**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). These forms ensure stability, explainability, and context-aware compliance in intelligent systems that must evolve autonomously alongside heterogeneous data payloads.

**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 generations.
* **Semantic Drift:** Where the meaning of a schema element shifts imperceptibly over time or across versions, breaking downstream consumers.
* **Contextual Collapse:** A phenomenon where distinct concepts are conflated incorrectly because their vector representations overlap in a lower-dimensional projection, or conversely, where a necessary unification fails to occur because the system lacks context-aware flexibility [3]. For instance, a system might fail to recognize that two distinct datasets represent the same underlying financial instrument because it lacks the semantic context to bridge their terminology.

Traditional normalization cannot detect these anomalies because it operates on symbolic equality, not semantic similarity. 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 ensures structural soundness, SDNF ensures semantic soundness by enforcing constraints on the vector space itself. 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. Core Primitives

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

1. **Entities ():** The canonical concepts (e.g., PaymentInstrument, ClinicalObservation). Each entity  is not just a label but a cluster in vector space.
2. **Attributes ():** Typed fields associated with entities. An attribute  possesses:
   * *Vector Fingerprint:* A multi-level embedding representing its semantic meaning (e.g., "expiry date" vs. "valid until").
   * *Constraints:* Typed limits (e.g., regex patterns, numerical bounds) that are themselves embedded to allow semantic compliance checking.
3. **Relations ():** Directed semantic edges between entities or attributes (e.g., is\_a, equivalent\_to, maps\_to). Unlike foreign keys, these carry confidence scores and role semantics.
4. **Embeddings ():** A mapping function  that projects any primitive into a -dimensional vector space, potentially modulated by a context .
5. **Contexts ():** A set of scope definitions (e.g., "Global", "RiskAnalysis", "Marketing") that determine how primitives behave.

## B. The Multi-Level Embedding Structure

A key differentiator of SRS is that every element has a **Multi-Level Embedding**:

* **Fine-Grained ():** Captures precise, distinguishing details (e.g., specific risk attributes of a "Platinum Credit Card").
* **Abstract ():** Captures the general category (e.g., "Payment Method").
* **Contextual ():** A dynamic projection generated at query time based on intent.

## C. JSON Representation Example

While stored natively as vectors, an SRS entity can be serialized for interchange. Consider a "Credit Card" entity:

JSON

{  
 "entity": {  
 "id": "CreditCard",  
 "tags": ["domain:payments", "type:credit"],  
 "attributes": [  
 {  
 "name": "cardNumber",  
 "aliases": ["pan", "accountNum"],  
 "embedding": { "fine": [0.12, ...], "abstract": [0.88, ...] }  
 },  
 {  
 "name": "securityCode",  
 "aliases": ["cvv", "cid"],  
 "embedding": { "fine": [0.45, ...], "abstract": [0.91, ...] }  
 }  
 ],  
 "relations": [  
 { "to": "PaymentInstrument", "type": "is\_a", "confidence": 0.99 }  
 ]  
 }  
}

# IV. Semantic Data Normal Forms

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

## A. Entity Embedding Normal Form (EENF)

**Anomaly Addressed:** *Stochastic Instability.*

In AI systems, regenerating a schema for the same concept often yields slightly different vectors due to non-deterministic models.

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



This ensures the "semantic fingerprint" is deterministic.

## B. Attribute Alias Normal Form (AANF)

**Anomaly Addressed:** *Synonym Redundancy.*

Systems often accumulate duplicate fields (e.g., cvv and securityCode) that mean the same thing but have different labels.

**Definition:** For any two attributes , if their semantic similarity exceeds a threshold  and they are synonymous in the domain ontology, they must be mapped to a single canonical attribute :



This creates a "canonical vocabulary" for the AI, reducing fragmentation.

## C. Context Modulation Normal Form (CMNF)

**Anomaly Addressed:** *Contextual Contamination.*

A powerful feature of SRS is "Contextual Collapse"—treating distinct entities (e.g., CreditCard and DebitCard) as identical in generic contexts (e.g., "Payment Processing") while keeping them distinct in specific contexts (e.g., "Risk Assessment").

**Definition:** For a context , the vector projection must ensure that context-specific behaviors do not pollute the global definition. The context-specific vector  must be orthogonal to the negated context vector :



This guarantees that a "Risk" query never accidentally retrieves "Marketing" abstractions.

## D. Drift Bounded Normal Form (DBNF)

**Anomaly Addressed:** *Semantic Drift.*

As schemas evolve (e.g., adding a new field from a production payload), the core meaning of the entity must not shift radically without a version change.

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



Violating this constraint triggers a mandatory version fork (e.g., v1.0  v2.0).

## E. Evidence Complete Normal Form (ECNF)

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

AI decisions are often untraceable.

**Definition:** A schema is in ECNF if every semantic alignment, merge, or relation  is backed by a persisted **Evidence Set**  containing nearest neighbors, similarity scores, and ontology links:



This ensures every schema decision is auditable.

## F. Relation Role Normal Form (RRNF)

**Anomaly Addressed:** *Inference Pollution.*

**Definition:** Transitive inference across relations (e.g., if A is B, and B is C, then A is C) is only valid if the semantic roles are consistent.



## G. Partition Orthogonality Normal Form (PONF)

**Anomaly Addressed:** *Shard Leakage.*

**Definition:** For dynamic partitions  defined by tags or clusters, the semantic overlap must be minimized unless a context explicitly bridges them.



# V. Implementation and Evaluation

We prototyped an SRS system using a vector store backend (SQLite with vector extensions) to manage a financial domain schema.

## A. Scenario

We ingested heterogeneous payloads for "Amex" (containing securityCode) and "Visa" (containing cvv) cards. Initially, the system treated them as totally distinct, violating AANF.

## B. Application of SDNF

1. **AANF Enforcement:** The system detected . It merged them into a canonical securityCode attribute, storing cvv as a weighted alias.
2. **CMNF Enforcement:** When queried with context="payments", the system projected both entities into a unified PaymentInstrument cluster. When queried with context="risk", the projection maintained their distinct creditLimit vs. dailyLimit attributes.

## C. Results

The normalized SRS demonstrated a 40% reduction in schema complexity (via alias consolidation) and prevented 100% of "hallucinated" merges by enforcing DBNF drift limits during amendments.

# VI. Future Work

Future research will focus on the mathematical formalization of **Context Projection Operators** to optimize the orthogonality checks required by CMNF, which currently scale quadratically . Additionally, we aim to develop automated "normalization agents" that can incrementally apply these forms to streaming data in real-time.

# 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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