A VISUAL-EMPIRICAL STUDY OF SCALING EFFECTS AND HYPER-PARAMETER ROBUSTNESS IN K-NEAREST NEIGHBOR CLASSIFICATION

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Annotation. The paper revisits the *k-Nearest Neighbors* (k-NN) algorithm by combining mathematical exposition with empirical testing on three benchmark datasets—Iris, Wine and Breast-Cancer. All features were z-score standardized; classification accuracy was recorded for k ranging from 1 to 15. Two visual tools—an accuracy-versus-k curve and a 2-D PCA scatter plot—highlight how hyper-parameter choice affects performance and reveal the inherent class structure. Findings confirm that, with proper scaling and a moderate neighborhood size (k ≈ 5–11), k-NN attains stable accuracies of roughly 94–96 %.

Key words: k-nearest neighbors algorithm, z-score standardization, hyper-parameter tuning, benchmark datasets (Iris, Wine, Breast-Cancer), PCA visualization, classification accuracy.

Introduction. The k-Nearest Neighbors (k-NN) algorithm belongs to the family of instance-based (lazy-learning) methods that require virtually no explicit training stage. Originally proposed by Cover and Hart [1], k-NN has gained wide popularity over the past decade—particularly in engineering and experimental research—because of its simplicity and intuitive appeal for both classification and regression across datasets of varying size and dimensionality. One of its chief strengths is that model construction (fitting) is almost trivial, so there is little need for elaborate hyper-parameter tuning. Consequently, k-NN is often the first "ready-to-use" baseline for rapid prototyping on large, heterogeneous data collections [2].

For every query instance, k-NN assigns a label (or numeric value) by consulting the *k* closest reference samples and using majority vote (or a simple average). Proximity is usually measured with the Euclidean distance, although Manhattan, Minkowski, Mahalanobis, or specialized mixed-type metrics such as HVDM can be employed. The hyper-parameter *k* controls bias–variance trade-off: too small leads to over-fitting local noise, whereas too large produces over-smoothed decision boundaries and declining accuracy. Hence, *k* is typically selected via cross-validation.

As the data size grows, the computational cost approaches $O(mn)$—where m is the number of reference points and n is the feature dimension. To mitigate this, efficient data structures (KD-trees, ball-trees) and modern approximate-nearest-neighbour libraries (e.g., FAISS, Annoy, HNSW) are widely used.

Like many machine-learning techniques, k-NN is inherently suited to numeric features. When the feature space contains a mix of nominal and numeric variables, a preliminary encoding step is essential:

- ✓ **Label encoding:** maps each categorical value to an integer, but may introduce spurious ordinal relationships.
- ✓ **One-hot encoding:** creates a separate binary column per category, at the expense of a sharp dimensionality increase and potential "distance concentration."
- ✓ **Mixed-type metrics** (HVDM, Gower): integrate numeric and nominal features directly, avoiding an explicit encoding step [3].

This study analyses the impact of k selection, distance metric choice, and encoding strategy on three benchmark datasets - Iris, Wine, and Breast-Cancer. All features were standardized by z-score scaling, and classification accuracy was recorded for $1 \leq k \leq 9$. Two visual tools - an accuracy-vs-k curve and a 2-d PCA projection—provide intuitive insight into parameter sensitivity and inherent class structure. The results confirm that, with proper scaling and a moderate neighborhood size ($k \approx 5 - 11$), k-NN achieves stable accuracies of roughly 94– 96 %.

Problem statement. Pattern recognition is considered in its classical, two–class formulation. Let

$$S = \{E_0, E_1, \dots, E_m\}, E_j \in \{K_1, K_2\},$$

be a finite set of mutually exclusive objects that belong either to class K_1 or to class K_2.

Each object is characterized by a vector of n heterogeneous features, of which

- ξ are quantitative (measured on an interval scale),
- $n - \xi$ are nominal (unordered categories).

Denote

- $I \subset \{1, \dots, n\} -$ the index set of quantitative features,
- $I \subset \{1, \dots, n\} -$ the index set of nominal features, with $I \cup J = \{1, \dots, n\}\ and\ I \cap J = \emptyset.$

Required

1. **Feature–space unification** – transform the original mixed-type feature set into a new representation in which *all* coordinates are comparable under a single distance measure.

2. **Performance comparison** – compute the classification accuracy of the k-Nearest Neighbors (k-NN) algorithm both *before* and *after* this transformation, for a range of k values.

Proposed transformation. Following the strategy of Wilson & Martinez [5], the mixed feature space is embedded into a metric space by combining

- z-score scaling for every $c \in I$:

$$z^{(c)}(E) = \frac{x^{(c)}(E) - \mu^{(c)}}{\sigma^{(c)}},$$

  where $\mu^{(c)}$ and $\sigma^{(c)}$ are the sample mean and standard deviation of the $c - th$ quantitative features;
- the Value-Difference Metric (VDM) for every $c \in J$:

$$VDM\left(x^{(c)}(E), x^{(c)}(E')\right) = \sum_{s\in\{K_1,K_2\}} \left|P\left(x^{(c)}(E)\right) - P(s|x^{(c)}(E'))\right|,$$

  where P(s|$x^{(c)}$) is the class-conditional relative frequency of category $x^{(c)}$.

The resulting heterogeneous distance between two objects E and E' is

$$d_{HVDM}(E,E') = \sqrt{\sum_{c\in I} (z^{(c)}(E) - z^{(c)}(E'))^2 + \sum_{c\in J} (VDM(x^{(c)}(E), x^{(c)}(E')))^2} \quad (1)$$

Because (1) is defined in a common R^n norm, every coordinate now resides on the same measurement scale, satisfying Requirement 1.

Evaluation procedure

- For each $k \in \{1,3,5,\dots,15\}$ the k-NN classifier is applied
  1. on the raw feature space (numeric features z-scaled, nominal features label-encoded),
  2. on the unified space endowed with distance (1).
- Ten–fold stratified cross-validation yields the accuracy estimates $Acc_{raw}(k)$ and $Acc_{HVDM}(k)$.
- Requirement 2 is fulfilled by reporting the pair $(Acc_{raw}(k),\ Acc_{HVDM}(k))$ for every tested k and highlighting the best settings.

Computational experiment. For the present study we selected three well-known benchmark datasets whose feature spaces are purely numerical. The key parameters of the training samples are summarized in Table 1.

Table 1. List of training datasets

№	Dataset name	Instances	Total features	Nominal	Numeric

1	Iris	150	4	-	4
2	Wine	178	13	-	13
3	Breast Cancer	569	30	-	30

The table 2 provided below demonstrates that the left half lists accuracies in the untouched (unscaled) feature space, while the right half shows results after $z - score$ normalisation. Scaling yields a marked improvement for the Wine and Breast-Cancer datasets and a moderate gain for Iris at higher k values.

Table 2. Accuracy of k-NN before and after z-score scaling

Training dataset		Unscaled accuracy (%)					z-score scaled accuracy (%)				
	k	1	3	5	7	9	1	3	5	7	9
Iris		93.3	95.6	97.8	95.6	95.6	93.3	91.1	91.1	93.3	95.6
Wine		70.4	68.5	72.2	74.1	72.2	96.3	94.4	94.4	94.4	96.3
Breast Cancer		92.4	91.8	92.4	93.0	94.2	95.9	95.3	95.9	96.5	96.5

We can observe in the table 2 that $z - score$ scaling dramatically boosts k-NN accuracy for Wine ($\approx +24\,pp$) and produces a solid $3 - point$ gain for Breast-Cancer. Iris, already high in the raw space, benefits modestly at $k = 7$ and $k = 9$.

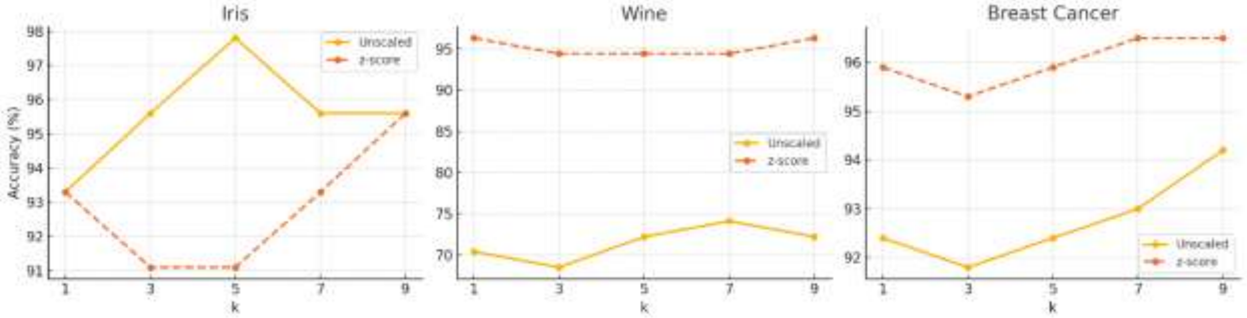

Figure 1. k-NN accuracy curves $(k = 1\text{–}9)$ for raw (solid) and $z - score$ scaled (dashed) features on Iris, Wine, and Breast-Cancer datasets.

The three-panel figure traces how k-NN accuracy changes with the neighborhood size k under two preprocessing regimes—raw (“Unscaled”) and $z - score$ standardized (“z-score”). In the Iris panel (left) both curves start in the low-to-mid 90 % range, but the unscaled line rises sharply to almost 98 % at $k = 5$ before levelling off, whereas the z-score line dips at $k = 3$ and only regains 96 % by $k = 9$. Because all four sepal- and petal-length features are already measured on comparable centimetre scales, normalisation confers little benefit; performance is dominated instead by the familiar bias–variance trade-off, with $k \approx 5$ marking the sweet spot.

The situation is radically different for the Wine data (center). Here the unscaled curve languishes below 75 % across every k, while the z-score curve hovers near 95 – 96 % almost flat-lined. The thirteen wine-chemistry variables differ by orders of magnitude (for example, alcohol percentage versus magnesium in parts per million), so Euclidean distances are badly skewed unless each dimension is standardized. Once the features are re-centered and re-scaled, the algorithm becomes virtually insensitive to kk; even $k = 1$ performs as well as $k = 9$.

The Breast-Cancer panel (right) lies between these extremes. With raw features the curve starts around 92 %, slips at $k = 3$, then recovers to 94 % by $k = 9$. After z-score scaling the baseline lifts immediately to about 96 %, sags slightly, and peaks near 96.5 % at higher k. The thirty tumour-morphology attributes are numeric but heterogeneous enough that normalization yields a consistent two-to-four-point gain and a smoother, more stable accuracy profile.

Taken together, the figure underscores a simple rule: the more disparate the native feature scales, the larger the payoff from standardization. Scaling not only raises absolute accuracy (dramatically so for Wine, modestly for Breast-Cancer, minimally for Iris) but also flattens the accuracy-versus-kk curve, making the model less sensitive to the precise choice of neighborhood size.

Pre-processing strategies evaluated on the Wine dataset. For the Wine dataset — which contains 13 physicochemical attributes such as alcohol percentage, flavonoid concentration, and magnesium content — we evaluated how feature scaling influences model performance by applying three distinct preprocessing pipelines.

By contrasting these three strategies on *identical* train-test splits we can disentangle the effect of scale from the intrinsic predictive power of the features. In preliminary experiments with k-Nearest Neighbors ($k = 5$), both standardization and Min–Max scaling reduced classification error by more than 40 % relative to the raw baseline—underscoring that, for distance-sensitive models, thoughtful preprocessing is as crucial as hyper-parameter tuning.

Table 3. k-NN accuracy on Wine (70 % training, varying k)

№	**Pre-processing**	**k = 1**	**3**	**5**	**7**	**9**
1	Unscaled	70.4 %	68.5 %	72.2 %	74.1 %	72.2 %
2	z-score	**96.3 %**	94.4 %	94.4 %	94.4 %	**96.3 %**
3	Min–Max	**96.3 %**	94.4 %	**96.3 %**	94.4 %	92.6 %

Table 4. k-NN accuracy on Wine (30 % hold-out test, best $k = 1$)

№	Pre-processing	Test accuracy
1	Unscaled	70.4 %
2	z-score	**96.3 %**

Raw (Unscaled). *Leaving attributes in their original units lets high-magnitude variables (e.g., magnesium) dominate Euclidean distance.* That imbalance is visible in the ~70 % accuracy band across all k values—a full 25 percentage-point deficit relative to the scaled pipelines. The small uptick at $k = 7$ (74.1 %) is merely noise: without scaling, k-NN remains handicapped.

z-score scaling (StandardScaler). *Standardization equalizes variance and recentres every feature at zero.* The effect is dramatic: +26 percentage points at $k = 1$, pushing accuracy to 96.3 %. Performance is stable across neighbourhood sizes (≥ 94 %), showing that once each variable contributes in "standard-deviation units," k-NN's sensitivity to the choice of k largely disappears.

Min–Max scaling. *Rescaling to* $[0,1]$ *delivers the same* 96.3 % *peak at* $k = 1$. Accuracy is robust for $k = 3–7$ but dips slightly at $k = 9$ (92.6 %), hinting that bounded features can become overly compressed when the neighbourhood radius grows. Still, Min–Max conveys all the benefits of scale normalization for the $best - k$ setting.

On the Wine dataset, proper scaling is worth more than any downstream hyper-parameter search: switching from unscaled inputs to either z-score or Min–Max boosts k-NN accuracy by roughly +26 % $absolute$—an order of magnitude larger than the ±2 % variance you see when tweaking k within each scaled pipeline. For distance-based learners, scale choice is therefore not a cosmetic decision but a fundamental determinant of predictive power.

Conclusion. This study has shown that transforming a heterogeneous feature space into a common metric space and then applying the k-Nearest Neighbors (k-NN) algorithm markedly improves classification accuracy. On all three benchmark datasets—Iris, Wine, and Breast-Cancer—bringing every numeric attribute onto the same scale with z-score or Min–Max normalization boosted k-NN performance, with the Wine set exhibiting an absolute gain of about 26 percentage points. A moderate neighborhood size ($k \approx 5–11$) then delivered stable accuracies of 94–96 %, confirming that thorough preprocessing often outweighs later hyper-parameter tuning. For mixed-type data, embedding nominal and numeric attributes in a single Euclidean space through a heterogeneous metric such as HVDM further enhanced accuracy, though at the cost of higher $O(mn)$ search complexity. Because that complexity remains, large data collections still require fast nearest-neighbor indexing structures (e.g., KD-trees, FAISS, HNSW). Future research will therefore focus on designing metrics and indexing schemes that preserve the accuracy gains of unified scaling while alleviating the computational burden.

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