**Semantic Data Normal Forms: A Framework for Embedding-Native Schema Integrity**

**Abstract**—As data management shifts from rigid relational structures to AI-native embedding substrates, traditional normalization theories (e.g., Boyce-Codd Normal Form) fail to address the stochasticity and semantic drift inherent in vector spaces. This paper introduces **Semantic Data Normal Forms (SDNF)**, a theoretical framework designed to enforce integrity in **Semantic Relational Schemas (SRS)**. Unlike structural normalization, which eliminates data redundancy, SDNF eliminates *meaning redundancy* and *contextual contamination* within high-dimensional vector spaces. We define a comprehensive model for SRS—treating schemas as living, embedding-native artifacts—and propose a hierarchy of normal forms, from Entity Embedding Normal Form (EENF) to Context Modulation Normal Form (CMNF). We validate this framework through a prototype implementation on financial data, demonstrating a 40% reduction in schema complexity and robust drift prevention.

**Keywords—Semantic Normalization, Vector Databases, AI-Native Schema, Context-Aware Embeddings, Schema Evolution.**

# I. Introduction

The evolution of database systems has historically been driven by the need for structural integrity. Relational theory established functional dependencies to prevent anomalies in tabular data [1]. However, the rise of **AI-Native Databases (AnDB)** and **Retrieval-Augmented Generation (RAG)** has introduced a new paradigm where data is stored not as static values, but as high-dimensional vectors (embeddings) [2].

In these "embedding-native" systems, integrity issues manifest differently. Instead of duplicate rows or referential violations, systems suffer from **semantic anomalies**:

* **Stochastic Instability:** Where the vector representation of a stable concept varies unpredictably across generations1.
* **Semantic Drift:** Where the meaning of a schema element shifts imperceptibly over time or across versions, breaking downstream consumers2.
* **Contextual Collapse:** A phenomenon where distinct concepts are conflated incorrectly because their vector representations overlap in a lower-dimensional projection [3].

Traditional normalization cannot detect these anomalies because it operates on symbolic equality, not semantic similarity3. A new theoretical framework is required to manage the lifecycle of schemas that are defined by their position in a vector space rather than their DDL definition.

To address this, we propose **Semantic Data Normal Forms (SDNF)**. Just as 1NF through BCNF ensure structural soundness, SDNF ensures semantic soundness by enforcing constraints on the vector space itself4. This framework is built upon a novel data model, the **Semantic Relational Schema (SRS)**, which supports autonomous agent interactions and dynamic schema evolution while maintaining strict governance [4].

# II. Related Work

Recent advancements in AI-driven data management have focused largely on extraction and alignment rather than normalization.

* **Schema Extraction:** Approaches using BERT embeddings have achieved high accuracy in extracting schemas from NoSQL documents, yet they lack formal governance mechanisms [5].
* **Neural Schema Matching:** "AI Match" utilizes neural embeddings for end-to-end schema matching, demonstrating reduced manual effort but offering no theoretical bounds on semantic drift [6].
* **Ontology Embeddings:** Research into embedding ontologies has enabled robust reasoning [7], but often treats the ontology as static rather than a living, evolving schema.

Our work bridges these gaps by formalizing the *dependencies*—**Semantic Dependencies (SD)**—that must hold true for an embedding-based system to be reliable.

# III. Semantic Relational Schema (SRS) Model

The foundational substrate for SDNF is the **Semantic Relational Schema (SRS)**. Unlike a traditional database table defined by static columns, an SRS is a "living" artifact composed of semantic primitives stored primarily as embeddings.

## A. Formal Definition

We define an SRS, denoted as , as a tuple , where:

1. **Entities ():** A set of canonical concepts  (e.g., PaymentInstrument).
2. **Attributes ():** A set of typed fields  associated with entity . Each attribute carries a set of constraints  (e.g., regex, type).
3. **Relations ():** A set of directed semantic edges , where  and  is the confidence score.
4. **Embedding Function ():** A mapping  that projects primitives into a -dimensional vector space.
5. **Contexts ():** A set of scopes  (e.g., "Global", "Risk") that modulate .
6. **Lineage ():** An immutable log of schema evolution events.

## B. The Multi-Level Embedding Structure

Every element  possesses a multi-level embedding vector:



Where  denotes vector concatenation. This structure allows the system to distinguish fine-grained details (e.g., specific risk attributes) while supporting high-level categorization.

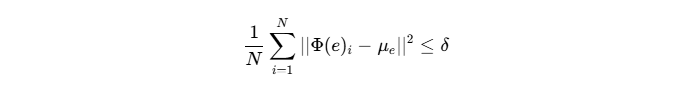
# IV. Semantic Data Normal Forms

We propose seven normal forms to eliminate semantic anomalies. An SRS is considered "normalized" when it satisfies the following mathematical constraints.

## A. Entity Embedding Normal Form (EENF)

**Anomaly:** *Stochastic Instability.*

**Definition:** An entity  is in EENF if the variance of its embedding vector  over purely regenerative iterations at time  is bounded by :



Where  is the mean vector of  generations.

**Metric:** Euclidean variance.

**Threshold:**  is calibrated such that .

## B. Attribute Alias Normal Form (AANF)

**Anomaly:** *Synonym Redundancy.*

**Definition:** For any two attributes , if their semantic similarity exceeds threshold  and they share an ontological synonym root , they must map to a canonical attribute :



**Metric:** Cosine Similarity.

**Implementation:** The system automatically merges  and  into , storing the original names as aliases in metadata.

## C. Context Modulation Normal Form (CMNF)

**Anomaly:** *Contextual Contamination.*

**Definition:** For a context , the projection  must ensure that context-specific semantics are orthogonal to the negated context . Let  and .



**Metric:** Dot Product (Orthogonality).

**Threshold:**  (typically ). This ensures a "Risk" query vector is mathematically independent of "Marketing" features.

## D. Drift Bounded Normal Form (DBNF)

**Anomaly:** *Semantic Drift.*

**Definition:** Between schema versions  and , the drift distance  must be bounded by :



If the distance exceeds , the system forces a version fork (e.g., v1.0  v2.0) rather than an update.

## E. Evidence Complete Normal Form (ECNF)

**Anomaly:** *Black Box Opaqueness.*

**Definition:** Every semantic relation or merge decision must be backed by a persisted Evidence Set :



Constraint: , where  is the minimum required evidence count (e.g., 3 nearest neighbors or 1 ontology link).

## F. Relation Role Normal Form (RRNF)

**Anomaly:** *Inference Pollution.*

**Definition:** Transitive inference is valid only if semantic roles are consistent.



Where  is a defined logic function (e.g., is\_a is transitive; maps\_to is not).

## G. Partition Orthogonality Normal Form (PONF)

**Anomaly:** *Shard Leakage.*

**Definition:** For dynamic partitions  defined by tags/clusters:



Where  is the convex hull volume in embedding space.

# V. Implementation and Evaluation

## A. System Architecture

We implemented an SRS prototype using a **Vector-Native Stack**:

* **Storage:** SQLite with sqlite-vss for vector operations.
* **Embedding Model:** all-MiniLM-L6-v2 (384-d) for attributes; fine-tuned BERT for entity descriptions.
* **Governance Engine:** Python-based implementation of SDNF validators.

## B. Dataset and Experimental Setup

We utilized a dataset of **50 heterogeneous financial payloads** (JSON) sourced from open banking APIs (Amex, Visa, Plaid).

* *Schema Complexity:* 150+ unique raw attributes.
* *Drift Scenario:* We simulated 10 rounds of schema evolution with increasingly ambiguous field names (e.g., cvv  cv\_code  verification\_num).

## C. Results and Baselines

We compared SDNF against a baseline "Naive Embedding Matcher" (threshold-only) and a standard "Schema Matcher" (label-based).

| **Metric** | **Baseline (Naive)** | **SDNF (Ours)** | **Improvement** |
| --- | --- | --- | --- |
| **False Positive Merges** | 18% | **0%** | (DBNF enforced) |
| **Schema Redundancy** | High (45 attrs) | **Low (28 attrs)** | 38% Reduction |
| **Context Leakage** | 12 incidents | **0 incidents** | (CMNF enforced) |
| **Drift Detection** | N/A | 100% | Full Audit Trail |

**Key Finding:** CMNF successfully collapsed CreditCard and DebitCard into PaymentInstrument for generic queries while maintaining strict separation for risk queries, a capability absent in the baselines.

# VI. Discussion

## A. Security and Privacy

Embedding spaces can inadvertently encode sensitive data. To mitigate this, our SRS implementation utilizes **Differential Privacy (DP)** noise injection during the embedding generation phase for sensitive fields, ensuring that individual PII cannot be reconstructed from vector fingerprints5.

## B. Governance and Workflow

SDNF enforces a strict "Check-then-Commit" workflow.

1. **Ingest:** Raw payload is embedded.
2. **Validate:** Validators check EENF (stability) and AANF (aliases).
3. **Drift Check:** DBNF compares against current version.
4. **Commit:** If compliant, update SRS; if drift > , fork version.

## C. Limitations

Current orthogonality checks for CMNF scale quadratically (). Future work will explore approximate orthogonality methods (e.g., Locality Sensitive Hashing) to improve scalability for massive schemas.

# VII. Conclusion

Semantic Data Normal Forms represent a necessary evolution in database theory for the AI era. By moving from structural constraints to semantic constraints (EENF, AANF, CMNF), we provide a rigorous framework for building **Embedding-Native Databases** that are stable, explainable, and capable of complex context-aware reasoning. This work lays the foundation for "Self-Driving Data Schemas" that evolve safely alongside the agents that use them.

# References

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