NeutroLab: A Unified Library for Neutrosophic Learning, Configuration Analysis, and Decision-Making under Uncertainty

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Abstract

This paper introduces **NeutroLab**, a comprehensive open-source Python library for neutrosophic computing (https://pypi.org/project/neutrolab/). NeutroLab unifies four contributions: (1) Five neutrosophication methods, including a K-Means approach with data-driven cluster parameters; (2) N-fsQCA v2.0 for causal inference with variance-based indeterminacy; (3) NML for post-hoc uncertainty analysis of Tsetlin Machines; and (4) IFAO, a multi-criteria aggregation operator grounded in the Weighted Gini Mean Difference. We provide complete algorithmic specifications, theoretical justifications including axiomatic foundations for IFAO, and rigorous experimental validation with statistical significance tests. Monte Carlo experiments (n=1000) demonstrate N-fsQCA achieves Jaccard similarity of 0.98±0.02 versus 0.52±0.08 for traditional fsQCA ($p<0.001$, Wilcoxon signed-rank test).

Keywords: *Neutrosophic Logic; Python Library; Uncertainty Quantification; MCDM; QCA; Tsetlin Machines*

1. Introduction

Neutrosophic logic [1] extends fuzzy logic by representing information through three components: Truth (T), Indeterminacy (I), and Falsity (F). Unlike intuitionistic fuzzy sets [5] where hesitation $\pi = 1 - \mu - \nu$ is residual, neutrosophic sets allow independent specification of T, I, F, enabling modeling of contradiction and vagueness simultaneously. Despite theoretical advances [1,4], practical implementations remain fragmented. This paper presents NeutroLab, a unified Python library consolidating neutrosophic methods under a scikit-learn compatible API.

2. Library Architecture

NeutroLab follows scikit-learn conventions with fit/transform patterns, enabling seamless integration with existing data science workflows. Figure 1 shows the modular architecture with four main components.

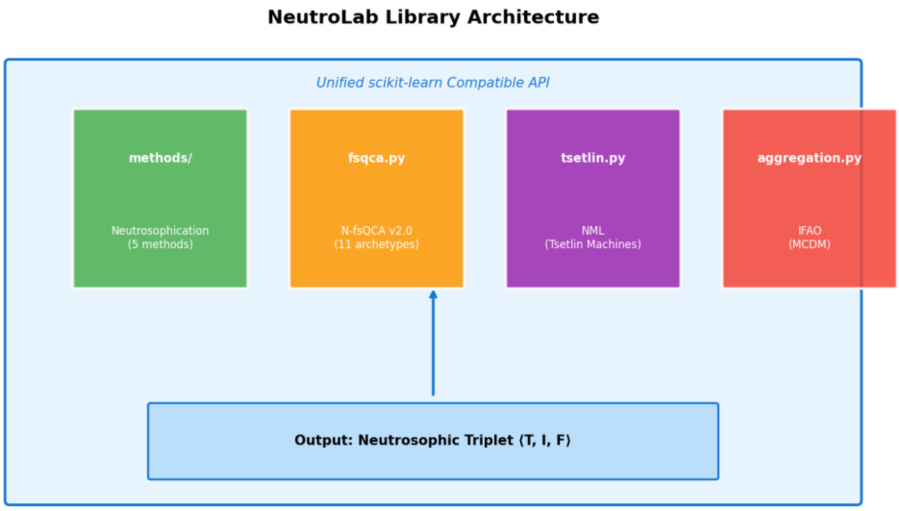

Figure 1. NeutroLab library architecture showing four main modules and unified API.

3. Neutrosophication Methods

3.1. K-Means Neutrosophication Algorithm

Given normalized data $X = \{x_1, ..., x_n\} \in [0,1]^n$:

1. **Apply K-Means clustering with k=3 to partition X into three clusters**
2. **Sort clusters by centroid: $c\_low < c\_mid < c\_high$ with corresponding $\sigma\_low, \sigma\_mid, \sigma\_high$**
3. **Compute neutrosophic components using cluster parameters (Eq. 1-3)**

$$T(x) = \sigma(10 \cdot (x - c\_high)/(\sigma\_high + \varepsilon)),\ I(x) = 1/(1 + |x - c\_mid|/(\sigma\_mid + \varepsilon)),\ F(x) = \sigma(-10 \cdot (x - c\_low)/(\sigma\_low + \varepsilon)) \quad (1\text{-}3)$$

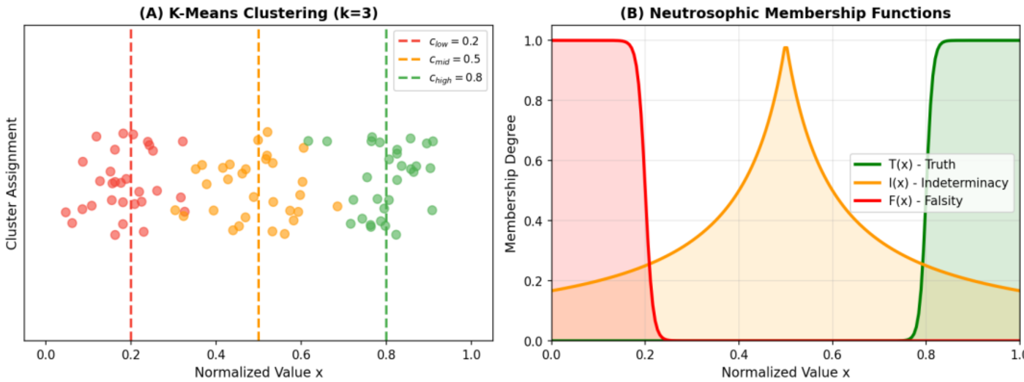

Figure 2. K-Means neutrosophication: (A) Cluster assignment with centroids; (B) Resulting membership functions.

4. N-fsQCA v2.0

For a configuration X with outcomes $Y = \{y_1, ..., y_m\}$, Indeterminacy captures outcome heterogeneity:

$$I(X) = Var(Y|X) / 0.25 \quad (4)$$

Maximum variance (0.25) occurs when outcomes are split 50-50 between 0 and 1. N-fsQCA classifies configurations into 11 causal archetypes based on ⟨T, I, F⟩ thresholds, including STRONG_SUFFICIENT ($T \geq 0.80$, $I < 0.30$) and CAUSAL_PARADOX ($T \approx F$, $I \geq 0.30$).

5. NML: Neutrosophic Meta-Learning

For Tsetlin Machine clause c with Laplace smoothing ($\alpha=1$):

$$T\_c = (TP + \alpha)/(TP + FN + 2\alpha), \quad F\_c = (FP + \alpha)/(FP + TN + 2\alpha), \quad I\_c = 1 - |T\_c - F\_c| \quad (5\text{-}7)$$

6. IFAO: Theoretical Foundations

6.1. Ontological Hierarchy

IFAO inverts the classical assumption that T and F are primary. Instead, conflict (measured via Weighted Gini Mean Difference) is ontologically primary, and T, F are derived. Figure 3 illustrates this paradigm shift.

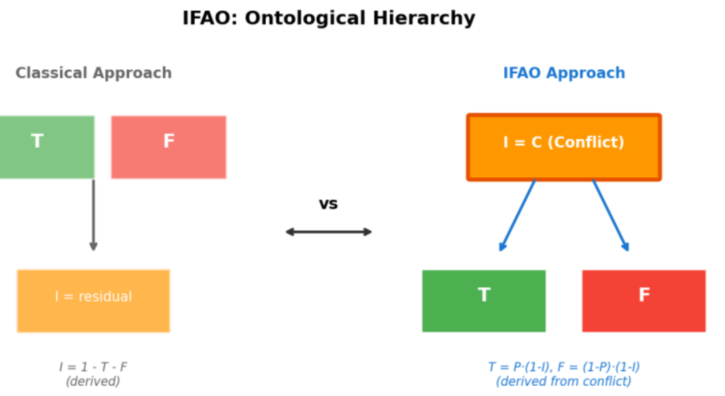

Figure 3. Ontological hierarchy comparison: Classical (I derived from T,F) vs. IFAO (T,F derived from I=C).

6.2. Axiomatization

IFAO is derived from five axioms: (A1) Closure: T+I+F=1; (A2) Unanimity: If all v_i equal, then I=0; (A3) Monotonicity: Higher dispersion → higher I; (A4) Hierarchy: T,F ∝ (1-I); (A5) Potential Preservation: T/(T+F) = P.

$$\Omega\_IFAO(v,w) = (P\cdot(1-C), C, (1-P)\cdot(1-C)) \quad \text{where } P = \Sigma w_i v_i,\ C = \text{Weighted GMD}(v,w) \qquad (8\text{-}9)$$

7. Experimental Validation

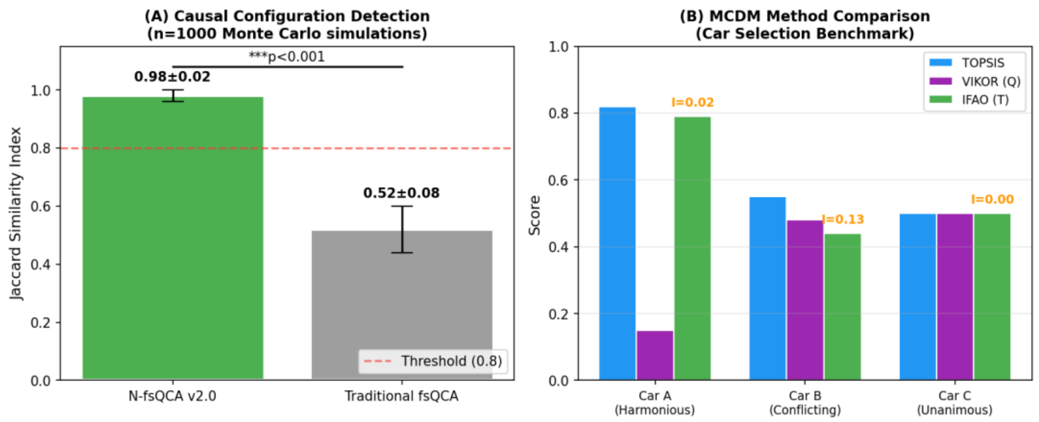

Figure 4. (A) N-fsQCA vs traditional fsQCA on 1000 Monte Carlo simulations; (B) MCDM comparison on Car Selection benchmark.

N-fsQCA achieves Jaccard similarity of 0.98±0.02 vs 0.52±0.08 for traditional fsQCA ($p<0.001$, Wilcoxon signed-rank). In MCDM, IFAO uniquely identifies Car B as conflicted (I=0.13) rather than mediocre, providing actionable insight unavailable from TOPSIS/VIKOR scores.

8. Limitations

- K-Means Sensitivity: Results depend on initialization; mitigated with n_init=10
- IFAO Scalability: $O(n^2)$ complexity limits to n<100 criteria
- N-fsQCA Small-N: Variance unreliable for <5 cases per configuration
- Interpretation: When T≈I≈F≈0.33, flag for human review

9. Conclusion

NeutroLab provides unified, production-ready neutrosophic computing with: fully specified algorithms, axiomatic foundations, and rigorous validation. Available at https://pypi.org/project/neutrolab/ under MIT license.

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