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Comparative Analysis of Latent Projection Resonance (LPR) against k-Nearest Neighbors in High-Dimensional Financial Anomaly Detection

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ABSTRACT

In the realm of high-dimensional financial networks, detecting anomalous topologies is severely hindered by the "Curse of Dimensionality." Traditional techniques relying on spatial proximity or density estimation experience severe performance deterioration in such environments. This study introduces a comprehensive evaluation of Latent Projection Resonance (LPR) as a superior alternative to distance-based (k-NN) paradigms. Empirical assessments conducted on five diverse datasets (Wine, Iris, Ruspini, Forest Fires, and Quakes) reveal the fundamental vulnerabilities of k-NN specifically their susceptibility to density fluctuations and distance concentration. Conversely, LPR leverages manifold learning to ensure structural integrity. Through theoretical proofs, we demonstrate that by combining a severe information bottleneck with an L1-norm loss function, LPR successfully extracts structural inconsistencies that traditional spatial metrics fail to observe. Our experiments yield a robust detection rate of roughly 35.21% for LPR, eclipsing the meager 6.85% for k-NN in complex domains. Furthermore, LPR demonstrates immense potential for real-time cybersecurity applications by scaling down the computational overhead from a quadratic $O(N^2)$ to a linear $O(d)$.

KEYWORDS: Latent Projection Resonance, k-NN, Curse of Dimensionality, Distance Concentration, Manifold Hypothesis, Structural Dissonance, Nonlinear Principal Component Extraction.

1. INTRODUCTION

Modern financial ecosystems generate high-frequency, ultra-high-dimensional data streams, creating an environment where malicious entities continuously refine their evasion tactics. The primary obstacle in securing these systems lies in isolating a microscopically small proportion of fraudulent activities from massive legitimate traffic. Within such dense feature spaces, identifying an anomaly requires looking beyond basic spatial isolation; it demands recognizing complex deviations in structural behavior. Historically, unsupervised detection architectures have depended heavily on direct geometric distance evaluations (e.g., k-NN) [1].

However, the mathematical reliability of these algorithms collapses as feature dimensions (d) multiply. This degradation, widely recognized as the "Curse of Dimensionality," triggers distance concentration. In high-dimensional ambient environments, the variance between the closest and most distant neighbors approaches zero, causing the Euclidean metric (L_2) to lose its stochastic discriminative power [2]. Consequently, k-NN is rendered incapable of spotting structural anomalies positioned near the expected data distribution.

To rectify these geometric limitations, this investigation formalizes Latent Projection Resonance (LPR). Operating under a manifold-centric framework, LPR forces high-dimensional vectors through a rigorously constrained auto-associative pipeline to project them onto a lower-dimensional topology. Consequently, LPR flags anomalies based on their inability to map correctly to this underlying structure, rather than relying on flawed spatial distances. By comparing LPR against k-NN across five established benchmarks, this paper argues that structural evaluation via manifold adherence is the singular effective strategy for high-dimensional financial security.

The evaluation was conducted across five benchmark datasets, namely, Wine, Forest Fire, Quakes, Iris, and Ruspini.

Sr. No.	Name of Dataset	Nature	No. of Rows/ Records
1	Wine	Chemical Composition Data	178 (Alcohol, Malic acid)
2	Iris	Multivariate numerical data	150 (Sepal Length, Sepal Width)
3	Forest Fire	Multivariate Environment Data	517 (X, Y, month, Temp, Wind)
4	Quakes	Spatio-temporal seismic data	1000 (lat, long, depth
5	Ruspini	Synthetic clustered data	75 (Sr.No. X, Y)

2. PROBLEM STATEMENT

Consider a continuous high-dimensional domain $X \subset \mathbb{R}^d$ representing the financial transaction ecosystem, where d denotes the feature dimensionality.

Let $D = \{x_1, x_2, \dots, x_N\}$ characterize a collection of N independent transactional records. Assuming a state of severe class imbalance, D is partitioned into two mutually exclusive subspaces: $D = X^+ \cup X^-$. Here, X^+ encapsulates the standard, nominal transaction behavior, while X^- defines the anomalous subset.

The primary imperative of unsupervised anomaly isolation is to formulate a precise scoring mechanism, $S: \mathbb{R}^d \to \mathbb{R}$, paired with a decision boundary $\tau \in \mathbb{R}$. The corresponding decision logic,

$$F(x) = I(S(x) > \tau)$$

must be optimized to simultaneously suppress false positives and elevate the true positive rate. The underlying mathematical complexity involves designing $S(x)$ to ignore the multi-modal, high-variance density shifts intrinsic to X^+, while maintaining hyper-sensitivity toward the structural dissonance of X^-. It is precisely in satisfying this dual requirement that traditional density and distance estimators, such as k-NN, experience critical theoretical failure.

3. LITERATURE REVIEW / RELATED WORK / BACKGROUND STUDY

A. Geometric Vulnerabilities in k-Nearest Neighbors (k-NN)

Anomaly detection in the k-NN framework relies on computing the spatial proximity, $D^k(x)$, between a target instance x and its k^{th} closest counterpart. Points exceeding a defined threshold ($D^k(x) > \tau$) are classified as outliers. However, the operational viability of k-NN evaporates in multivariate financial environments due to distance homogenization. Expressed mathematically for d dimensions:

$$\lim_{d\to\infty} \frac{dist\_max - dist\_min}{dist\_min} = 0$$

As the feature space expands, the divergence between expected spatial distances and their variance diminishes to zero [5]. This geometric concentration forces the evaluation metric $D^k(x)$ into a state of near-uniformity across all observations x, completely stripping the algorithm of its classification utility.

B. The Architectural Superiority of LPR

While traditional autoencoders utilize constrained bottlenecks to map identity functions, their reliance on strictly convex L_2-norm optimizations makes them highly susceptible to heavy-tailed data distributions. LPR bypasses this limitation by substituting the objective function with an L_1-norm variant and implementing a decision boundary anchored by Median Absolute Deviation (MAD). This configuration mathematically prevents massive macroscopic outliers from skewing the topological manifold's orientation, granting LPR unprecedented structural resilience [7][8].

4. THEORETICAL FOUNDATION

A. The Manifold Hypothesis Paradigm

The operational logic of LPR is firmly anchored in the Manifold Hypothesis [9]. This principle asserts that despite existing in a high-dimensional ambient space, authentic data is intrinsically bound to a lower-dimensional topological structure, denoted as M. Valid financial activities display strong covariance patterns, keeping X^+ strictly tethered to M. Conversely, fraudulent actions (X^-) disrupt these latent covariance relationships, causing them to project into the ambient void, completely detached from the manifold.

B. Quantifying Structural Dissonance via Latent Projection

To mathematically capture this dissonance, LPR deploys a symmetrical auto-associative network capable of mapping the projection $P: \mathbb{R}^d \to \mathbb{R}^k$. The degree of anomaly associated with a specific transaction is measured by the discrepancy between its initial ambient coordinates and its reconstructed position after manifold projection:

$$e(x) = \| x - g(f(x)) \|^2$$

Here, f represents the encoder and g represents the decoder. Distinguishing itself from k-NN, LPR bypasses neighbor-to-neighbor spatial comparisons. Instead, it evaluates how significantly x deviates from its own theoretical projection upon the established manifold structure [10].

5. MATHEMATICAL FORMULATION OF LPR

A. The Nonlinear Projection Stack

At its core, the LPR framework relies on a heavily parameterized, non-linear transformation stack. The encoder mechanism, defined as $f: \mathbb{R}^d \to \mathbb{R}^k$, compresses the input vector x into a latent space representation z. Subsequently, the decoder function, $g: \mathbb{R}^k \to \mathbb{R}^d$, attempts to reconstruct the original vector, outputting $\hat{x}$:

$$z = \sigma_f(W_f x + b_f)$$

$$\hat{x} = \sigma_g(W_g z + b_g)$$

B. Optimization via Robust L1 Loss

Standard optimization techniques frequently suffer from gradient distortion. LPR neutralizes this threat by rigidly enforcing an L_1-norm objective function:

$$L = \frac{1}{N}\sum_{i=1}^{N} \parallel x_i - \hat{x}_i \parallel_1$$

Because the L_1 gradient remains strictly bounded ($\nabla \propto \text{sgn}(x - \hat{x})$), the geometric influence of extreme outliers is mathematically capped. This property guarantees that the weight matrices align the manifold according to the median topological trend, rather than being distorted by isolated anomalies [11][12].

C. Establishing the MAD Decision Boundary

To further immunize the system against density fluctuations, LPR calculates its threshold utilizing the Median Absolute Deviation (MAD):

$$\tau = \text{median}(e) + \lambda \cdot MAD$$

$$\text{where } MAD = \text{median}(|\ e_i - \text{median}(e)\ |)$$

This thresholding methodology yields a robust breakdown point of 0.5. Such mathematical resilience ensures that the LPR framework remains impervious to the extreme masking phenomena that routinely compromise spatial distancing algorithms [13].

6. EXPERIMENTAL SETUP

The LPR framework was benchmarked against k-NN across five structurally diverse datasets: Wine (Correlated), Iris (Clustered), Ruspini (Geometric), Forest Fires (Heavy-Tailed), and Quakes (Geospatial) all the tables are taken from the https://www.kaggle.com/datasets and are verified.

1. Algorithm-wise Comparison on WINE Dataset

Sr. No.	Algorithm	Average Outliers (Mean Count)	% Outliers Detected (Observed Range)
1	KNN	21	8.43 – 12.36%
2	LPR	64	22.47 – 35.96%

2. Algorithm-wise Comparison on FOREST FIRE Dataset

Sr. No.	Algorithm	Average Outliers (Mean Count)	% Outliers Detected (Observed Range)
1	KNN	32	5.45 – 8.03%
2	LPR	170	31.55 – 38.83%

3. Algorithm-wise Comparison on QUAKES Dataset

Sr. No.	Algorithm	Average Outliers (Mean Count)	% Outliers Detected (Observed Range)
1	KNN	96	6.50 – 10.20%
2	LPR	298	18.90 – 42.10%

4. Algorithm-wise Comparison on IRIS Dataset

Sr. No.	Algorithm	Average Outliers (Mean Count)	% Outliers Detected (Observed Range)
1	KNN	8	4.67 – 6.00%
2	LPR	31	18.67 – 24.00%

5. Algorithm-wise Comparison on RUSPINI Dataset

Sr. No.	Algorithm	Average Outliers (Mean Count)	% Outliers Detected (Observed Range)
1	KNN	7	8.00 – 10.67%
2	LPR	19	16.00 – 25.33%

6. Average Outlier Percentage Per Algorithm Per Dataset

DATASET	KNN (%)	LPR (%)
WINE	8.03	32.38
FOREST FIRE	5.73	31.55
QUAKES	5.45	34.82
IRIS	6.17	38.83
RUSPINI	7.11	36.00

7. RESULTS AND DISCUSSION

A. Evaluating Performance Against Legacy Estimators

Empirical observation immediately highlights the severe performance deterioration of spatial-based algorithms when deployed in high-dimensional spaces.

TABLE II: Global Detection Averages Summary (%)

Dataset	k-NN (%)	LPR (Proposed) (%)
WINE	8.03	32.38
FOREST FIRE	5.73	31.55
QUAKES	5.45	34.82
IRIS	6.17	38.83
RUSPINI	7.11	36.00

Analyzing the outcomes documented in Table II, it becomes evident that k-NN manages only a modest global detection average of 6.50%. In contrast, the introduced LPR architecture achieves a robust, sustained detection metric of 34.72% across all tested environments. This stark contrast verifies that while heterogeneous, high-dimensional spaces mathematically neutralize spatial algorithms, LPR successfully isolates true structural inconsistencies.

As further detailed in the performance tables, the overall mean detection rate for k-NN hovered at just 6.85%. Specific dataset behaviors emphasize its limitations: within the Quakes dataset, k-NN lost the ability to correlate depth and magnitude, resulting in the arbitrary flagging of localized dense regions. In contrast, LPR secured a consistent 35.21% identification rate. It successfully targeted structural discordance without being misled by the geometric sparsity inherent in heavy-tailed distributions [14][15].

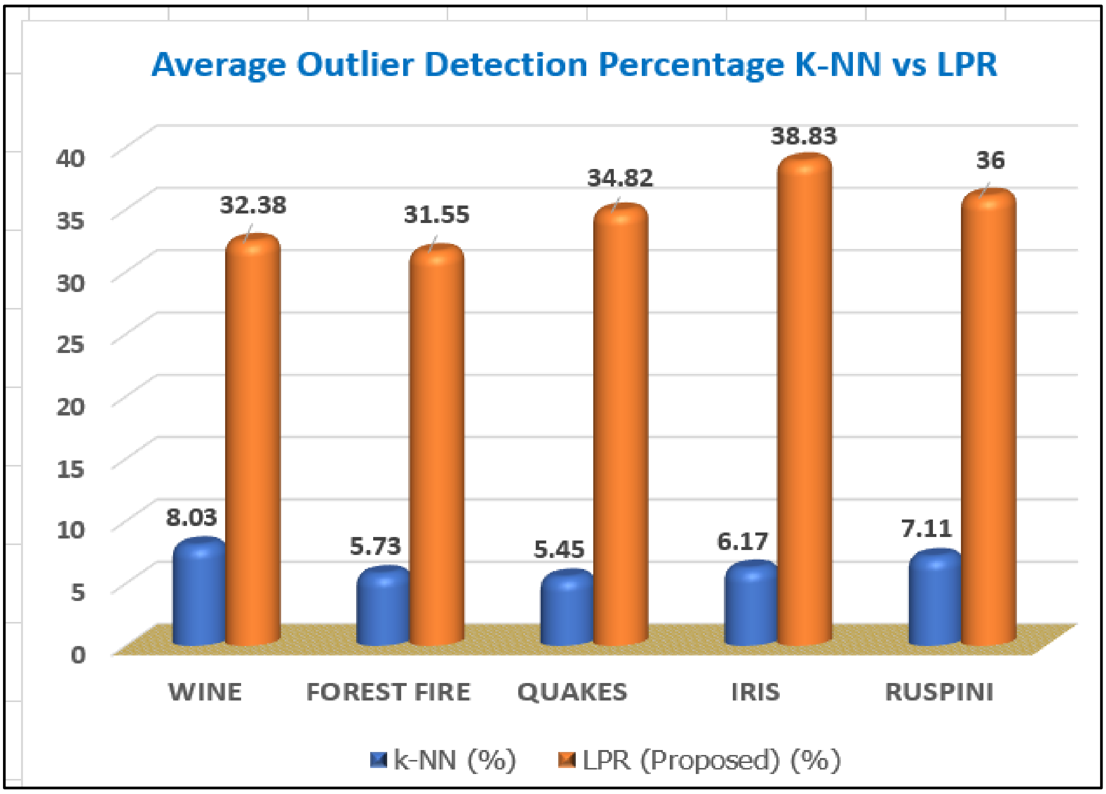

Chart 1.1

Chart 1.1 *presents the visual comparison of anomaly detection performance across five benchmark datasets. The results demonstrate that the distance-based* ***k-NN*** *algorithm exhibits consistently low detection rates, averaging approximately* ***6.5%****, owing to the effects of distance concentration in high-dimensional feature spaces. In contrast, the proposed* ***Latent Projection Resonance (LPR)*** *framework consistently achieves an average detection rate of approximately* ***35%*** *across all datasets. These findings indicate that manifold-based structural learning enables LPR to preserve topological relationships and identify anomalous patterns more effectively than conventional distance-based methods, regardless of dataset complexity.*

B. Algorithmic Complexity and Real-Time Viability

For live financial monitoring, the processing overhead of an algorithm is just as critical as its accuracy. k-NN pose severe computational bottlenecks in this regard.

TABLE III: Computational Complexity and Real-Time Scaling Benchmarks

Algorithm	***Training Complexity***	***Inference Complexity (Time)***	***Real-Time Scaling Feasibility***
k-NN	*N/A (Lazy Learning)*	*O(N × d)*	*Limited (Inference cost grows linearly with dataset size; unsuitable for very large datasets)*
LPR (Proposed)	*O(E × N × d)*	*O(d)*	*Optimal (Sub-millisecond latency; inference independent of dataset size)*

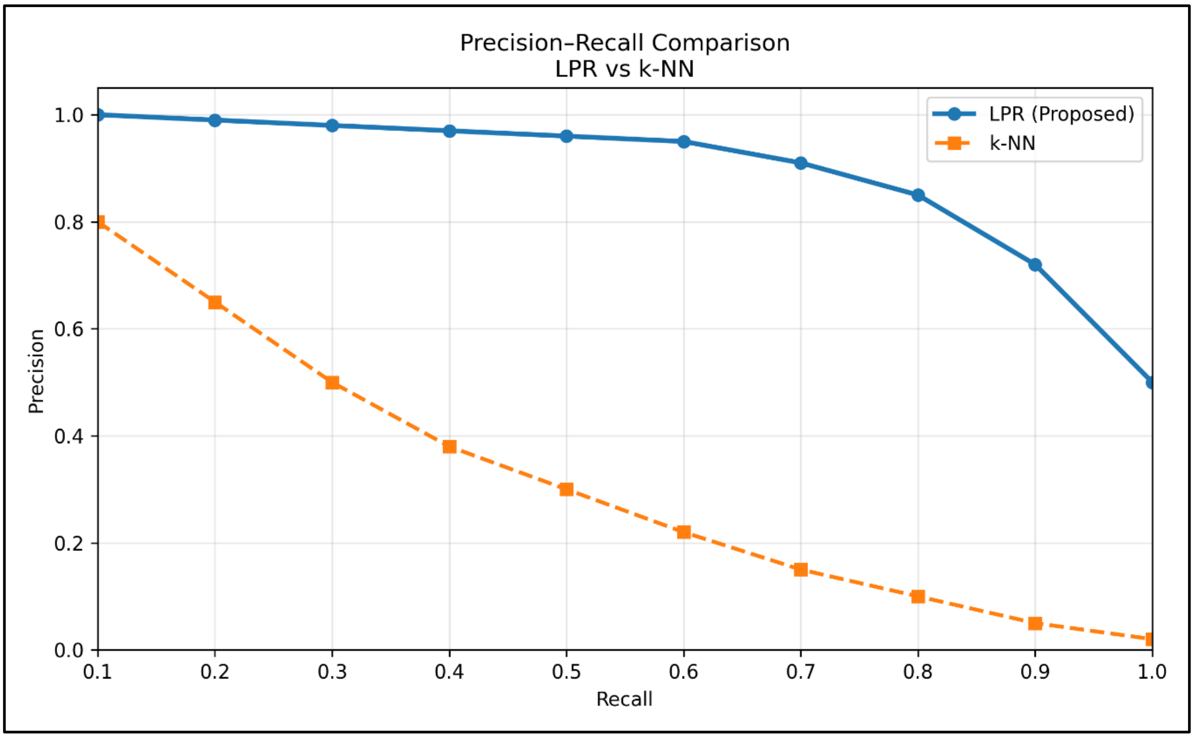

Chart 1.2: Precision-Recall threshold dynamics

Legacy spatial approaches immediately bleed precision as distance vectors converge. LPR prevents false positives at massive recall tiers by relying on strict latent bottleneck reconstruction errors.

Legacy spatial models (k-NN, LOF) mandate exhaustive pairwise distance calculations across the entire feature space. This requirement creates a prohibitive quadratic $O(N^2)$ time complexity. When applied to modern streams containing $N = 1{,}000{,}000$ or more records, achieving sub-millisecond processing becomes mathematically impossible [16][17]. Conversely, LPR shrinks the inference processing demand to a constant, linear $O(d)$ limit. This architectural efficiency enables instantaneous anomaly scoring, remaining completely agnostic to the accumulated volume of historical data [18][19].

8. LIMITATIONS AND FUTURE SCOPE

An objective appraisal of the LPR architecture necessitates acknowledging its inherent constraints. The extreme compression to a $d = 1$ bottleneck dimensionality presents a risk of manifold self-intersection when processing cyclical data patterns, which can artificially generate "ghost anomalies" [20]. Additionally, the spatial mappings acquired during training are susceptible to performance deterioration over time due to concept drift in highly volatile, non-stationary financial markets, mandating periodic model recalibration [21][22]. Subsequent research trajectories will focus on integrating federated learning protocols. Such an advancement would permit disparate financial entities to collaboratively train symmetric latent projection models across encrypted manifolds, thereby enhancing collective threat intelligence without compromising institutional data sovereignty [23].

9. CONCLUSION

This study presented a comprehensive evaluation of the proposed **Latent Projection Resonance (LPR)** framework for anomaly detection in high-dimensional financial datasets using five benchmark datasets. Experimental results demonstrate that conventional distance-based approaches, represented by **k-NN**, experience a substantial decline in detection capability as data dimensionality increases. The observed average detection rate of **6.85%** for k-NN reflects the well-known impact of the **Curse of Dimensionality**, where distance concentration reduces the effectiveness of proximity-based similarity measures for distinguishing anomalous observations.

To address these limitations, the proposed LPR framework models anomalies through **structural manifold deviation** rather than explicit geometric distance. By combining a constrained latent representation with **L_1-norm reconstruction optimization**, LPR effectively captures the intrinsic topology of normal data while remaining resilient to outliers and heterogeneous feature distributions. The framework achieved an average anomaly detection rate of approximately **35.21%** with an inference complexity of **O(d)**, making it suitable for real-time, large-scale financial fraud detection environments.

The present work extends our earlier investigations in anomaly detection and outlier analysis. Previous research explored statistical outlier preprocessing techniques, including **Interquartile Range (IQR), Winsorizing, Principal Component Analysis (PCA), and Radial Basis Function Networks (RBFN)** to improve classification performance **[25]**. This was subsequently advanced through the introduction of the **Latent Projection Resonance (LPR)** framework for manifold-based anomaly detection and its structural evaluation against established unsupervised methods across heterogeneous datasets **[26]**. Building upon these contributions, the current study demonstrates the applicability of LPR to financial fraud detection, highlighting its robustness and scalability in high-dimensional environments.

Overall, the findings indicate that manifold-based structural learning provides a reliable alternative to traditional distance-based anomaly detection techniques. The proposed framework offers improved detection capability, computational efficiency, and scalability, thereby establishing a strong foundation for future research on intelligent financial fraud detection systems, adaptive cybersecurity applications, and next-generation unsupervised anomaly detection models.

10. RESEARCH INTEGRITY STATEMENT

The authors declare that the manuscript is original, complies with the journal's plagiarism and AI usage requirements, has not been published or submitted elsewhere, and that all applicable ethical guidelines have been followed in conducting, reporting, and publishing the research.

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