

# Proximal Pairing and Scoring Algorithm

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**Abstract**—This paper describes the Proximal Pairing algorithm for matching points between two matrices by aligning regional measurements. The algorithm iteratively establishes pairings using heuristic approaches such as selecting the closest item to each truth. Experimental results demonstrate improved accuracy when using Cosine Distance (1 - Sim) over Euclidean Distance. Pairings are evaluated through various scoring metrics, including identification label accuracy and percentage of points correctly paired.

## I. INTRODUCTION

The Proximal Pairing algorithm is used to match points between two matrices based on regional similarity measurements. The goal is to iteratively generate pairings using heuristic-based selection criteria. This approach has applications in data alignment, computer vision, and clustering tasks.

## II. ALGORITHM DESCRIPTION

### A. Notation

Let:

- $M_1$  and  $M_2$  be two distance matrices of size  $n \times n$ .
- $T$  be the set of known ground-truth pairings  $(i, j)$  where  $i \in M_1$  and  $j \in M_2$ .
- $P_k$  be the set of pairs generated through the algorithm.
- $D(i)$  be the distance between elements for index  $i \in M_1$ .

### B. Proximal Pairing Algorithm

New pairs are iteratively added based on the following selection criteria:

- 1) **Closest:** Assigns a pair  $(i_1, j_1)$  by finding the indexes with the minimum distance in  $M_1$  and  $M_2$ .
- 2) **Average:** Computes the average distance from all existing pairs and assigns the closest match:

$$\frac{\sum_{i \in M_1} D(i)}{n}, \quad \frac{\sum_{j \in M_2} D(j)}{n} \quad (1)$$

The algorithm proceeds as follows:

## III. SCORING FUNCTION

The generated pairings are evaluated based on:

- Proximity to ground-truth set.
- Distribution of distances between predicted pairs and ground truth.

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### Algorithm 1 Proximal Pairing Algorithm

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- 1: **Input:** Initial truth set  $T$ , distance matrices  $M_1, M_2$
  - 2: **Initialize:** Mark paired indices in  $M_1$  and  $M_2$
  - 3: Set  $P \leftarrow T$
  - 4: **while** New pairs are found **do**
  - 5:   Determine new pairs using selected heuristic:
  - 6:   **if** Metric = Closest **then**
  - 7:     Select  $(i_1, j_1)$  minimizing  $D(i)$  and  $D(j)$
  - 8:   **else if** Metric = Average **then**
  - 9:     Compute mean distance from all current pairs and assign closest
  - 10:   **end if**
  - 11:   Mark selected indices and update  $P$
  - 12: **end while**
  - 13: **Output:** Set of new pairings  $P_k$
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- Computation of the final score:

$$S = \frac{1}{|P_k|} \sum_{(i,j) \in P_k} \text{rate}(i, j) \quad (2)$$

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### Algorithm 2 Scoring Function

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- 1: **Input:** Set of predicted pairs  $P_k$ , ground truth  $T$ , distance matrices
  - 2: **Initialize:** Scores list  $S$
  - 3: **for** each pair  $(i, j)$  in  $P_k$  **do**
  - 4:   Compute the similarity rate based on distance metric
  - 5:   Append score to  $S$
  - 6: **end for**
  - 7: Compute final average score  $S = \frac{1}{|P_k|} \sum S$
  - 8: **Output:** Final score
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## IV. EXPERIMENTAL SETUP

To evaluate the algorithm, experiments were conducted under three conditions:

### A. Experiment 1: Correct Pairings

The initial  $k$  pairings are correct, providing an ideal benchmark.

### B. Experiment 2: Incorrect Pairings

All initial  $k$  pairings are incorrect, testing robustness against erroneous initial conditions.

### C. Experiment 3: Mixed Pairings

Half of the initial  $k$  pairings are correct, simulating real-world noisy datasets.

## V. EXPERIMENTAL RESULTS

Each experiment is iterated 30 times for robustness. The final performance is measured as:

$$\text{Score} = f(k) \quad (3)$$

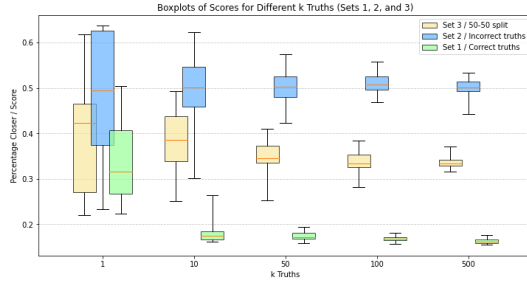


Fig. 1. Score variation with increasing  $k$  pairs

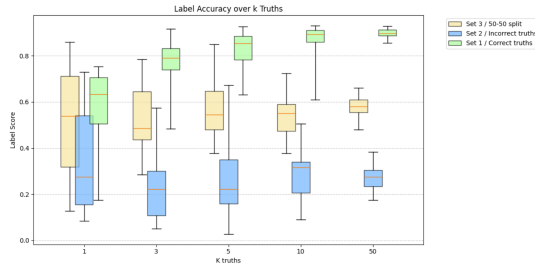


Fig. 2. Label Accuracy over  $k$  pairs

## VI. CONCLUSION

The Proximal Pairing algorithm efficiently identifies optimal pairings in distance matrices. The scoring function evaluates different heuristics and selection strategies. Future improvements may include additional similarity metrics and adaptive pairing strategies.

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## REFERENCES