

# Novelty Assessment Report

**Paper:** Metric K-clustering using only Weak Comparison Oracles

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## Abstract

Clustering is a fundamental primitive in unsupervised learning. However, classical algorithms for K-clustering (such as K-median and K-means) assume access to exact pairwise distances—an unrealistic requirement in many modern applications. We study clustering in the **Rank-model (R-model)**, where access to distances is entirely replaced by a **quadruplet oracle** that provides only relative distance comparisons. In practice, such an oracle can represent learned models or human feedback, and is expected to be noisy and entail an access cost.

Given a metric space with  $N$  input items, we design randomized algorithms that, using only a noisy quadruplet oracle, compute a set of  $O(k \cdot \text{polylog}(n))$  centers along with a mapping from the input items to the centers such that the clustering cost of the mapping is at most constant times the optimum K-clustering cost. Our method achieves a query complexity of  $O(n \cdot k \cdot \text{polylog}(n))$  for arbitrary metric spaces and improves to  $O((n+k^2) \cdot \text{polylog}(n))$  when the underlying metric has bounded doubling dimension. When the metric has bounded doubling dimension we can further improve the approximation from constant to  $1+\epsilon$ , for any arbitrarily small constant  $\epsilon \in (0,1)$ , while preserving the same asymptotic query complexity. Our framework demonstrates how noisy, low-cost oracles, such as those derived from large language models, can be systematically integrated into scalable clustering algorithms.

### Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

If you have any questions, please contact: mingzhang23@m.fudan.edu.cn

## Core Task Landscape

This paper addresses: **clustering using only weak comparison oracles**

A total of **50 papers** were analyzed and organized into a taxonomy with **20 categories**.

### Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Comparison-Based Clustering with Noisy Oracles**
- **Ordinal and Ranking-Based Clustering**
- **Semi-Supervised Clustering with Weak Supervision**
- **Feature-Based and Multi-View Clustering**
- **Correlation Clustering and Graph Synchronization**
- **Specialized Clustering Applications and Models**

### Complete Taxonomy Tree

- clustering using only weak comparison oracles Survey Taxonomy
- Comparison-Based Clustering with Noisy Oracles
  - Metric Clustering via Weak Comparison Oracles ★ (4 papers)
    - [0] Metric K-clustering using only Weak Comparison Oracles (Anon et al., 2026) [View paper](#)
    - [2] Metric Clustering and Graph Optimization Problems using Weak Comparison Oracles (Rahul Raychaudhury, 2025) [View paper](#)
    - [3] How to Design Robust Algorithms using Noisy Comparison Oracle (Raghavendra Addanki, 2021) [View paper](#)
    - [13] Relative Error Fair Clustering in the Weak-Strong Oracle Model (Braverman, 2025) [View paper](#)
  - Clustering with Noisy Pairwise Queries (3 papers)
    - [17] Top-k and clustering with noisy comparisons (Susan Davidson, 2014) [View paper](#)
    - [28] Clustering with Noisy Queries (Arya Mazumdar, 2022) [View paper](#)
    - [39] Optimal Clustering with Noisy Queries via Multi-Armed Bandit (Xia, 2022) [View paper](#)
  - Top-k Selection and Ranking with Noisy Comparisons (3 papers)
    - [15] Parallel algorithms for select and partition with noisy comparisons (Mark Braverman, 2016) [View paper](#)
    - [16] Top- Rank Aggregation From  $\ell$ -Wise Comparisons (M Jang, 2018) [View paper](#)
    - [18] Active top-k ranking from noisy comparisons (Soheil Mohajer, 2016) [View paper](#)
- Ordinal and Ranking-Based Clustering
  - Clustering from Ordinal Comparisons (3 papers)
    - [19] Near-optimal comparison based clustering (Perrot, 2020) [View paper](#)
    - [20] Clustering of Data Represented by Pairwise Comparisons (Dvoenko, 2022) [View paper](#)
    - [25] Foundations of comparison-based hierarchical clustering (Ghoshdastidar, 2019) [View paper](#)
  - Ranking and Clustering from Pairwise Preferences (3 papers)
    - [8] Clustering and Inference From Pairwise Comparisons (Rui Wu, 2022) [View paper](#)
    - [32] Joint Clustering and Ranking from Heterogeneous Pairwise Comparisons (Chen-Hao Hsiao, 2021) [View paper](#)
    - [38] Sync-Rank: Robust Ranking, Constrained Ranking and Rank Aggregation via Eigenvector and Semidefinite Programming Synchronization (Cucuringu, 2022) [View paper](#)
  - Graph Clustering with Comparison Data (2 papers)

- [9] Graph clustering using one-bit comparison data (Naveed Naimipour, 2018) [View paper](#)
- [44] Belief propagation for permutations, rankings, and partial orders (Cantwell, 2022) [View paper](#)
- Semi-Supervised Clustering with Weak Supervision
  - Active Clustering with Pairwise Constraints (3 papers)
  - [5] Semi-supervised multi-view clustering with active constraints (Chao Zhang, 2025) [View paper](#)
  - [24] Semi-Supervised Active Clustering with Weak Oracles (kim tae-wan, 2017) [View paper](#)
  - [35] Correlation Clustering with Active Learning of Pairwise Similarities (Aronsson, 2023) [View paper](#)
  - Constrained Clustering with Imperfect Oracles (2 papers)
  - [14] Constrained clustering: Effective constraint propagation with imperfect oracles (Xiatian Zhu, 2013) [View paper](#)
  - [34] Relaxed oracles for semi-supervised clustering (kim tae-wan, 2017) [View paper](#)
  - Deep Clustering with Noisy Pairwise Annotations (2 papers)
  - [4] Deep Clustering with Incomplete Noisy Pairwise Annotations: A Geometric Regularization Approach (Nguyen Tri, 2023) [View paper](#)
  - [23] Neural network-based clustering using pairwise constraints (Hsu, 2015) [View paper](#)
- Feature-Based and Multi-View Clustering
  - Multi-View Clustering with Incomplete Information (2 papers)
  - [1] Robust multi-view clustering with incomplete information (Mouxing Yang, 2022) [View paper](#)
  - [6] Animc: A soft approach for autoweighted noisy and incomplete multiview clustering (Fang Xiang, 2021) [View paper](#)
  - Clustering with Noisy Features and Constraints (2 papers)
  - [27] Constraint-Aware Multi-View Clustering via Graph Contrastive Learning (Zhengnan Chen, 2025) [View paper](#)
  - [50] Adaptive Spectral Rotation via Joint Cluster and Pairwise Structure (Tong Wu, 2021) [View paper](#)
  - Face Clustering in Videos with Weak Supervision (2 papers)
  - [26] A simple and effective technique for face clustering in tv series (Vivek Sharma, 2017) [View paper](#)
  - [31] Joint face representation adaptation and clustering in videos (Zhanpeng Zhang, 2016) [View paper](#)
- Correlation Clustering and Graph Synchronization
  - Correlation Clustering with Noisy Partial Information (1 papers)
  - [49] Correlation Clustering with Noisy Partial Information (Makarychev, 2022) [View paper](#)
  - Group Synchronization with Incomplete Measurements (2 papers)
  - [46] Orthogonal Group Synchronization with Incomplete Measurements: Error Bounds and Linear Convergence of the Generalized Power Method (Zhu, 2021) [View paper](#)
  - [47] Sparse Partial Least Squares for Coarse Noisy Graph Alignment (Michael Weylandt, 2021) [View paper](#)
- Specialized Clustering Applications and Models
  - Hierarchical Entity Resolution with Oracles (1 papers)
  - [10] Hierarchical Entity Resolution using an Oracle (Sainyam Galhotra, 2022) [View paper](#)
  - Noisy Group Testing and Adaptive Algorithms (1 papers)
  - [45] Noisy Adaptive Group Testing via Noisy Binary Search (Teo, 2022) [View paper](#)
  - Robust Ordinal Representation Learning (1 papers)
  - [43] Robust Ordinal VAE: Employing Noisy Pairwise Comparisons for Disentanglement (Chen Jun-Xiang, 2019) [View paper](#)
  - Clustering in Specialized Domains (3 papers)
  - [11] Multi-Criteria Decision Analysis of Supply Chain Practices and Firms Performance in Nigeria (Bilqis Bolanle Amole, 2021) [View paper](#)
  - [29] Efficient Algorithms for Road Networks and Noisy Sorting: an Experimental and Theoretical Perspective (Ozel, 2024) [View paper](#)
  - [30] Overview of the Potentials of Multiple Instance Learning in Cancer Diagnosis: Applications, Challenges, and Future Directions (Tagne Poupi Theodore Armand, 2024) [View paper](#)
  - Noise Impact Studies and Evaluation (2 papers)
  - [12] A study of the effect of different types of noise on the precision of supervised learning techniques (David F. Nettleton, 2010) [View paper](#)
  - [33] Semi-supervised clustering: Learning with limited user feedback (Basu, 2003) [View paper](#)
  - Unrelated or Peripheral Works (9 papers)
  - [7] Efficient and accurate range counting on privacy-preserving spatial data federation (Maocheng Li, 2023) [View paper](#)
  - [21] Randomized Smoothing Meets Vision-Language Models (Emmanouil Seferis, 2025) [View paper](#)
  - [22] XXL Survey groups and clusters in the Hyper Suprime-Cam Survey. Scaling relations between X-ray properties and weak lensing mass (Serenio, 2019) [View paper](#)
  - [36] Pairwise comparison in teacher evaluation: feedback instead of competition (WoŹoszyn, 2015) [View paper](#)
  - [37] Mining of temporal coherent subspace clusters in multivariate time series databases (Hardy Kremer, 2012) [View paper](#)
  - [40] Question answering system for incomplete and noisy data: Methods and measures for its evaluation (Lili Aunimo, 2003) [View paper](#)
  - [41] Learning with Diverse Forms of Imperfect and Indirect Supervision (Boecking, 2023) [View paper](#)
  - [42] Cooperative Coevolutionary CMA-ES With Landscape-Aware Grouping in Noisy Environments (Yapei Wu, 2022) [View paper](#)
  - [48] The missing link: Predicting connectomes from noisy and partially observed tract tracing data. (Max Hinne, 2017) [View paper](#)

## Narrative

Core task: clustering using only weak comparison oracles. This field addresses the challenge of grouping data when direct feature measurements are unavailable or expensive, relying instead on limited pairwise comparisons or ordinal feedback. The taxonomy reveals several complementary directions. Comparison-Based Clustering with Noisy Oracles focuses on algorithms that tolerate imperfect or probabilistic similarity judgments, often analyzing sample complexity and robustness guarantees. Ordinal and Ranking-Based Clustering exploits relative ordering information—such as top-k lists or partial rankings—to infer cluster structure without metric embeddings. Semi-Supervised Clustering with Weak Supervision incorporates sparse human feedback or constraints to guide partitioning, while Feature-Based and Multi-View Clustering leverages multiple data representations when available. Correlation Clustering and Graph Synchronization tackle consensus problems over noisy pairwise relationships, and Specialized Clustering Applications and Models address domain-specific scenarios ranging from entity resolution to face clustering in videos.

A particularly active line of work examines the trade-off between query efficiency and noise tolerance in comparison oracles. Studies such as Noisy Comparison Oracle[3] and Metric Clustering Weak Oracles[2] investigate how many noisy triplet or pairwise queries suffice to

recover ground-truth clusters with high probability, balancing statistical guarantees against practical query budgets. Weak Comparison Oracles[0] sits squarely within this branch, emphasizing metric clustering under minimal oracle assumptions and analyzing the interplay between oracle noise models and algorithmic sample complexity. Compared to Noisy Comparison Oracle[3], which explores broader noise regimes, and Metric Clustering Weak Oracles[2], which refines query strategies for specific metric spaces, Weak Comparison Oracles[0] contributes refined theoretical bounds and algorithmic techniques for handling weak feedback. This work exemplifies ongoing efforts to understand the fundamental limits of clustering when only indirect, noisy relational information is accessible.

## Related Works in Same Category

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The following **3 sibling papers** share the same taxonomy leaf node with the original paper:

### 1. Metric Clustering and Graph Optimization Problems using Weak Comparison Oracles

**Authors:** Rahul Raychaudhury, Wen-Zhi Li, Syamantak Das, Sainyam Galhotra, Stavros Sintos | **Year/Venue:** 2025 • Annual Conference Computational Learning Theory | **URL:** [View paper](#)

#### Abstract

N/A

#### △ Similarity Notice

The titles are nearly identical (both focus on metric clustering using weak comparison oracles), and both papers address k-clustering in metric spaces using noisy quadruplet oracles in the R-model. Given the extremely similar titles and the identical taxonomy classification, these are highly likely to be the same paper or very close variants. Manual verification is recommended to confirm whether this is a duplicate submission or a revised version.

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### 2. How to Design Robust Algorithms using Noisy Comparison Oracle

**Authors:** Raghavendra Addanki, Sainyam Galhotra, Barna Saha | **Year/Venue:** 2021 • Proceedings of the VLDB Endowment | **URL:** [View paper](#)

#### Abstract

Metric based comparison operations such as finding maximum, nearest and farthest neighbor are fundamental to studying various clustering techniques such as k-center clustering and agglomerative hierarchical clustering. These techniques crucially rely on accurate estimation of pairwise distance between records. However, computing exact features of the records, and their pairwise distances is often challenging, and sometimes not possible. We circumvent this challenge by leveraging weak superv...

#### Relationship Analysis

Both papers belong to the same taxonomy category focusing on metric clustering using weak comparison oracles (quadruplet queries) under noisy conditions. The original paper addresses k-median and k-means clustering in the R-model (quadruplet oracle only) with probabilistic noise, achieving  $O(nk \text{ polylog } n)$  query complexity for general metrics and  $O((n+k^2) \text{ polylog } n)$  for bounded doubling dimension. The candidate paper studies k-center clustering and hierarchical clustering using quadruplet oracles under both adversarial and probabilistic noise models, but requires structural assumptions (optimal clusters of size  $\Omega(\sqrt{n})$ ) for probabilistic noise guarantees, and focuses on different clustering objectives than the original paper's k-median/k-means focus.

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### 3. Relative Error Fair Clustering in the Weak-Strong Oracle Model

**Authors:** Braverman, Vladimir, Dharangutte, Prathamesh, Jiang, et al. (12 authors total) | **Year/Venue:** 2025 • International Conference on Machine Learning | **URL:** [View paper](#)

#### Abstract

We study fair clustering problems in a setting where distance information is obtained from two sources: a strong oracle providing exact distances, but at a high cost, and a weak oracle providing potentially inaccurate distance estimates at a low cost. The goal is to produce a near-optimal fair clustering on  $N$  input points with a minimum number of strong oracle queries. This models the increasingly common trade-off between accurate but expensive similarity measures (e.g., large-scale embeddings...

#### Relationship Analysis

Both papers belong to the same taxonomy category of metric clustering via weak comparison oracles, addressing k-clustering problems using noisy oracle queries rather than exact distances. The candidate paper focuses specifically on fair clustering with a weak-strong oracle model (combining inexpensive weak oracles with expensive strong oracles) and achieves  $(1+\epsilon)$ -coresets for fair k-median, while the original paper works exclusively with weak comparison oracles (no strong oracle) and constructs  $O(1)$ -Coreset+ for general k-clustering. The key difference is that the candidate incorporates fairness constraints and uses a hybrid oracle model, whereas the original paper eliminates the need for any strong oracle entirely and focuses on general (non-fair) clustering with only noisy quadruplet comparisons.

## Contributions Analysis

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**Overall novelty summary.** The paper develops randomized algorithms for k-clustering in metric spaces using only noisy quadruplet oracles, achieving constant-factor approximation with  $O(nk \text{ polylog } n)$  query complexity. It resides in the 'Metric Clustering via Weak Comparison Oracles' leaf, which contains four papers total. This leaf sits within the broader 'Comparison-Based Clustering with Noisy Oracles' branch, indicating a moderately populated research direction focused on clustering without exact distances. The taxonomy shows this is an active but not overcrowded area, with sibling leaves addressing noisy pairwise queries and top-k selection problems.

The taxonomy reveals neighboring work in 'Clustering with Noisy Pairwise Queries' (three papers) and 'Ordinal and Ranking-Based Clustering' (five papers across three leaves). The paper's focus on quadruplet comparisons in metric spaces distinguishes it from ordinal methods that avoid metric assumptions and from pairwise-query frameworks that use different oracle models. The scope note for this leaf explicitly excludes non-metric or ordinal embedding approaches, positioning the work at the intersection of metric geometry and weak supervision. Related branches explore semi-supervised constraints and correlation clustering, but these assume different information models.

Among 21 candidates examined across three contributions, no clearly refuting prior work was identified. Contribution A (randomized algorithms using noisy quadruplet oracles) examined one candidate with no refutation. Contributions B (improved approximation for bounded doubling dimension) and C (framework for noisy low-cost oracles) each examined ten candidates, again with no refutations found. This suggests that within the limited search scope—top-K semantic matches plus citation expansion—the specific combination of quadruplet oracles, metric clustering objectives, and doubling-dimension analysis appears relatively underexplored. The absence of refutations does not imply exhaustive novelty but indicates limited overlap in the examined candidate set.

Based on the restricted literature search of 21 papers, the work appears to occupy a distinct position within comparison-based clustering. The taxonomy structure and contribution-level statistics suggest the paper addresses a specific gap—metric k-clustering via quadruplet oracles with doubling-dimension refinements—that neighboring work does not directly cover. However, the analysis is constrained by the search scope and does not capture the full landscape of comparison-based learning or metric clustering beyond the examined candidates.

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This paper presents **3 main contributions**, each analyzed against relevant prior work:

### **Contribution 1: Randomized algorithms for k-clustering using only noisy quadruplet oracles**

**Description:** The authors develop algorithms that construct an  $O(1)$ -Coreset+ for k-clustering in metric spaces using only a noisy quadruplet oracle (R-model), without requiring any distance oracle. The algorithms achieve query complexity of  $O(n \cdot k \cdot \text{polylog}(n))$  for general metrics and  $O((n+k^2) \cdot \text{polylog}(n))$  for bounded doubling dimension metrics.

This contribution was assessed against **1 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### **1. k-Clustering with Comparison and Distance Oracles**

URL: [View paper](#)

##### **Brief Assessment**

Comparison Distance Oracles[51] requires both quadruplet and distance oracles, while the original paper claims to use only quadruplet oracles. This is a fundamental difference in oracle requirements.

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### **Contribution 2: Improved approximation for bounded doubling dimension metrics**

**Description:** For metrics with bounded doubling dimension, the authors present an algorithm that constructs an  $\epsilon$ -Coreset+ for k-median and k-means clustering, achieving  $(1+\epsilon)$ -approximation for any small constant  $\epsilon$  while maintaining  $O((n+k^2) \cdot \text{polylog}(n))$  query complexity using only the quadruplet oracle.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### **1. Fully Dynamic k-Center Clustering in Low Dimensional Metrics**

URL: [View paper](#)

##### **Brief Assessment**

Dynamic k Center[64] addresses fully dynamic k-center clustering with insertions/deletions, while the original paper focuses on static k-median/k-means clustering using only noisy comparison oracles. These are fundamentally different problem settings and algorithmic challenges.

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#### **2. A PTAS Framework for Clustering Problems in Doubling Metrics**

URL: [View paper](#)

##### **Brief Assessment**

PTAS Doubling Metrics[60] focuses on PTAS frameworks for clustering in doubling metrics with distance oracle access, while the original paper addresses clustering using only noisy quadruplet oracles without distance information. The technical approaches and oracle models are fundamentally different.

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#### **3. Coresets for Clustering in Geometric Intersection Graphs**

URL: [View paper](#)

##### **Brief Assessment**

Coresets Geometric Intersection[66] focuses on geometric intersection graphs (unit-disk graphs, unit-square graphs) with specific geometric properties, not general bounded doubling dimension metrics as studied in the original paper.

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#### **4. Improved fixed-parameter bounds for Min-Sum-Radii and Diameters k-clustering and their fair variants**

URL: [View paper](#)

##### **Brief Assessment**

Min Sum Radii Fair[65] focuses on min-sum-radii and min-sum-diameters clustering problems with fairness constraints, not k-median/k-means clustering with quadruplet oracles in the R-model.

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#### **5. Fast and accurate fair k-center clustering in doubling metrics**

URL: [View paper](#)

##### **Brief Assessment**

Fair k Center Doubling[57] focuses on fair k-center clustering with color constraints in doubling metrics, not on k-median/k-means clustering with quadruplet oracles as in the original paper.

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#### **6. On optimal coreset construction for euclidean (k, z)-clustering**

URL: [View paper](#)

##### **Brief Assessment**

Optimal Coreset Construction[63] focuses on coreset construction for Euclidean (k,z)-clustering with improved bounds, not on clustering algorithms using only weak comparison oracles in the rank-model. The technical approaches and problem settings are fundamentally different.

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#### **7. Local Search Yields a PTAS for -Means in Doubling Metrics**

URL: [View paper](#)

##### **Brief Assessment**

Local Search PTAS[62] focuses on k-means clustering using local search algorithms in doubling metrics, not on the rank-model (R-model) framework with quadruplet oracles that the original paper addresses. The candidate paper does not challenge the novelty of constructing  $\epsilon$ -Coreset+ using only quadruplet oracles.

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#### **8. Approximation schemes for clustering with outliers**

URL: [View paper](#)

##### **Brief Assessment**

Clustering with Outliers[61] focuses on clustering problems with outliers using local search heuristics in doubling metrics, not on coreset construction using weak comparison oracles. The technical approaches and problem settings are fundamentally different.

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#### **9. Approximation schemes for capacitated clustering in doubling metrics**

URL: [View paper](#)

##### **Brief Assessment**

Capacitated Clustering Doubling[59] addresses uniform capacitated k-median/k-means with capacity constraints, while the original paper focuses on uncapacitated clustering using only noisy comparison oracles without distance access. These are fundamentally different problem settings.

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## 10. Near-linear time approximation schemes for clustering in doubling metrics

URL: [View paper](#)

### Brief Assessment

Near Linear Doubling Metrics[58] focuses on facility location, k-median, and k-means clustering with a different algorithmic approach (split-tree decomposition with portals), not on the RL framework with quadruplet oracles presented in the original paper.

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## Contribution 3: Framework for integrating noisy low-cost oracles into clustering

**Description:** The authors establish a systematic framework showing how noisy quadruplet oracles, which can be implemented via large language models or learned models, can replace expensive distance computations in clustering algorithms while maintaining theoretical guarantees on clustering quality.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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### 1. Clustering with Queries under Semi-Random Noise

URL: [View paper](#)

#### Brief Assessment

Semi Random Noise[53] focuses on same-cluster queries with semi-random noise for recovering latent clusters, not on replacing distance computations with quadruplet oracles or using LLMs/learned models as the original paper proposes.

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### 2. Learning from noisy similar and dissimilar data

URL: [View paper](#)

#### Brief Assessment

Noisy Similar Dissimilar[56] addresses binary classification from noisy pairwise similar/dissimilar labels, not k-clustering with quadruplet oracles for distance comparisons. The oracle types, problem formulations, and algorithmic approaches are fundamentally different.

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### 3. Learning from noisy pairwise similarity and unlabeled data

URL: [View paper](#)

#### Brief Assessment

Noisy Pairwise Similarity[55] focuses on binary classification from noisy similarity pairs and unlabeled data, not clustering algorithms. The paper addresses a different problem domain (classification vs. clustering) and does not demonstrate prior work on integrating noisy oracles into clustering frameworks.

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### 4. Correlation Clustering with Active Learning of Pairwise Similarities

URL: [View paper](#)

#### Brief Assessment

Active Learning Pairwise Similarities[35] focuses on correlation clustering with pairwise similarity queries, not on k-clustering algorithms using quadruplet oracles for distance comparisons. The oracle types and clustering objectives differ fundamentally from the original paper's framework.

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### 5. Query-Efficient Correlation Clustering with Noisy Oracle

URL: [View paper](#)

#### Brief Assessment

Query Efficient Correlation Clustering[52] focuses on correlation clustering with noisy similarity oracles in a bandit setting, not on k-clustering (k-median/k-means) with quadruplet comparison oracles as in the original paper. The oracle types and clustering objectives are fundamentally different.

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### 6. Correlation clustering with adaptive similarity queries

URL: [View paper](#)

#### Brief Assessment

Adaptive Similarity Queries[54] focuses on correlation clustering with comparison oracles, not general k-clustering frameworks with quadruplet oracles derived from LLMs or learned models as in the original paper.

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### 7. Optimal Clustering with Noisy Queries via Multi-Armed Bandit

URL: [View paper](#)

#### Brief Assessment

Noisy Queries Bandit[39] focuses on clustering with same-cluster queries (binary oracle responses), not on replacing distance computations with quadruplet comparisons or using LLMs/learned models as oracles for metric clustering.

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### 8. How to Design Robust Algorithms using Noisy Comparison Oracle

URL: [View paper](#)

#### Brief Assessment

Noisy Comparison Oracle[3] focuses on quadruplet comparison oracles for k-center and hierarchical clustering with adversarial/probabilistic noise models, not on general k-median/k-means clustering frameworks using learned models or LLMs as the original paper describes.

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### 9. Clustering of Data Represented by Pairwise Comparisons

URL: [View paper](#)

#### Brief Assessment

Pairwise Comparisons Data[20] focuses on clustering algorithms using pairwise distance/similarity comparisons directly, not on integrating noisy oracles (like LLMs or learned models) as weak comparison functions. The candidate does not address oracle noise models or theoretical guarantees for noisy oracle-based clustering.

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## 10. k-Clustering with Comparison and Distance Oracles

URL: [View paper](#)

### Brief Assessment

Comparison Distance Oracles[51] uses a weak-strong oracle framework with both quadruplet and distance oracles, not a framework based solely on noisy low-cost oracles as claimed in the original paper.

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## Appendix: Text Similarity Detection

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No high-similarity text segments were detected across any compared papers.

## References

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- [0] Metric K-clustering using only Weak Comparison Oracles [View paper](#)
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