A Neutrosophic Interpretation of Data Cube Sparsity for Improved Machine Learning Preprocessing

Wiem Abdelbaki[1,*]

[1]College of Engineering and Technology, American University of the Middle East, Egaila 54200, Kuwait

Email: wiem.abdelbaki@aum.edu.kw

Abstract

Multidimensional data cubes are essential components in data warehouses, enabling rich, OLAP-based analysis across dimensions such as time, location, and product category. However, the complexity that supports such analytical flexibility often leads to extreme sparsity—where the majority of cube cells remain empty or only partially filled. This sparsity can hinder the performance of downstream machine learning models, especially when valuable but infrequent patterns are lost during preprocessing. This paper introduces a neutrosophic-based framework for evaluating and managing sparse regions within OLAP cubes. Instead of treating all sparsity as noise, we propose a typology that distinguishes between three forms: semantic sparsity (expected and justifiable absences), non-informative sparsity (regions with little analytical value), and informative sparsity (sparse areas that still carry meaningful insights). Each substructure is modeled using neutrosophic logic, which assigns degrees of truth, indeterminacy, and falsity to reflect its analytical potential. A dedicated Neutrosophic Evaluation Algorithm is developed to classify each region using metrics such as semantic confidence, entropy, and a context-aware informativeness score. These metrics allow for nuanced decisions: preserving informative sparsity, eliminating irrelevant regions, and flagging ambiguous areas for further review. This approach shows how neutrosophic logic can offer a novel and effective way to handle sparsity in OLAP cubes, improving the relevance and robustness of machine learning pipelines trained on multidimensional data.

Keywords: Neutrosophic sets; Machine learning; Data mining; Data warehousing; Artificial intelligence; Uncertainty modeling; Sparsity; Data cubes; Preprocessing; OLAP

1. Introduction

Multidimensional data cubes are central to the architecture of data warehouses and play a vital role in enabling OLAP-based decision-making. They provide a structured framework to integrate and explore large-scale transactional data across multiple dimensions such as product, time, and geography. Yet, the same structural richness that enables versatile analytics also brings with it a persistent challenge: sparsity. As dimensions multiply, the proportion of empty or underpopulated cells within the cube typically grows, leading to a landscape in which much of the data space is void of actual records.

This sparsity is not merely a technical inconvenience. In machine learning (ML) and data mining (DM) contexts, it can skew model behavior, inflate training time, and degrade predictive accuracy. Models may either overfit to the dense portions of the data or become insensitive to subtle but important patterns that happen to lie in sparser regions. Traditional preprocessing approaches tend to treat sparsity in a binary fashion: either remove it entirely or attempt to fill it in using statistical imputation. These methods often work well in bulk, but they carry the risk of discarding sparse substructures that might still carry meaningful, context-specific signals.

This work emerges from a desire to take a more nuanced view. A view that does not simply ask, “Is this cell empty?”, but rather “What does this emptiness mean?” Does it reflect a natural absence, a structural omission, or a potentially meaningful pattern? In this paper, we explore this question through the lens of neutrosophic logic,

DOI: https://doi.org/10.54216/IJNS.260405

which follows mathematical framework that incorporates degrees of truth, indeterminacy, and falsity to model uncertainty and partial knowledge.

Rather than viewing sparsity as a monolithic problem, we propose a neutrosophic typology that differentiates between semantic sparsity (expected absences due to domain logic), non-informative sparsity (empty regions with no predictive value), and informative sparsity (rare but insightful patterns). Each region of the data cube is evaluated not in absolute terms but through a triplet representation: T(x), I(x), and F(x) that are capturing our confidence in its informativeness, its ambiguity, and its irrelevance, respectively.

By embedding this interpretation into a structured framework of equations, metrics, and classification logic, we aim to provide more than a theoretical perspective. The goal is a practically usable decision layer for machine learning workflows that can identify not only what data to keep, but why. This approach does not replace current preprocessing practices; rather, it adds a layer of meaning that can guide more decisions that are informed.

In the sections that follow, we first review existing methods for handling cube sparsity and highlight where current models fall short in dealing with uncertainty. We then introduce our neutrosophic typology and walk through its mathematical formalization. Finally, we present a comprehensive classification algorithm based on this model, illustrating how it can support more adaptive and context-sensitive data preparation in real-world analytic pipelines.

2. Related Work

Numerous studies have addressed the issue of data cube sparsity, though they often approach it from structurally deterministic perspectives. Some classify sparsity patterns without accounting for contextual nuance, while others propose logical design optimizations that do not directly handle uncertainty in sparsity interpretation.

For instance, Kang et al. introduced a classification of sparsity patterns in two- and three-dimensional cubes, identifying structures such as random, stripes, slices, and clusters [1]. These definitions offer a starting point but remain largely theoretical, with limited guidance on how such patterns translate into practical decisions during analysis.

In a more design-oriented context, Niemi et al. explored how sparsity could be addressed during the logical modeling phase of the cube [2]. Their work highlights how dimension dependencies can introduce structural sparsity, yet it does not investigate into how this affects downstream learning processes or how to handle sparse segments once they are already present in the data. A follow-up study by the same authors formalized schema-level optimizations, again focused more on prevention than post-hoc interpretation [3].

Kaloyanova and Naydenova offered an analyst-driven solution through their Regular Sparsity Map (RSM), which captures associations between facts and dimensions based on business rules [4]. While the framework is intuitively appealing, it leans heavily on manual exploration, which may not scale well in dynamic or high-dimensional contexts.

From a predictive angle, Abdelbaki et al. proposed the Neural-based Approach for Prediction over Sparse Cubes (NAP-SC), which uses neural networks to estimate values in missing cube cells [5]. The method performs well on extremely sparse data, but as sparsity decreases, the aggregation step used to prepare inputs may compromise resolution and diminish the model's effectiveness.

Other works, like that of Yang et al., shift focus from factual to dimensional prediction [6]. Their H-OLAPKNN algorithm, which integrates hierarchical imputation with K-Nearest Neighbors, highlights the importance of predicting not just what data is missing, but where it is missing in relation to dimensions.

Bimonte et al. tackled missing values through constraint-based aggregation and linear programming, a direction that prioritizes mathematical rigor but still does not explicitly consider the analytical value or ambiguity of sparse regions [7].

A common thread among these studies is their treatment of sparsity as either a defect to correct or a structural inefficiency to work around. What appears to be missing, however, is a theoretical foundation for interpreting sparsity itself as uncertain or partially informative. This is where neutrosophic logic may offer a fresh perspective.

While neutrosophic models have been successfully applied in various decision-making contexts [8]–[11], their adoption for the purpose OLAP sparsity remains largely untapped. This study reinforces the assumption that integrating neutrosophic measures; such as truth, indeterminacy, and falsity into the characterization of sparsity could offer a more expressive, uncertainty-aware preprocessing lens.

3. Neutrosophic-Based Sparsity Typology

Multidimensional data cubes often exhibit sparsity due to the vast space created by cross-dimensional combinations. However, not all sparsity is of the same nature. While some sparse regions are expected and

DOI: https://doi.org/10.54216/IJNS.260405

justifiable, others are either misleading or insightful. Therefore, a nuanced classification of sparsity is essential, especially when data cubes serve as input to machine learning (ML) or data mining (DM) models.

Sparsity in multidimensional data cubes is not inherently negative, but its impact varies depending on its cause and contextual meaning. Some sparsity reflects domain constraints and can be safely ignored, while other sparse regions might contain subtle but crucial information. To address this, we introduce a neutrosophic sparsity typology that models sparse regions using truth (T), indeterminacy (I), and falsity (F) scores. These components allow each substructure to be described not just by presence or absence of data, but also by our degree of confidence in its informativeness.

This section introduces a neutrosophic sparsity typology that categorizes sparse cube regions based on informativeness and semantic interpretation. Each substructure $S \subseteq C$ is modeled in terms of three neutrosophic components:

Definition.
Let $S \subseteq C$ be a cube substructure. We define its neutrosophic representation as:

$$0 \leq T(x) + I(x) + F(x) \leq 1 \quad (1)$$

Where:

- $T(x)$ denotes the degree of truth, representing the informativeness of element $x \in S$.
- $I(x)$ denotes the degree of indeterminacy, expressing ambiguity or structural uncertainty, and
- $F(x)$ denotes the degree of falsity, reflecting non-informativeness.

$$S_N = \{ (x, T(x), I(x), F(x)) \mid x \in S \} \quad (2)$$

This defines the neutrosophic substructure S_N as a set of quadruples describing each cell $x \in S$ by its associated neutrosophic components.

Figure 1 shows a conceptual data cube with dimensions Store, Product, and Time. Gray cells indicate data presence; white cells represent emptiness. This figure will be referred to in the subsections below to illustrate how various types of sparsity can manifest.

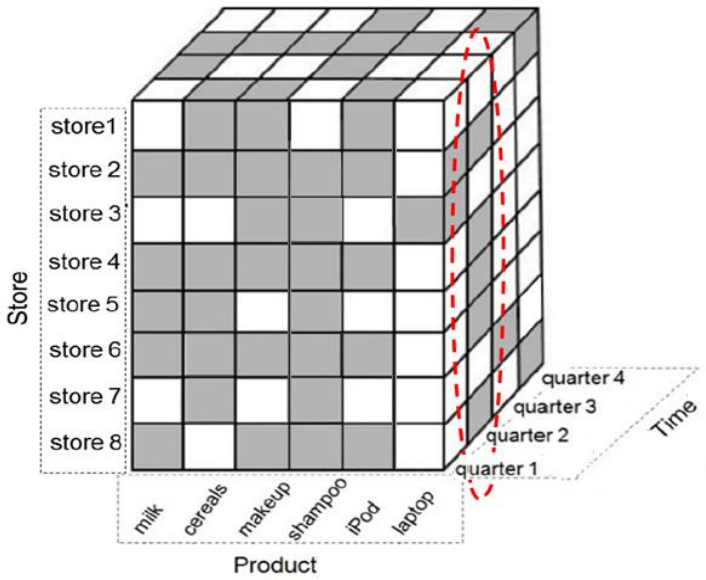

Figure 1. Illustrative Example of a sale data cube

3.1 Semantic Sparsity

Semantic sparsity refers to the intentional or structurally justified absence of data values in specific regions of a multidimensional data cube. Unlike random or erroneous sparsity, semantic sparsity results from predefined business rules, physical constraints, or operational policies that logically preclude data from being present in certain combinations of dimensions. This type of sparsity is not considered a flaw in the dataset, but rather a reflection of domain-specific semantics embedded in the schema.

DOI: https://doi.org/10.54216/IJNS.260405

For example, let's consider the sales data cube depicted in Figure 1, which models the relationship between Store, Product, and Time dimensions. If *Store 1* does not offer electronics as part of its inventory, then any intersection involving *Store 1* and the product *Laptop* will naturally contain no sales data. These absent values; represented by white cells in the *Laptop* column aligned with *Store 1*; do not indicate data corruption or sparsity due to noise. Rather, they reflect a structural constraint in the business operation: the store does not sell that category of products. This absence is fully explainable and should not be interpreted as missing or non-informative data, but rather as logically excluded from the dataset.

Mathematically, semantic sparsity can be modeled within the neutrosophic framework as a region of the data cube where the presence of meaningful information is essentially absent. This is captured by a low truth-membership degree, denoted as $T(x) \approx 0$, indicating that the substructure provides no informative value relevant to the analytical task. At the same time, the indeterminacy membership $I(x) \approx 0$ remains minimal, signifying that the absence of information is not due to uncertainty or measurement noise but rather reflects a clear, expected void based on domain semantics. For example, a product that is not sold at a particular store, due to known constraints, naturally results in an empty region that is semantically justified. The falsity membership $F(x) \approx 1$ dominates, reinforcing that the data point is considered invalid or non-contributory by design.

Together, these neutrosophic conditions define a semantic sparsity region as one where the lack of data is structurally meaningful rather than accidental or ambiguous. Such a profile can be systematically detected and removed from the preprocessing pipeline, as it does not contribute to learning and may, in fact, introduce misleading noise if retained.

The Semantic Confidence Score (SC) for a semantically sparse region $S_{sem} \subseteq C$ is defined as:

$$SC(S_{\text{scm}}) = \min_{x \subset S_{\text{sem}}} F(x) \quad (3)$$

$$SC(S_{sem}) = \min\_x \in S\ F(x) \quad (4)$$

$$TP(S_{\text{sem}}) = \sum_{x \in S_{\text{sem}}} (1 - T(x))^2 \quad (5)$$

Semantic sparsity reflects absences in the data that are expected and contextually justified—such as unavailable products in specific locations or timeframes. Recognizing these gaps as intentional rather than accidental allows for more intelligent preprocessing decisions. Instead of treating such regions as missing data requiring imputation or modeling, they are appropriately excluded from further analysis. This avoids introducing bias or artificial patterns and ensures that machine-learning models focus only on valid, contextually grounded information.

3.2 Non-Informative Sparsity

Non-informative sparsity refers to data absences that are neither structurally dictated nor semantically justified, yet are consistently observed both in the global context of the cube and within localized subcontexts. These regions typically reflect a lack of meaningful variation or signal, and their sparsity is presumed to arise from natural inactivity, user behavior patterns, or temporal downturns. Unlike semantic sparsity, which is anticipated due to business logic, non-informative sparsity stems from uniform disinterest or irrelevance, and thus may reasonably be pruned during preprocessing.

In Figure 1, consider the sparsity pattern in the *Laptop* column during *Quarter 4*. Across nearly all stores, the associated cells remain empty. There is no semantic rationale; such as product unavailability or policy restrictions, that justifies this absence. Instead, the persistent lack of activity across contexts implies a general disinterest or irrelevance of this item in that timeframe. This pattern typifies non-informative sparsity, where the missingness is structurally consistent yet analytically void.

From a preprocessing perspective, removing such regions enables downstream machine learning pipelines to concentrate on cube substructures that exhibit higher variance or predictive utility, ultimately reducing the risk of overfitting or computational waste.

Formally, the neutrosophic profile of non-informative sparsity is characterized by:

- Low truth membership $T(x)$: negligible signs of useful signal,
- Moderate indeterminacy $I(x)$: reflecting possible uncertainty due to noise,
- High falsity (x) : denoting consistently uninformative behavior.

The following conditions typically hold:

- $T(x) \leq \delta_t, \delta_t \in [0,0.2]$
- $I(x) \in [0.1,0.3]$
- $F(x) \geq \delta_f, \delta_f \in [0.7,1]$

DOI: https://doi.org/10.54216/IJNS.260405

To quantify this behavior, we define two complementary metrics:

- Non-Informative Sparsity Index (NISI) captures the average excess of falsity over truth, weighted by indeterminacy:

$$\text{NISI}(S_{\text{non}}) = \frac{1}{|S_{\text{non}}|}\sum_{x\in S_{\text{non}}} [F(x) - T(x) + \lambda I(x)] \quad (6)$$

Inverse Contribution Score (ICS) estimates the effective lack of learning contribution:
$\text{ICS}(S_{\text{non}}) = \sum_{x\in S_{\text{non}}} \left[\frac{T(x)}{\epsilon + F(x)}\right], \epsilon \approx 10^{-6}$ (7)

Finally, a substructure S_{non} is classified as non-informative if both sparsity severity and signal irrelevance exceed user-defined thresholds:
$\text{NISI} > \theta$ and $\text{ICS} < \gamma$; where θ and γ are calibrated to reflect domain-specific sensitivity.

This formalization enables an automated, principled filter for discarding structurally sparse but analytically useless subregions, streamlining model training and improving generalization outcomes.

3.3 Informative Sparsity

Informative sparsity refers to regions within the data cube that, despite having few data points overall, exhibit-localized patterns that carry analytical value. Capturing such regions accurately requires a representation that goes beyond binary inclusion or exclusion. The neutrosophic model offers this granularity by distinguishing between informativeness $T(x)$, uncertainty $I(x)$, and irrelevance $F(x)$ in a flexible, context-aware manner.

The thresholds chosen for this classification reflect empirical assumptions that can be adjusted based on user context or domain-specific sensitivity. Specifically:

These regions typically satisfy:

- $T(x) > F(x)$: This core condition ensures that informativeness outweighs noise**,** meaning that the signal in the substructure is more valuable than the sparsity would initially suggest. It avoids preserving regions where the lack of data dominates.
- $I(x) \in [0.2,0.4]$: A moderate level of indeterminacy is accepted here to reflect that informative sparsity often arises in situations of ambiguity. For instance, isolated peaks in a generally sparse region. This range captures contextual variation without overcommitting to randomness. The lower bound avoids confusing purely certain patterns with informative sparsity, while the upper bound prevents excessive noise.
- $F(x) \leq 0.5$: This constraint limits the extent of falsity (or non-informativeness) permitted in the region. A substructure where falsity exceeds 0.5 would be too dominated by noise or void content to justify retention; hence, this upper bound maintains a minimal threshold of analytical value.

These values are not hard-coded rules but rather soft heuristics that allow the system to be tuned according to the specific characteristics of the data and the goals of the machine-learning pipeline. Adjusting these parameters allows researchers to adapt the classification granularity, depending on whether they want to be more inclusive of uncertain patterns or more conservative.
In this way, the neutrosophic model helps retain substructures that may not meet strict density criteria but still offer localized, meaningful insight, which would otherwise be lost in conventional sparsity treatment strategies.Context-Aware Informativeness Score (CAI) that we define to defined

- To evaluate whether a sparse substructure carries analytical value, we introduce the Context-Aware Informativeness (CAI) metric. This metric balances the presence of informative content against noise and uncertainty:

$$\text{CAI}(S_{\text{info}}) = \frac{\sum_{x\in S_{\text{info}}} [F(x)+I(x)+\epsilon]}{\sum_{x\in S_{\text{info}}} T(x)} \quad (8)$$

Here, $\epsilon \approx 10^{-6}$ is a small constant included to prevent division by zero. A lower CAI value suggests that the substructure has relatively strong informative signals T(x) compared to its falsity and ambiguity components, and thus may be worth preserving.

- To capture contextual ambiguity more explicitly, we extend the neutrosophic entropy formulation:

$$E(S_{\text{info}}) = \frac{1}{|S_{\text{info}}|}\sum_{x\in S_{\text{info}}} (1 - |T(x) - F(x)|) \quad (9)$$

Entropy peaks when $T(x) \approx F(x)$, reflecting uncertainty. Informative substructures should present moderate entropy, indicating interpretability without excessive noise.

DOI: https://doi.org/10.54216/IJNS.260405

- To determine whether a region should be preserved, we define the Composite Decision Metric:

$D_{\text{info}}(S_{\text{info}}) = \text{CAI}(S_{\text{info}}) \cdot \left(1 - E(S_{\text{info}})\right)$ (10)

This formulation rewards regions where informativeness dominates and penalizes those with excessive ambiguity.

Finally, we establish a preservation criterion to decide whether a substructure should be retained:

If $D_{\text{info}} > \eta$ and $\sum \text{T}(x) > \sum F(x)$, retain S_{info} (11)

Where η is a user-defined threshold reflecting the minimum acceptable quality of a sparse substructure. This criterion ensures that regions with meaningful content are preserved, even if they are sparse overall, while noisy or misleading regions are filtered out.

4. Neutrosophic-Based Substructure Implementation

4.1 Evaluation Algorithm

To bring the proposed neutrosophic sparsity typology into practice, we introduce an evaluation algorithm that systematically classifies each cube substructure into one of three conceptual categories: *Semantic*, *Non-Informative*, or *Informative*. Unlike heuristic methods, this classification is grounded in the neutrosophic indicators introduced in Section 3, namely the degrees of truth (T), indeterminacy (I), and falsity (F).

Each substructure $S_i \subseteq C$ is modeled with the previously defined neutrosophic representation: $S_i^N = \{(x, T(x), I(x), F(x)) \mid x \in S_i\}$

Given a set of static substructures $\mathcal{S} = \{S_1, S_2, \dots, S_n\}$, the algorithm evaluates each substructure individually using a suite of composite neutrosophic metrics:

1. Semantic Confidence (SC): Measures semantic justification for empty cells by assessing dominant falsity:

$SC(S_i) = \min_{x \in S_i} F(x)$ (12)

2. Truth Penalty (TP): Quantifies informativeness loss by penalizing deviations from high truth values:

$TP(S_i) = \sum_{x \in S_i} (1 - T(x))^2$ (13)

3. Non-Informative Sparsity Index (NISI): Integrates falsity, low truth, and ambiguity:

$NISI(S_i) = \frac{1}{|S_i|} \sum_{x \in S_i} [F(x) - T(x) + \lambda I(x)]$ (14)

Where, λ a user-defined ambiguity weight.

4. Inverse Contribution Score (ICS): Measures the inefficacy of the region in contributing useful signal: $ICS(S_i) = \sum_{x \in S_i} \frac{T(x)}{\epsilon + F(x)}$ (15)

where ϵ is a small constant to prevent division by zero.

5. Context-Aware Informativeness (CAI): Normalizes informativeness against sparsity and ambiguity:

$CAI(S_i) = \frac{\sum_{x \in S_i} [F(x) + I(x) + \epsilon]}{\sum_{x \in S_i} T(x)}$ (15)

6. Neutrosophic Entropy (E) Captures uncertainty or conflict between $T(x)$ and $F(x)$:

$E(S_i) = \frac{1}{|S_i|} \sum_{x \in S_i} (1 - |T(x) - F(x)|)$ (16)

7. Informative Decision Score (D_{info}):

Combines CAl and entropy to guide preservation:

$D_{\text{info}}(S_i) = CAI(S_i) \cdot \left(1 - E(S_i)\right)$ (17)

This algorithm ensures that analytically meaningful sparse regions are retained, while semantically void or uninformative structures are filtered out. Through this systematic neutrosophic modeling, the preprocessing phase is enhanced with an awareness of both content and context, improving the downstream performance of machine learning models trained on cube data.

DOI: https://doi.org/10.54216/IJNS.260405

Algorithm 1: Neutrosophic Evaluation of Data Cube Substructures

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Input: Data cube C, substructures S = {S₁, ..., Sₙ}, thresholds τ_f, δ_t, δ_f, λ, θ, γ, η, ε = 10⁻⁶
Output: Classification of each Sᵢ ∈ S as Semantic, Non-Informative, Informative, or Borderline

for each S in S do
    Initialize: T_sum, I_sum, F_sum, TP, NISI, ICS, CAI_num, CAI_denom, E ← 0
    for each x in S do
        Retrieve neutrosophic values: T(x), I(x), F(x)
        TP += (1 - T(x))²
        NISI += F(x) - T(x) + λ * I(x)
        ICS += F(x) / (T(x) + ε)
        CAI_num += T(x); CAI_denom += F(x) + I(x) + ε
        E += 1 - |T(x) - F(x)|
    end for
    N ← |S|
    Normalize: NISI ← NISI / N; E ← E / N; CAI ← CAI_num / CAI_denom
    Compute D_info ← CAI * (1 - E)
    if min F(x) ≥ τ_f and TP is high then
        Label S as Semantic
    else if T_avg ≤ δ_t and F_avg ≥ δ_f and NISI > θ and ICS > γ then
        Label S as Non-Informative
    else if D_info > η and T_sum > F_sum then
        Label S as Informative
    else
        Label S as Borderline
    end if
end for
return classification for all S ∈ S
```

4.2 Algorithmic Workflow Explanation

The classification algorithm follows a phased, bottom-up procedure that iteratively processes each substructure$S_i \subseteq C$, aiming to assign it to one of four labels: Semantic, Non-Informative, Informative, c Borderline. The evaluation begins by initializing aggregates for all neutrosophic components across the region: $T(x), I(x)$, and $F(x)$.

In each iteration, cells are scanned one by one to update the composite metrics:

- TP increases when truth scores are low.
- ICS inflates when falsity dominates, due to low $T(x)$ relative to $F(x)$.
- Entropy rises when $T(x) \approx F(x)$, indicating conflict or uncertainty.
- CAI highlights regions with imbalanced truth-to-noise ratios.

After aggregation, the algorithm computes the final decision score D_{info} . The classification proceeds as follows:

- Semantic Sparsity if:

$SC(S_i) \geq 0.9$ and $TP(S_i) \geq \theta_{\text{sem}}$

- Non-Informative Sparsity if:

$NISI(S_i) > \theta_{\text{nisi}}$ and $\text{ICS}(S_i) < \gamma$

- Informative Sparsity if:

$D_{\text{info}}(S_i) > \eta$ and $\sum T(x) > \sum F(x)$

- Borderline otherwise: Regions not meeting these thresholds are left unclassified, pending expert review or further refinement.

This algorithm provides a principled approach to preprocessing sparse OLAP data cubes. By leveraging a layered neutrosophic representation, it enables the intelligent retention of rare yet analytically valuable sub patterns, while systematically eliminating structurally void regions. Additionally, it flags ambiguous areas for deeper inspection.

DOI: https://doi.org/10.54216/IJNS.260405

The outcome is a sparsity-aware data pipeline that integrates seamlessly with modern machine learning workflows, supporting more accurate and context-sensitive model training.

5. Conclusion

Sparsity remains one of the most persistent and underestimated challenges in multidimensional data modeling. While traditional OLAP cube preprocessing often treats empty or underpopulated regions as uniformly irrelevant, this paper has proposed a more nuanced and analytically grounded perspective. By adopting a neutrosophic logic framework, we reframe sparsity not as a monolithic obstacle, but as a spectrum of structural behaviors with varying analytical significance.

Through the introduction of a formal typology—distinguishing between semantic, non-informative, and informative sparsity—we provide the groundwork for a context-aware evaluation strategy. Each cube substructure is represented using a neutrosophic profile of truth, indeterminacy, and falsity, which reflects its potential informativeness, ambiguity, or irrelevance. This representation, combined with a suite of tailored metrics such as entropy, semantic confidence, and the Context-Aware Informativeness (CAI) score, guides the classification of each region with mathematical clarity.

The resulting Neutrosophic Evaluation Algorithm ensures that analytically valuable substructures—even if sparse—are retained for model training, while structurally void or misleading regions are excluded. This enables a preprocessing pipeline that is not only more sensitive to the underlying data patterns but also more compatible with modern machine learning workflows.

Ultimately, this study highlights the promise of neutrosophic theory as a flexible and effective modeling tool for handling sparsity in high-dimensional analytical systems. Its ability to capture uncertainty, subtlety, and signal imbalance introduces a novel mechanism for improving data preparation in contexts where both precision and interpretability matter.

Funding: “This research received no external funding”

Conflicts of Interest: “The authors declare no conflict of interest.”

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DOI: https://doi.org/10.54216/IJNS.260405