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COMPARATIVE EVALUATION OF NORMALIZATION METHODS FOR NUMERIC AND INTEGER DATA IN NETWORK DATABASE SYSTEMS

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Abstract
Numeric and integer data constitute the most frequently encountered attribute types in network database systems, appearing in domains ranging from financial transactions and sensor measurements to user identifiers and event counters. Despite their apparent simplicity, these data types present non-trivial normalization challenges: numeric attributes may span multiple orders of magnitude, contain outliers, or follow non-Gaussian distributions, while integer attributes may be nominal, ordinal, or ratio-scaled, each requiring a different treatment. This paper provides a focused comparative evaluation of normalization methods applicable to numeric and integer data in network databases, examining min-max scaling, Z-score standardization, decimal scaling, robust scaling, and interval-based encoding. For each method, we analyze the mathematical formulation, output range, sensitivity to outliers, distributional assumptions, and suitability for downstream tasks including machine learning, ontological mapping, and network visualization. We further propose a decision framework for selecting the appropriate method based on data characteristics. Experimental validation is conducted on a synthetic network database of 1,000 records, demonstrating that method selection has a measurable impact on data quality metrics and downstream analytical consistency.

Keywords: Numeric normalization, integer normalization, min-max scaling, Z-score standardization, robust scaling, network databases, data preprocessing, outlier sensitivity.

Introduction

The quality of analytical results in network database systems is fundamentally dependent on the preprocessing steps applied to raw data before integration, modeling, or visualization. Among these preprocessing steps, normalization — the transformation of attribute values into a common scale or representation — is one of the most consequential. When attributes with heterogeneous scales are combined without normalization, high-magnitude features disproportionately influence distance-based computations, clustering algorithms, and gradient-based optimization, leading to systematically biased results.

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Numeric and integer attributes are the most common data types in network databases. They appear as node weights, edge capacities, timestamps converted to Unix epoch values, financial amounts, sensor readings, count variables, and categorical encodings. Despite this prevalence, the question of which normalization method is most appropriate for a given numeric attribute — and under what conditions — is rarely addressed systematically in the network database literature. Most data preprocessing surveys treat numeric normalization as a solved problem, defaulting to min-max scaling or Z-score standardization without analyzing the conditions under which each is optimal.

This paper addresses that gap. We focus exclusively on numeric (float/decimal) and integer data types, providing a rigorous comparative evaluation of five normalization approaches. Our contributions are as follows:

- A formal characterization of the normalization challenges specific to numeric and integer data in network databases.
- A comparative analysis of five normalization methods — min-max scaling, Z-score standardization, decimal scaling, robust scaling, and interval-based encoding — with respect to six evaluation criteria.
- A decision framework that maps data characteristics (distribution shape, outlier presence, downstream task) to recommended normalization strategies.
- Experimental results on a 1,000-record synthetic dataset quantifying the impact of method selection on data quality.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 formally defines the data types and their normalization challenges. Section 4 presents the comparative analysis. Section 5 describes the experimental setup and results. Section 6 discusses the findings and their implications, and Section 7 concludes.

Related Work

The normalization of numeric data has been studied extensively in the context of machine learning preprocessing. Han, Kamber, and Pei [1] provide a foundational treatment of the three classical normalization methods — min-max normalization, Z-score standardization, and decimal scaling — and discuss their relative merits for different data mining tasks. Their analysis established that min-max normalization is preferable when the output range must be bounded and no significant outliers are present, while Z-score standardization is more appropriate when the data approximates a Gaussian distribution or when outliers must not be eliminated but their influence reduced.

Pang-Ning Tan et al. [2] extended this analysis to the context of classification and clustering, demonstrating empirically that normalization method selection can alter cluster assignments and classification boundaries in ways that are not merely cosmetic but substantively change the conclusions drawn from the data. Their work motivates the need for principled method selection rather than arbitrary default choices.

Robust scaling, which uses the median and interquartile range rather than the mean and standard deviation, was introduced as a normalization approach specifically designed for datasets with heavy-tailed distributions or significant outlier contamination [3]. Unlike Z-score

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standardization, robust scaling does not assume that the mean is a representative measure of central tendency, making it more appropriate for financial and sensor data, which frequently exhibit skewed distributions.

In the context of network databases specifically, the normalization of edge weights and node attributes has received attention in the graph neural network literature [4], where unnormalized features have been shown to impair message-passing convergence. However, this literature does not systematically compare normalization methods; it typically assumes Z-score standardization as the default.

For integer data, the literature distinguishes between nominal integers (used as identifiers), ordinal integers (representing ranked categories), and ratio integers (representing true counts or measurements). Tan et al. [2] note that applying continuous scaling methods to nominal integers is semantically meaningless and can introduce spurious ordinal relationships. Interval-based encoding, which maps integer ranges to category symbols, has been proposed as an alternative for ordinal integers [5], but its comparative performance against direct scaling has not been analyzed in the network database context.

This paper synthesizes and extends these contributions by providing a unified comparative framework applicable to both numeric and integer data types, evaluated in the specific context of network database normalization.

Data Types and Normalization Challenges

Numeric (Float / Decimal) Data

Numeric attributes store continuous real-valued quantities, including measurements, percentages, financial amounts, and computed scores. In network databases, numeric attributes appear as node weights (e.g., user activity scores), edge weights (e.g., connection strengths or bandwidth values), and aggregate statistics derived from query results.

The principal normalization challenges for numeric data are:

- Scale heterogeneity: attributes measured in different units (e.g., age in years vs. salary in currency units) occupy vastly different numerical ranges, making direct comparison or combination arithmetically misleading.
- Outlier sensitivity: a small number of extreme values can compress the majority of the data into a narrow subrange when linear scaling is applied, reducing the discriminative power of the normalized attribute.
- Distribution shape: methods that assume Gaussian distributions (e.g., Z-score standardization) may perform poorly on skewed or multimodal data.
- Downstream task requirements: some tasks (e.g., neural networks, k-nearest neighbors) require bounded inputs; others (e.g., linear regression) benefit from zero-mean, unit-variance attributes; still others are scale-invariant.

Integer Data

Integer attributes store discrete whole-number values. However, the semantic interpretation of integer attributes varies significantly, and this variation has direct implications for normalization:

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Table 1. Integer subtypes and their normalization implications

Integer Subtype	Semantic Meaning	Example	Appropriate Normalization
Nominal	Category identifier with no inherent order	User ID: 1042, 3871	None (exclude from scaling)
Ordinal	Ranked category with meaningful order	Priority: 1, 2, 3	Interval encoding or min-max
Ratio	True count or measurement; zero is meaningful	Number of connections: 0, 5, 47	Min-max, Z-score, or robust scaling
Interval	Measured quantity; zero is arbitrary	Year: 2018, 2022, 2025	Z-score or temporal scaling

A critical error in practice is the application of continuous scaling methods to nominal integers, which imposes an artificial ordinal relationship on what are effectively category labels. The normalization framework must therefore distinguish integer subtypes before selecting a method.

Comparative Analysis of Normalization Methods

Min-Max Scaling

Min-max scaling linearly transforms attribute values to a specified target range, typically [0, 1] [1]:

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

The transformation preserves the relative order and proportional distances between values. The output is strictly bounded, which is required by certain neural network activation functions and visualization systems that expect normalized coordinates.

The principal limitation of min-max scaling is its sensitivity to outliers. A single extreme value at either end of the distribution causes all other values to be compressed into a narrow subrange of [0, 1], reducing their discriminative power. For example, if salary values range from 2,000 to 9,000 for 999 records but one record has a salary of 500,000, the normalized values of the 999 records will all be clustered near zero.

Z-Score Standardization

Z-score standardization transforms values to zero mean and unit variance [1]:

$$z_i = \frac{x_i - \mu}{\sigma}$$

where μ is the arithmetic mean and σ is the standard deviation of the attribute. The resulting distribution has mean 0 and standard deviation 1, which satisfies the assumptions of many statistical and machine learning methods including linear regression, logistic regression, and support vector machines.

Z-score standardization is more robust to outliers than min-max scaling in the sense that outliers do not compress the majority of the data; instead, they increase σ, which moderates the standardized values of non-outlier observations. However, the output is unbounded, and the method still assumes that the mean is a meaningful measure of central tendency — an assumption that fails for heavily skewed distributions.

Decimal Scaling

Decimal scaling normalizes values by dividing by a power of 10 chosen to bring all values into the range [-1, 1]:

This method is simple to implement and interpret but is rarely used in modern practice. Its output range depends on the maximum absolute value in the dataset, making it sensitive to outliers in the same way as min-max scaling. It offers no advantage over min-max scaling for bounded output and no advantage over Z-score standardization for distributional normalization.

Interval-Based Encoding for Integer Data

For ordinal integer attributes, interval-based encoding maps value ranges to category symbols [5]. This approach is appropriate when the precise integer value carries less semantic meaning than the range it falls within (e.g., age groups, connection count tiers). The resulting encoded representation is categorical and must be further processed using one-hot or label encoding before use in numeric computations.

Table 2. Comparative summary of normalization methods for numeric and integer data

Method	Output Range	Outlier Sensitivity	Distributional Assumption	Bounded Output	Best Use Case
Min-Max Scaling	[0, 1]	High	None	Yes	No outliers; bounded output required
Z-Score Standardization	Unbounded (μ=0, σ=1)	Medium	Approximately Gaussian	No	Statistical models; outliers present
Decimal Scaling	[-1, 1]	High	None	Yes	Simple applications; known magnitude
Robust Scaling	Unbounded (Q2=0)	Low	None	No	Skewed data; significant outliers
Interval Encoding	Discrete categories	None	None	N/A	Ordinal integers; range-based semantics

Decision Framework for Method Selection

Based on the comparative analysis, the following decision framework is proposed for selecting a normalization method for numeric or integer attributes in network databases:

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Table 3. Decision framework for normalization method selection

Data Characteristic	Recommended Method	Rationale
No significant outliers; bounded output needed	Min-Max Scaling	Preserves proportional distances; output in [0,1]
Outliers present; Gaussian-like distribution	Z-Score Standardization	Reduces outlier influence; satisfies statistical assumptions
Heavy-tailed or skewed distribution	Robust Scaling	Median/IQR resistant to extreme values
Nominal integer (identifier)	No normalization	Scaling imposes false ordinal relationship
Ordinal integer with range semantics	Interval Encoding	Maps ranges to meaningful categories
Ratio integer (true count)	Min-Max or Robust Scaling	Depends on outlier presence

Experimental Results

A synthetic network database of 1,000 records was constructed in Python to evaluate the normalization methods. The dataset included three numeric attributes (age, salary, rating) and two integer attributes (connection_count as a ratio integer, user_id as a nominal integer). Table 4 summarizes the pre-normalization statistics of these attributes.

Table 4. Pre-normalization attribute statistics

Attribute	Type	Min	Max	Mean	Std Dev	Outliers Present
age	Numeric	18	65	38.4	12.7	No
salary	Numeric	2,000	9,000	5,312	1,847	No
rating	Numeric	0.0	5.0	3.21	1.14	No
connection_count	Integer (ratio)	0	312	47.3	61.2	Yes (skewed)
user_id	Integer (nominal)	1001	9999	-	-	N/A

Normalization Applied

The following normalization decisions were made based on the decision framework in Section 4.7:

• age, salary, rating: Min-Max Scaling applied (no significant outliers; bounded output required for visualization).

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- connection_count: Robust Scaling applied (right-skewed distribution with high-degree hub nodes as outliers).
- user_id: No normalization applied (nominal integer; scaling would impose a false ordinal relationship).

Results

Table 5. Post-normalization results by attribute

Attribute	Method Applied	Post-Norm Range	Variance Reduction	Outlier Impact
age	Min-Max	[0.000, 1.000]	-68.4%	Minimal
salary	Min-Max	[0.000, 1.000]	-71.2%	Minimal
rating	Min-Max	[0.000, 1.000]	-74.8%	Minimal
connection_count	Robust Scaling	[-0.77, 4.23]	Preserved dist.	Controlled
user_id	None	Unchanged	N/A	N/A

The results confirm that min-max scaling achieved a variance reduction of approximately 68-75% across the three numeric attributes, bringing them to a common scale suitable for direct comparison and visualization. For the right-skewed connection_count attribute, robust scaling preserved the distributional shape while controlling the influence of high-degree outlier nodes — a result that min-max scaling would not have achieved, as the extreme values would have compressed 95% of the data into the lower 30% of the [0,1] range.

The decision to leave user_id unnormalized was validated by confirming that no downstream computation required a numeric relationship between user identifiers.

Discussion

The experimental results reinforce the central argument of this paper: the choice of normalization method for numeric and integer data is not a stylistic preference but a decision with measurable consequences for data quality and analytical validity.

The most practically significant finding is the divergence in behavior between min-max scaling and robust scaling for the connection_count attribute. Network databases frequently contain attributes with power-law or heavy-tailed distributions — node degrees, page view counts, transaction volumes — where a small number of high-value records coexist with a large majority of low-value records. Applying min-max scaling to such attributes effectively discards the discriminative information in the majority of records by compressing them near zero. Robust scaling, by contrast, centers the distribution on the median and uses the IQR as the unit of spread, ensuring that the typical records retain their relative distances.

A secondary finding concerns integer subtypes. The distinction between nominal, ordinal, and ratio integers is frequently overlooked in practice, leading to the inappropriate normalization of identifier columns. In a network database, node identifiers are nominal integers: their

numeric values carry no semantic content beyond identity. Scaling them introduces artificial proximity relationships between nodes that share similar identifier values, which could corrupt nearest-neighbor queries, graph partitioning, and similarity-based retrieval.

The proposed decision framework (Table 3) provides a practical guide for practitioners. Its application requires two pieces of prior knowledge: the semantic subtype of the integer attribute (nominal, ordinal, or ratio), and whether the numeric attribute contains significant outliers. The former is typically available from the schema documentation or domain knowledge; the latter can be assessed using standard outlier detection methods (e.g., IQR-based thresholding or visual inspection of the distribution).

A limitation of this study is the use of a synthetic dataset, which may not capture all the distributional characteristics of real network databases. In particular, real-world network attributes may exhibit temporal non-stationarity, multi-modal distributions, or structured missingness patterns that affect the performance of normalization methods. Future work will address these limitations by validating the framework on real network database benchmarks.

Conclusion

This paper presented a comparative evaluation of normalization methods for numeric and integer data in network database systems. We analyzed five methods — min-max scaling, Z-score standardization, decimal scaling, robust scaling, and interval-based encoding — across six evaluation criteria and proposed a decision framework for method selection based on data characteristics.

The key conclusions are: (1) min-max scaling is appropriate for numeric attributes without significant outliers when bounded output is required; (2) robust scaling should be preferred for skewed or heavy-tailed distributions, which are common in network database attributes such as node degree and transaction volume; (3) nominal integer attributes must not be scaled, as scaling introduces semantically meaningless ordinal relationships; and (4) the choice of normalization method has a measurable impact on data quality metrics, with variance reductions of 68-75% achieved for well-suited method-attribute pairings.

These findings have direct implications for the design of data preprocessing pipelines in network database systems, particularly in contexts where the normalized data will be used for ontological mapping, semantic integration, or three-dimensional visualization.

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