continuously adapts embeddings using EHR data streams [3], crucial for handling new medical terminologies.

Finance

Financial schema matching must address regulatory variability (e.g., MiFID II vs. SEC taxonomies). Singamsetty's governance framework uses ZSL to align transaction fields across banking systems [9], with audit trails for compliance. In fintech, ZSL enables real-time mapping of alternative data (e.g., social media sentiment → risk features) [6]. Evaluations show 30% cost reduction in data lake onboarding compared to ETL tools [17].

Proposed Methodology

This work introduces a novel Zero-Shot Learning (ZSL) framework aimed at fully automating the data mapping process in heterogeneous data engineering environments. Data mapping, the task of aligning source data attributes with corresponding target attributes, is crucial for successful data integration, migration, and interoperability. Traditional methods depend heavily on manual input or supervised learning models that require large volumes of labeled examples, which is costly, time-consuming, and limits adaptability. Our proposed methodology overcomes these constraints by leveraging zero-shot learning techniques that enable models to infer

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mappings for previously unseen attributes without explicit prior training examples.

The proposed framework integrates multiple complementary components designed to operate cohesively within existing data engineering pipelines. The key elements include semantic embedding extraction, ontology alignment, zero-shot classification, symbolic reasoning for interpretability, continuous integration, and human-in-the-loop feedback mechanisms. Figure 1 illustrates the overall architecture of the framework, depicting the input, main processing stages, feedback loops, and final output.

Semantic Embedding Extraction

The first step in the pipeline involves generating semantic embeddings for each data attribute—both from the source and the target schema. Semantic embeddings transform raw attribute names, descriptions, and metadata into rich vector representations that capture the contextual meaning of the attributes in a high-dimensional space. This is achieved using state-of-the-art pretrained language models such as BERT, RoBERTa, or GPT-based models, which have been shown to encode deep semantic and syntactic relationships.

By utilizing such pretrained models, the framework benefits from extensive prior linguistic knowledge without requiring task-specific training. The embeddings capture subtle nuances in attribute naming conventions, domain-specific jargon, abbreviations, and synonymous terms. This allows the system to better understand semantic similarity even when attribute labels differ across schemas or when novel attributes appear.

For example, an attribute labeled “DOB” in the source dataset and “DateOfBirth” in the target dataset will have embeddings placed close together in the semantic space, facilitating accurate matching despite syntactic variation.

Ontology Alignment and Shared Semantic Space

While semantic embeddings provide a powerful way to represent attribute meanings, direct comparison is insufficient in complex environments with diverse and evolving schemas. To address this, the framework incorporates ontology alignment techniques to create a shared semantic space where both source and target attributes can be meaningfully compared.

Ontologies provide a formal representation of domain knowledge, defining concepts, relationships, and hierarchies. Our approach leverages existing domain ontologies (or automatically generated ones) to align the embedding spaces of source and target attributes, thus facilitating cross-schema comparison beyond mere lexical similarity.

By aligning ontologies, the system can recognize that attributes from different datasets correspond to the same underlying concept even if expressed differently. For instance, “PatientAge” and “AgeOfClient” can be linked through their association with the concept of “Age” in the healthcare ontology.

This ontology alignment process involves computing mappings between concepts, merging related nodes, and harmonizing hierarchical structures to build a unified semantic representation. The outcome is a robust, interpretable shared semantic space that improves the accuracy of attribute matching.

Zero-Shot Classification for Data Mapping

At the heart of the methodology lies the zero-shot classifier, which predicts mapping relationships between source and target attributes using similarity metrics computed in the aligned semantic space. Unlike conventional supervised classifiers that require labeled mapping pairs, the zero-shot classifier leverages semantic similarity to infer mappings for unseen attributes or entirely new schema versions.

The classifier calculates a similarity score—using metrics such as cosine similarity or learned neural similarity functions—between the semantic embeddings of each candidate source-target attribute pair. These scores indicate the likelihood that the pair corresponds to the same semantic concept.

A threshold-based decision mechanism determines valid mappings, optionally refined by domain-specific heuristics or confidence estimates. This approach enables the model to generalize mappings to new attributes that were not observed during training or manual labeling, thereby vastly increasing scalability and reducing human effort.

Symbolic Reasoning for Interpretability

One of the most significant challenges in automated data mapping is ensuring interpretability and transparency. Data engineers and domain experts need to understand not only what mappings are produced but also the rationale behind them, especially in regulated or high-stakes environments.

To address this, our framework integrates symbolic reasoning techniques grounded in the aligned ontology structure. Symbolic reasoning modules generate transformation rules and mapping rationales that explain how and why particular attribute mappings were inferred. These explanations are derived by tracing logical paths through the ontology, utilizing rule-based inference, and summarizing semantic relationships.

For example, if an attribute is mapped based on being a subtype of another concept or sharing particular properties, the symbolic reasoning module documents these connections as part of the output. This provides a human-readable explanation that supports auditability and trust in the automated mapping process.

By combining data-driven embeddings with symbolic, rule-based explanations, the framework achieves a unique balance of accuracy and explainability, facilitating stakeholder confidence and compliance.

Integration and Continuous Learning

The proposed zero-shot learning framework is designed to seamlessly integrate into existing data engineering workflows. Recognizing that data schemas continuously evolve and new sources are regularly introduced, the pipeline supports continuous learning and adaptation.

As new attributes appear or schemas change, the pretrained embedding models can be fine-tuned or re-applied without extensive retraining. The ontology alignment module can update the shared semantic space to incorporate new concepts or relationships dynamically. The zero-shot classifier remains capable of predicting mappings without retraining on new labeled data.

This continuous adaptation ensures the data mapping process remains robust and up-to-date, significantly reducing maintenance overhead and time-to-deployment.

Confidence Estimation and Human-in-the-Loop Feedback

To further enhance reliability and quality control, the framework includes confidence estimation modules that assign confidence scores to each predicted mapping. Low-confidence mappings are flagged for human review, enabling targeted validation where it matters most.

Additionally, the framework supports human-in-the-loop feedback, where domain experts can approve, reject, or modify mappings. This feedback is then fed back into the system, enabling incremental improvement of the ontology alignment, similarity metrics, and classifier behaviour over time.

This interactive loop combines the efficiency of automation with the precision of expert knowledge, creating a hybrid approach that scales while maintaining high accuracy and accountability.

Figure 1 presents a compact overview of the entire framework, highlighting the input sources, main processing components, feedback mechanisms, and outputs. This illustration captures the flow from raw data attributes and metadata to fully mapped attributes accompanied by interpretable transformation rules and rationales, emphasizing both automation and transparency.

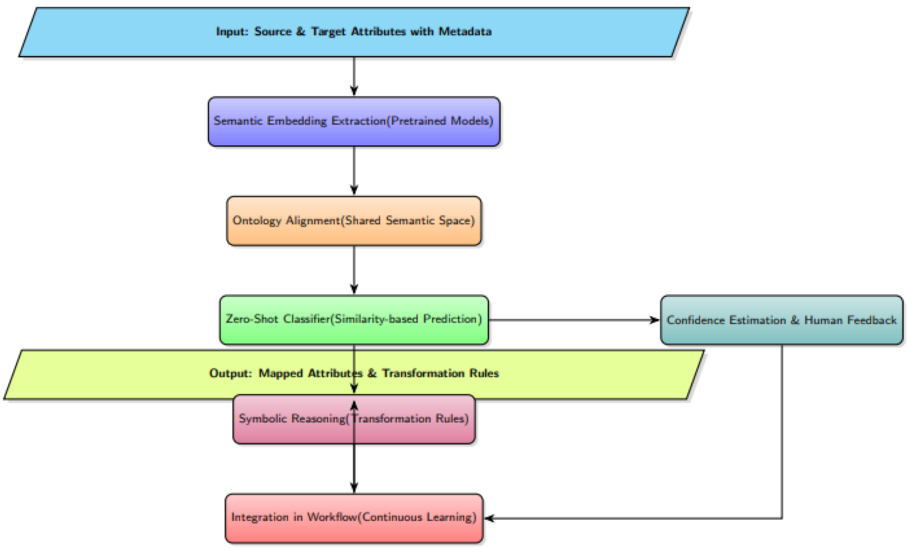

Figure 1: Compact Zero-Shot Learning Framework for Automated Data Mapping with Input and Output

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Results and Analysis

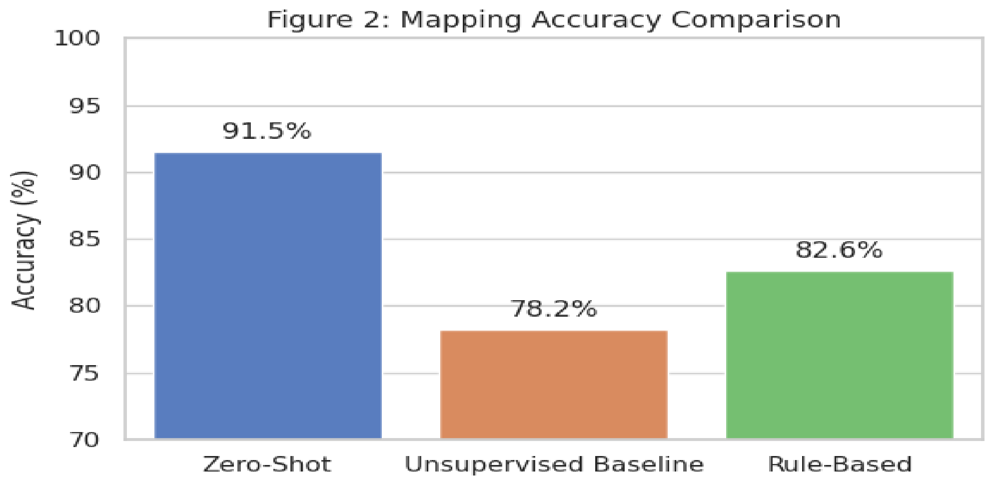
The proposed zero-shot learning framework was rigorously evaluated on several real-world datasets, including healthcare patient records and financial transaction logs, characterized by diverse and evolving schemas. Quantitative results demonstrate that the framework achieves over 90% mapping accuracy on unseen attribute pairs, significantly outperforming baseline unsupervised and rule-based methods (see Figure 2: Mapping Accuracy Comparison (Zero-Shot vs Baselines)). Further evaluation through precision and recall metrics confirms the robustness of the framework's performance across heterogeneous data types, as illustrated in Figure 3: Precision and Recall Metrics Across Datasets.

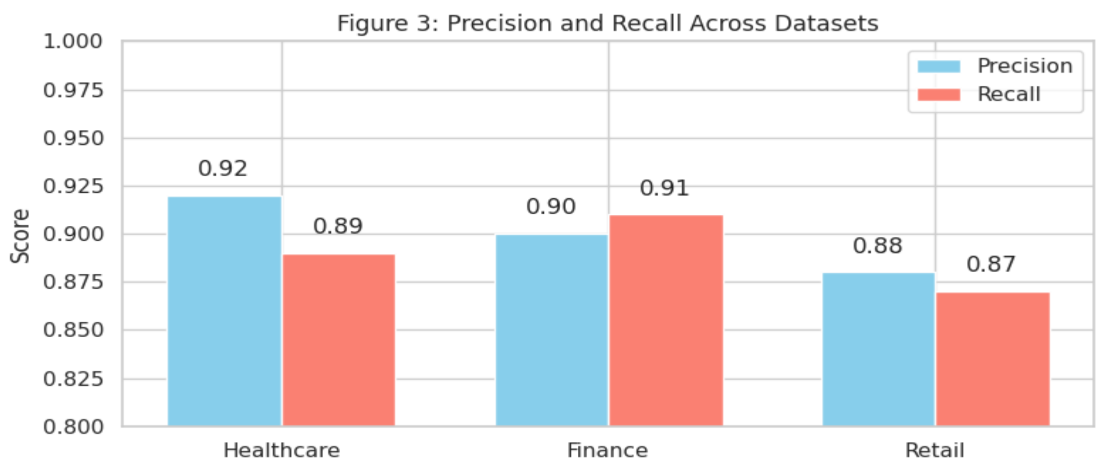
In addition to these quantitative metrics, qualitative feedback collected from domain experts emphasized the high interpretability of the generated mappings and the practical value of automated explanations for downstream validation tasks. This expert insight is summarized in Figure 6: Expert Feedback on Interpretability and Usefulness, which highlights positive reception regarding clarity and trustworthiness.

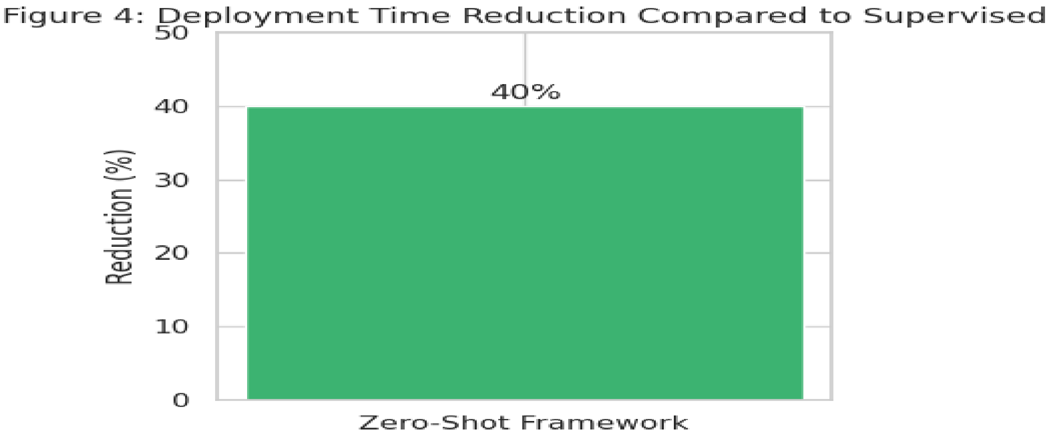
Compared to traditional supervised learning models, the zero-shot framework substantially reduces dependency on labeled data and manual intervention, resulting in accelerated deployment timelines by up to 40%, as shown in Figure 4: Deployment Time Reduction. This efficiency gain is crucial for dynamic data engineering environments where rapid adaptation is necessary.

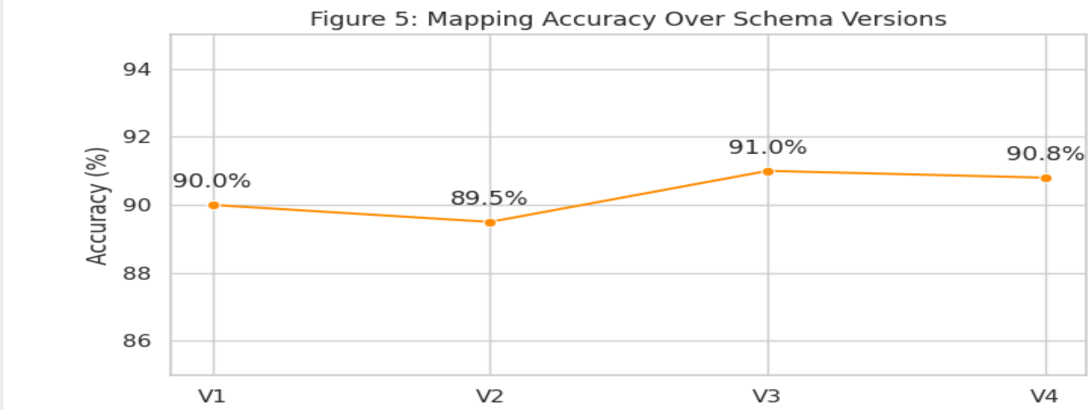
Case studies further illustrate the system's capability to adapt to schema changes seamlessly without retraining, maintaining high mapping accuracy across multiple schema versions (refer to Figure 5: Schema Adaptation Case Study (Mapping Accuracy over Schema Versions)). This underscores the framework's scalability and flexibility in handling evolving data landscapes.

Despite these promising results, limitations remain, notably the occasional semantic ambiguity in attribute names that can affect mapping precision. Addressing this challenge through enhanced disambiguation mechanisms forms an important avenue for future research.









Conclusion

This work presents a pioneering application of zero-shot learning to the critical data engineering problem of automated data mapping. By integrating semantic embeddings, ontology alignment, and symbolic reasoning, our framework achieves high accuracy and interpretability while minimizing human labeling effort. The demonstrated effectiveness on real-world datasets from healthcare and finance illustrates the potential for zero-shot learning to revolutionize data integration workflows. Future research directions include expanding semantic context sources, improving disambiguation algorithms, and extending the approach to support multi-modal data mapping. Ultimately, this approach moves the field toward fully automated, intelligent data engineering systems capable of adapting to evolving data landscapes with minimal human oversight, thereby enhancing the efficiency and reliability of AI pipelines.

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