Rank-Based Unsupervised Similarity Learning: Framework and Applications

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***Abstract*—Multimedia data collections have grown exponentially due to advances in acquisition and sharing technologies, creating a pressing need for robust similarity learning methods that do not depend on costly annotations. Deep features extracted by convolutional and transformer networks provide powerful embeddings, but often lie on complex manifolds that simple pairwise comparisons fail to capture. Unsupervised similarity learning addresses this gap by post-processing these embeddings with rank-based strategies that leverage the ordering of neighbors and manifold geometry through different approaches, e.g., graph and hypergraph constructions. This paper discusses foundational concepts in contextual similarity and presents a comprehensive overview of rank-based methods for unsupervised distance and similarity learning. It discusses the Unsupervised Distance Learning Framework (UDLF), along with its Python wrapper, pyUDLF, and the web-based interface UDLFWeb, which automates and simplifies the processes of experimentation and result visualization. We also show how these tools enhance the effectiveness of image retrieval, classification, and clustering, and outline future directions for expanding rank-based methods to additional modalities and scaling them to large datasets. The complete source code and documentation for UDLF and its associated tools are publicly available at: udlf.lucasvalem.com.**

I. Introduction

Recent advances in data acquisition and storage technologies have contributed to the rapid growth of multimedia databases. This scenario has intensified the demand for effective retrieval systems capable of identifying and ranking relevant visual content in a wide range of domains [1]. A central aspect of these systems is the ability to rank images and multimedia items in a way that reflects their relevance, which is important not only for retrieval tasks but also for learning-based methods.

In general, ranking-based approaches are built upon two essential pillars [2]: (*i*) generating descriptive representations of the data and (*ii*) establishing a meaningful comparison between them. Although deep learning has greatly enhanced data representation by producing expressive and semantically rich embeddings, determining similarity between these embeddings remains a complex and still largely open challenge. This issue has attracted growing attention within the machine learning community, especially in the context of multimedia retrieval [3], [4].

While many similarity learning methods operate under supervised or semi-supervised conditions, these approaches face limitations when dealing with large datasets and scarce labeled data. Manual annotation is often expensive and time-consuming, motivating the development of unsupervised solutions that can improve similarity estimation without relying on annotated samples [2].

Among unsupervised methods, those that rely on ranked lists have gained attention for their ability to capture context from the data itself. Instead of depending on fixed distance metrics, these techniques consider the relative positions of samples, revealing patterns that emerge from the way items are ranked with respect to each other. By refining initial similarity estimates using this contextual information, they can produce more meaningful ranked lists, which in turn improve the effectiveness of retrieval and other learning tasks [5].

This work explores unsupervised similarity learning with a focus on rank-based methods. Section II introduces the main concepts and background on contextual similarity learning and ranking-based strategies. Section III details the proposed unsupervised distance learning framework. Section IV demonstrates applications in multimedia retrieval and machine learning tasks. Finally, Section V concludes the paper and outlines directions for future research.

II. Contextual Rank-based Similarity Learning

A. Overview of Unsupervised Affinity Learning

Despite advances in image feature extraction through Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), the reliance on pairwise distance functions remains a significant limitation [2], as these methods often fail to capture the true relationships between objects due to the complex structure of high-dimensional feature spaces [6]. To address this, recent research explores strategies that better approximate human-like similarity by incorporating the intrinsic structure and contextual information of datasets [2]. Among these, methods considering geodesic paths on data manifolds have shown promise [7].

Post-processing techniques have emerged to enhance pairwise similarities by integrating global contextual information in an unsupervised manner. These approaches aim to unwrap structural similarities grounded in the data manifold [3], improving performance in tasks like image retrieval. Context-aware similarity methods can be broadly categorized into three groups [3]: (i) diffusion-based methods [4], [7], which refine similarities via graph propagation; (ii) rank-based methods [2], [8], which exploit ordered similarity relations; and (iii) deep learning-based approaches [9], [10], which learn context-sensitive representations directly from data.

Furthermore, Figures 1 and 2 illustrate the contrast between traditional pairwise similarity and a contextual rank-based similarity learning method. While Figure 1 reflects the limitation of Euclidean distance, which often fails to separate structurally distinct regions [11], Figure 2 shows how the Correlation Graph method [11] captures contextual relationships by considering neighborhood structure, resulting in a more meaningful separation of the data. This gain in structural awareness is also reflected in the distance distributions observed during retrieval. As illustrated in Figure 3, by comparing two unrelated query images, the Correlation Graph algorithm was able to reorganize the similarity space, promoting the grouping of similar samples while effectively isolating dissimilar ones.

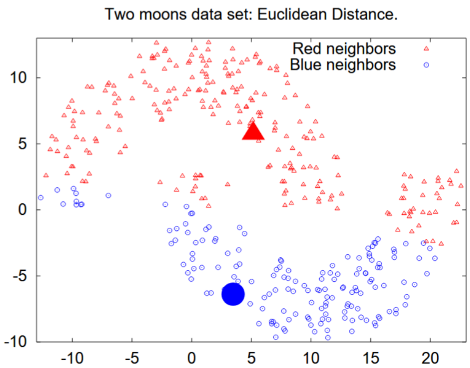


Fig. 1: Example of similarity assessment using Euclidean distance. Source: [11].

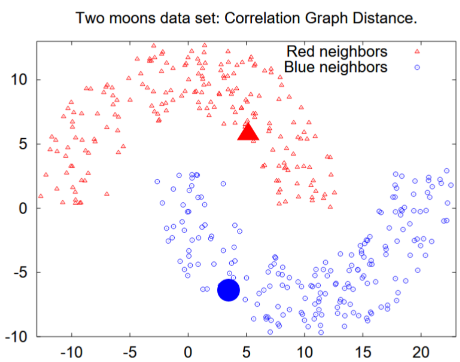


Fig. 2: Example of similarity assessment using the *Correlation Graph Distance*. Source: [11].

B. Rank-based Methods

Several ranking-based algorithms have been explored in the literature and incorporated into the Unsupervised Distance Learning Framework (UDLF) [12]. These methods aim to refine initial similarity estimates by leveraging the relative ordering of data, extracting richer contextual information that is often not captured by simple pairwise comparisons. This section briefly lists the rank-based approaches available in UDLF.

- **Breadth-First Search Tree (BFSTree) [13]**: This approach constructs a breadth-first search tree using ranking-derived references. The resulting tree structure captures latent similarity relationships, which are then used as a more effective distance measure for refining similarity rankings.
- **Correlation Graph (CORGRAPH) [11]**: This method constructs a graph using high-confidence edges between highly similar instances. The similarity is then propagated throughout the graph by leveraging the structure of its strongly connected components.
- **Log-based Hypergraph of Ranking References (LHRR) [8]**: It computes a hypergraph from ranked lists, encoding complex similarity relationships. It then derives improved similarity scores by measuring the overlap/connectivity among hyperedges.
- **Rank Flow Embedding (RFE) [2]**: The method generates embeddings sensitive to contextual similarity by processing ranking data through a structured pipeline. It integrates hypergraph representations, Cartesian product operations, and the identification of connected components to extract embeddings from similarity patterns.
- **Cartesian Product of Ranking References (CPRR) [14]**: It operates by applying Cartesian product operations between k-nearest neighbors and reverse nearest neighbors. These operations capture rich similarity cues from the overlapping structure of forward and reverse ranking sets.
- **Rank Diffusion with Assured Convergence (RDPAC) [15]**: This method performs an efficient approximation to traditional diffusion methods by relying on rank-based data. It retains the benefits of diffusion processes while limiting computations to the highest-ranking neighbors, enhancing both effectiveness and efficiency.
- **Ranked Lists Similarity (RL-Sim) [5]**: This approach is grounded in the idea that ranked lists encode valuable contextual information. The method uses iterative reranking, driven by rank correlation metrics, to refine similarity estimates.
- **Ranked Lists Recommendation (RL-Recom) [16]**: This method draws inspiration from recommendation systems. It uses this recommendation perspective in conjunction with similarity information to suggest images to mutual rankings.
- **Contextual Re-ranking (ContextRR) [17]**: This method creates a contextual image structure from ranked data and pairwise distances. It utilizes this structure to extract neighborhood context and compute a new distance function that better reflects the data's underlying organization.
- **Manifold Reciprocal kNN Graph (ReckNN-Graph) [18]**: The approach builds a graph from reciprocal nearest neighbors found within the top-ranked elements. The resulting graph structure is analyzed to explore the manifold geometry and generate refined ranked lists.
- **Ranked List Graph Distance (Rk Graph Dist.) [19]**: Each ranked list is modeled as a weighted subgraph where edges reflect top-k similarities. These subgraphs are merged into a unified graph, enabling similarity refinement via the aggregation of weighted links.

III. Unsupervised Distance Learning Framework (UDLF)

The Unsupervised Distance Learning Framework (UDLF) is an open-source software designed to facilitate the easy use and evaluation of unsupervised learning methods for multimedia retrieval. Developed to address the challenges of increasing image and multimedia collections, UDLF aims to improve the effectiveness of retrieval results without requiring user intervention. It was created to fill a gap where many effective post-processing methods were not publicly available or lacked standardization, making them difficult to use.

The framework provides a general and extensible model that allows for the implementation of various unsupervised

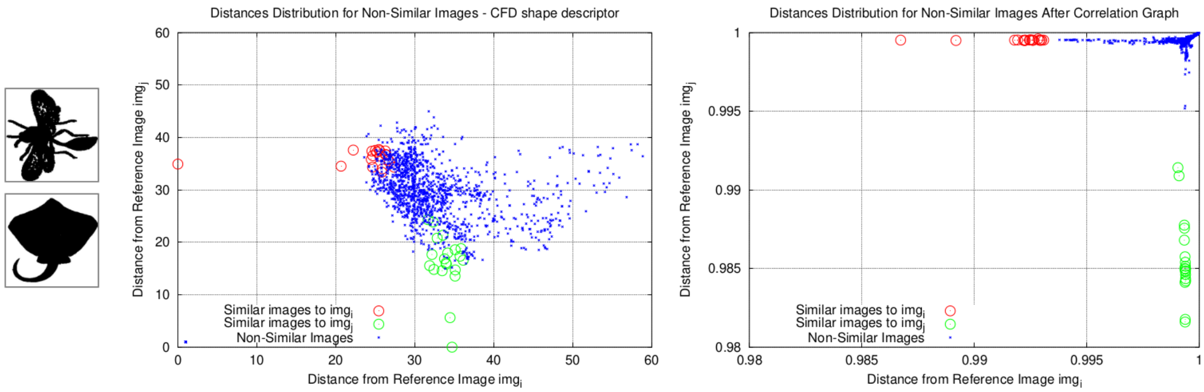


Fig. 3: Impact of the Correlation Graph method on distance distributions for non-similar queries. The left plot shows the original pairwise distances from two unrelated query images (img_i and img_j), while the right plot illustrates the refined distances after applying the Correlation Graph, revealing a more coherent grouping of semantically similar samples. Source: [11].

methods based on distance measures or rank information. UDLF supports diverse file formats for input and output, offers an easy setup via a configuration file without the need for recompilation, and includes robust evaluation capabilities for both effectiveness (e.g., Precision, Recall, mAP) and efficiency measures. As of this writing, UDLF implements eleven unsupervised methods and remains under active development. Its source code is openly available [1] under the GPLv2 license, fostering unrestricted access, use, modification, and redistribution.

A. pyUDLF

Running the UDLF requires manual intervention, such as editing configuration files and executing the C++ binary. This is manageable for a single run, but it quickly becomes time-consuming when trying different parameters or integrating distance learning into larger experiments.

To address this, pyUDLF [20] was developed as a Python wrapper that automates the configuration and execution steps. It assumes that the required input files, such as ranked lists and class labels, are already prepared. From there, it creates the configuration file, calls the UDLF binary, and parses the output back into Python objects. This makes it easier to perform multiple experiments, conduct grid searches, or incorporate the learned distances into pipelines with libraries like NumPy and Pandas. Figure 4 shows a simplified overview of the process.

The output can then be directly used in further tasks, such as retrieval, classification, or clustering, as discussed in Section IV.

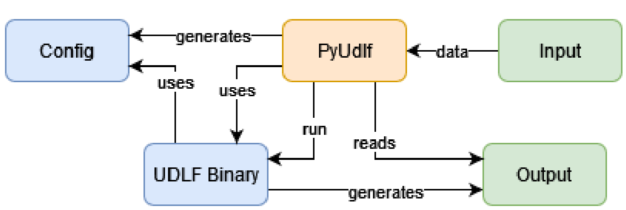


Fig. 4: Overview of the pyUDLF architecture. Source: [20].

Below is a minimal example showing how to configure and execute UDLF through pyUDLF:

[1]UDLF available: https://github.com/UDLF/UDLF

```
from pyUDLF import run_calls as udlf
from pyUDLF import inputType
# Set the paths to the UDLF binary and config file
udlf.setBinaryPath("UDLF/bin/udlf")
udlf.setConfigPath("UDLF/bin/config.ini")
# Create input object
input_data = inputType.InputType()
input_data.set_method_name("CPRR")
input_data.set_input_files("acc.txt")
input_data.set_lists_file("lists.txt")
input_data.set_classes_file("classes.txt")
# Set general parameters for the method
input_data.set_param("UDL_TASK", "UDL")
input_data.set_param("PARAM_NONE_L", 1400)
# Run the method and retrieve the output
output = udlf.run(input_data, get_output = True)
output.get_log()
# This function returns a dictionary, where the keys
# are the metrics and the values are the results.
```

Listing 1: Basic usage of pyUDLF. Source: [20].

B. UDLFWeb

UDLFWeb is an open-source web platform developed with technologies such as React, JavaScript, and TypeScript. Its main goal is to simplify and enhance the user experience of the UDLF framework.

The UDLFWeb interface is structured in a logical sequence of 5 steps, intuitively guiding the user from the initial method selection to the consolidated results visualization. This step-by-step approach simplifies the process of configuring and executing image retrieval experiments:

1) **Method selection**: In this initial step, the user establishes the foundation of the experiment by selecting one of the image retrieval algorithms available in the UDLF framework. The goal is to allow the user to select the most suitable image retrieval method for their needs. A clear and organized list of all the methods is presented in the interface.
2) **Input settings**: After method selection, this step focuses on defining the images and datasets that will be processed by the chosen method. At this stage, the goal is to collect all the necessary images and datasets for method execution, with options for the user to specify the image dataset where the retrieval will be performed.
3) **Output settings**: This step allows the user to define how the results will be presented or stored. The objective is

to offer control over the format and destination of the generated results.

4) **Evaluation settings**: The user can configure the evaluation by selecting measures that assess both the effectiveness and the efficiency of the execution. UDLFWeb supports several measures, including Mean Average Precision (mAP), one of the most widely used to evaluate image retrieval effectiveness. It also includes Recall, which measures the proportion of relevant documents that were retrieved out of all relevant documents available, and Precision, which quantifies how many of the retrieved documents are relevant among all retrieved results. For efficiency, the system can report execution time and resource usage.
5) **Summary and execution**: The final step provides a comprehensive summary of all configured settings before initiating the execution. The user can review the selected method, input paths for images and datasets, output preferences, and chosen evaluation metrics. An "Execute" button is also displayed, which submits all configurations to the backend API for processing.

Figures 5 and 6 illustrate the summary view of the configured parameters and the evaluation setup, including the option to save the configuration file or execute the experiment.

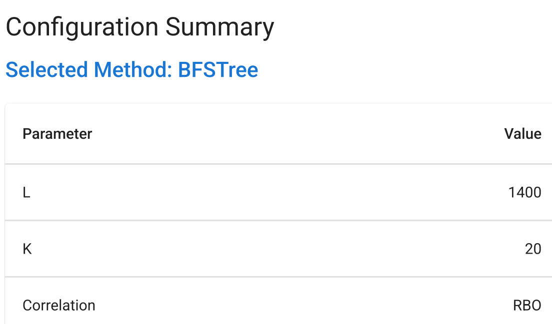


Fig. 5: Summary of parameters defined in UDLFWeb.

IV. Retrieval and Machine Learning Applications

This section explores the practical uses of rank-based unsupervised similarity learning across three tasks: retrieval, classification, and clustering. First, we discuss retrieval scenarios where contextual post-processing of deep embeddings leads to improved ranked lists and results. Next, we discuss classification that leverages refined similarity measures to expand or enhance labeled sets and to construct graph-based models that improve accuracy under limited supervision. Finally, we present clustering approaches that exploit learned distances to produce more coherent groupings, illustrating how UDLF integrates into distinct workflows and applications through unsupervised distance and similarity learning.

A. Retrieval

Image retrieval, a central solution for managing the increasing volume of visual content, usually relies on traditional Content-Based Image Retrieval (CBIR) systems that rank images based on similarity computed from their low-level features, employing similarity measures such as Manhattan, Euclidean, or Cosine distances. However, this approach is often limited because it primarily considers pairwise comparisons and overlooks the global relationships and intrinsic

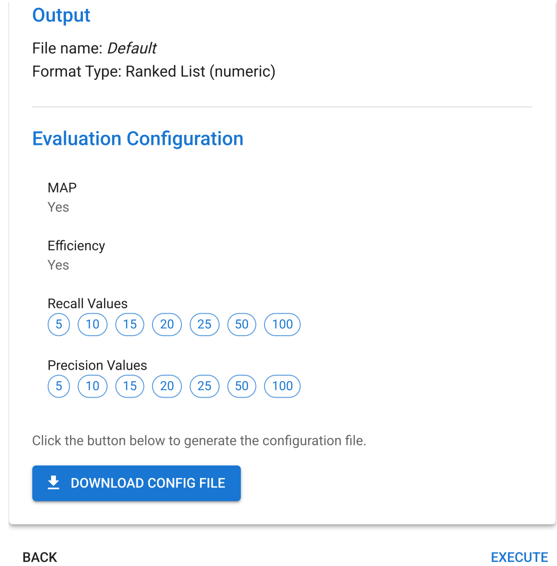


Fig. 6: Summary of the evaluation defined in UDLFWeb, with options to save and execute the methods.

manifold structure embedded within the dataset. The UDLF addresses this limitation by providing unsupervised post-processing methods that improve retrieval effectiveness without requiring user intervention. The core objective is to compute more effective, context-sensitive distances or similarities among images by accounting for the relationships among data items and the dataset's global structure.

Many of the unsupervised distance learning methods within UDLF have been specifically evaluated on image retrieval applications, considering various features. These comprise eleven distinct approaches, each contributing to advances in image re-ranking and contextual rank aggregation. This task allows the combination of different descriptors to further improve retrieval results.

Figure 7 presents an example of rank-aggregation using Correlation Graph [11] combined with Jaccardmax [21] on the Market person re-identification dataset [22]. The results, obtained from two different descriptors (OSNET-AIN and TransReID), reveal the improvements achieved through fusion.

B. Classification

Extracting new information and similarity patterns from the data can improve classification, especially in weakly supervised scenarios with limited labeled samples. By capturing relationships that are not evident in the original feature space, these approaches provide additional information that supports the learning process.

For example, [23] introduces a hypergraph-based method that expands the labeled set by selecting reliable unlabeled samples. It builds hypergraphs over ranked lists to capture higher-order relationships, incorporating confident samples into the training data. This strategy enhances the performance of classifiers such as Support Vector Machines (SVMs), Optimum Path Forest (OPF) [24], and various Graph Convolutional Networks (GCNs) across multiple datasets. In [25], manifold-based reranking is applied to refine the ranked lists before constructing kNN or reciprocal kNN graphs, leading to improved neighborhood structures for GCN models. This

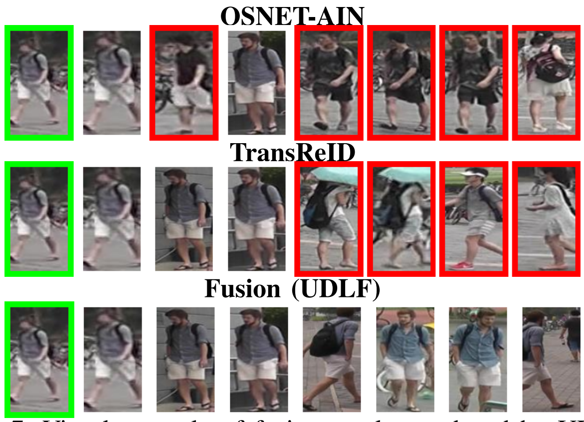
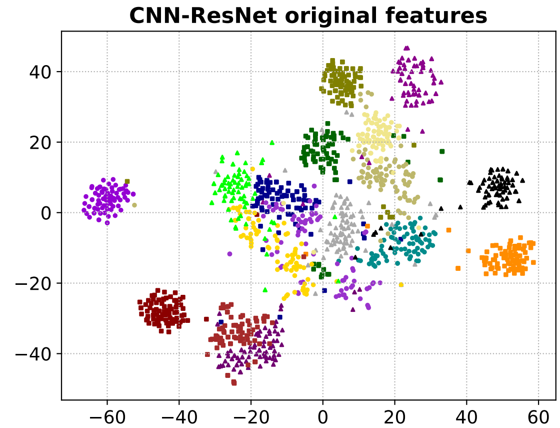
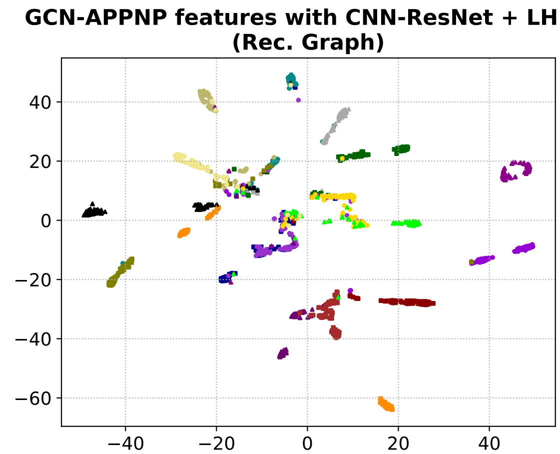


Fig. 7: Visual example of fusion results produced by UDLF with CorrelationGraph [11], [21]. The query image is highlighted in green, while incorrect results are shown in red. Source: [21].



(a) **Original Features**



(b) **GCN-APPNP Features with LHRR (Rec. Graph)**

Fig. 8: t-SNE visualizations showing how manifold learning and reciprocal graphs improve the feature space used by GCNs. Results were obtained using CNN-ResNet features on the Flowers dataset. Each class is represented by a different shape and color. Source: [25].

effect is illustrated in Figure 8, reproduced from [25], where t-SNE projections highlight the improvement in feature space organization when using manifold learning.

Another approach [26] combines neighborhood projection techniques with reranking before generating ranked lists, producing graphs that more accurately represent the data structure and further improve classification with GCNs.

Other applications can also be mentioned. In [27] and [28], Reciprocal kNN Graph distances [18] were employed to enhance contextual distance measurement. The work in [27] assessed their impact on Optimum Path Forest (OPF) classifiers [24], using both complete and kNN graph structures across varying train/test splits, demonstrating significant advantages, especially with limited training data. In [28], a Combined Unsupervised and Semi-Supervised Learning (CUSSL) strategy was proposed, integrating Reciprocal kNN distances into the Particle Competition and Cooperation (PCC) framework [29], yielding effective semi-supervised classification results.

Further, manifold learning was utilized for contextual rank aggregation in [30], enabling the fusion of unidimensional representations from multivariate time series and exploring channel complementarity. This led to improved performance in both retrieval and kNN-based classification tasks across diverse datasets. Additionally, [31] proposed a training set expansion strategy for Graph Convolutional Networks (GCNs), using a margin-based selection criterion inspired by active learning, which also addresses data imbalance. A rank aggregation technique was also introduced to combine outputs from multiple GCN models and training runs, enhancing the quality of the labeled training set.

C. Clustering

Clustering algorithms group data based on inherent similarities, and their performance can be enhanced through unsupervised similarity learning, which aims to map data into a space where similar elements are closer together while dissimilar ones are farther apart. In [32], four manifold learning algorithms were applied as a pre-processing step to incorporate contextual information contained in pairwise Euclidean distances information. The approach was evaluated across various image and toy datasets (e.g., two moons, spiral, flame) using four clustering algorithms, and consistent improvements were observed across all scenarios.

In another direction, Self-Supervised Graph Convolutional Clustering (SGCC) [33] integrates unsupervised, self-supervised, and semi-supervised learning in a unified clustering framework. It utilizes LHRR [8], an unsupervised similarity learning method based on hypergraphs, to identify representative elements for each cluster. Soft labels are employed for these elements and then used to train a GCN in a semi-supervised manner, which subsequently clusters the remaining data. SGCC achieved competitive performance across diverse experimental settings when compared to other methods.

V. Conclusion and Future Directions

Throughout this paper, we have shown how rank-based unsupervised similarity learning methods exploit manifold geometry to reorder data according to contextual neighborhood relationships, yielding significant gains in retrieval, classification, and clustering tasks. Graph-based constructions capture higher-order similarities that simple pairwise measures overlook, and UDLF unifies a diverse set of algorithms under a single, extensible framework. The introduction of pyUDLF and the UDLFWeb interface further lowers the barrier to entry by automating configuration, execution, and result visualization, enabling researchers and practitioners to focus on experimentation rather than tooling concerns.

There are several promising directions to broaden the impact of this work. Extending the UDLF software to other multimedia modalities, such as text streams, audio signals, video sequences, and three-dimensional data, could reveal new contextual cues. Investigating alternative strategies for graph construction and embedding generation may uncover richer representations of complex data structures. At the same time, optimizing the core UDLF engine and refining both pyUDLF and UDLFWeb through parallel execution, streamlined APIs, and performance improvements will support more efficient studies at scale. Finally, scaling the framework to distributed and cloud environments will enable unsupervised similarity learning on even larger multimedia collections, paving the way for the development of advanced retrieval and analysis systems.

Acknowledgments

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References

[1] W. Chen, Y. Liu, W. Wang, E. M. Bakker, T. Georgiou, P. Fieguth, L. Liu, and M. S. Lew, "Deep learning for instance retrieval: A survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 6, pp. 7270–7292, 2023.

[2] L. P. Valem, D. C. G. Pedronette, and L. J. Latecki, "Rank flow embedding for unsupervised and semi-supervised manifold learning," *IEEE Transactions on Image Processing*, vol. 32, pp. 2811–2826, 2023.

[3] V. Pereira-Ferrero, T. Lewis, L. Valem, L. Ferrero, D. Pedronette, and L. Latecki, "Unsupervised affinity learning based on manifold analysis for image retrieval: A survey," *Computer Science Review*, vol. 53, p. 100657, 2024.

[4] M. Donoser and H. Bischof, "Diffusion processes for retrieval revisited," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2013, pp. 1320–1327.

[5] C. Y. Okada, D. C. G. Pedronette, and R. da S. Torres, "Unsupervised distance learning by rank correlation measures for image retrieval," in *Proceedings of the 5th ACM on International Conference on Multimedia Retrieval*, ser. ICMR '15. New York, NY, USA: Association for Computing Machinery, 2015, p. 331–338.

[6] A. Iscen, Y. Avrithis, G. Tolias, T. Furon, and O. Chum, "Fast spectral ranking for similarity search," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 7632–7641.

[7] S. Bai, X. Bai, Q. Tian, and L. J. Latecki, "Regularized diffusion process on bidirectional context for object retrieval," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 41, no. 5, pp. 1213–1226, 2018.

[8] D. C. G. Pedronette, L. P. Valem, J. Almeida, and R. da S. Torres, "Multimedia retrieval through unsupervised hypergraph-based manifold ranking," *IEEE Transactions on Image Processing*, vol. 28, no. 12, pp. 5824–5838, 2019.

[9] Y. Zhao, L. Wang, L. Zhou, Y. Shi, and Y. Gao, "Modelling diffusion process by deep neural networks for image retrieval." in *BMVC*, 2018, p. 161.

[10] A. Iscen, G. Tolias, Y. Avrithis, and O. Chum, "Mining on manifolds: Metric learning without labels," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 7642–7651.

[11] D. C. G. Pedronette and R. da S. Torres, "A correlation graph approach for unsupervised manifold learning in image retrieval tasks," *Neurocomputing*, vol. 208, pp. 66–79, 2016, sI: BridgingSemantic.

[12] L. P. Valem and D. C. G. Pedronette, "An unsupervised distance learning framework for multimedia retrieval," in *ACM on International Conference on Multimedia Retrieval, ICMR*, 2017, pp. 107–111.

[13] D. C. G. Pedronette, L. P. Valem, and R. da S. Torres, "A bfs-tree of ranking references for unsupervised manifold learning," *Pattern Recognition*, vol. 111, p. 107666, 2021.

[14] L. P. Valem and D. C. G. Pedronette, "Unsupervised similarity learning through cartesian product of ranking references for image retrieval tasks," in *2016 29th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*, 2016, pp. 249–256.

[15] D. C. G. Pedronette, L. P. Valem, and L. J. Latecki, "Efficient rank-based diffusion process with assured convergence," *Journal of Imaging*, vol. 7, no. 3, 2021.

[16] L. P. Valem, D. C. G. Pedronette, R. d. S. Torres, E. Borin, and J. Almeida, "Effective, efficient, and scalable unsupervised distance learning in image retrieval tasks," in *Proceedings of the 5th ACM on International Conference on Multimedia Retrieval*, ser. ICMR '15. New York, NY, USA: Association for Computing Machinery, 2015, p. 51–58.

[17] D. C. G. Pedronette and R. Da S. Torres, "Exploiting contextual information for image re-ranking," in *Proceedings of the 15th Iberoamerican Congress Conference on Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications*, ser. CIARP'10. Berlin, Heidelberg: Springer-Verlag, 2010, p. 541–548.

[18] D. C. G. Pedronette, O. A. Penatti, and R. da S. Torres, "Unsupervised manifold learning using reciprocal knn graphs in image re-ranking and rank aggregation tasks," *Image and Vision Computing*, vol. 32, no. 2, pp. 120–130, 2014.

[19] D. C. G. Pedronette, J. Almeida, and R. da S. Torres, "A graph-based ranked-list model for unsupervised distance learning on shape retrieval," *Pattern Recognition Letters*, vol. 83, pp. 357–367, 2016, efficient Shape Representation, Matching, Ranking, and its Applications.

[20] G. Leticio, L. P. Valem, L. T. Lopes, and D. C. G. Pedronette, "pyudlf: A python framework for unsupervised distance learning tasks," in *Proceedings of the 31st ACM International Conference on Multimedia*, ser. MM '23. New York, NY, USA: Association for Computing Machinery, 2023, p. 9680–9684.

[21] L. P. Valem, V. Atsushi Sato Kawai, V. H. Pereira-Ferrero, and D. C. G. Pedronette, "A novel rank correlation measure for manifold learning on image retrieval and person re-id," in *2022 IEEE International Conference on Image Processing (ICIP)*, 2022, pp. 1371–1375.

[22] L. Zheng, L. Shen, L. Tian, S. Wang, J. Wang, and Q. Tian, "Scalable person re-identification: A benchmark," in *2015 IEEE International Conference on Computer Vision (ICCV)*, 2015, pp. 1116–1124.

[23] J. G. C. Presotto, S. F. dos Santos, L. P. Valem, F. A. Faria, J. P. Papa, J. Almeida, and D. C. G. Pedronette, "Weakly supervised learning based on hypergraph manifold ranking," *Journal of Visual Communication and Image Representation*, vol. 89, p. 103666, 2022.

[24] J. Papa and A. Falcão, "Optimum-path forest: A novel and powerful framework for supervised graph-based pattern recognition techniques," in *Anais do XXII Concurso de Teses e Dissertações*. Porto Alegre, RS, Brasil: SBC, 2009, pp. 41–48.

[25] L. P. Valem, D. C. G. Pedronette, and L. J. Latecki, "Graph convolutional networks based on manifold learning for semi-supervised image classification," *Computer Vision and Image Understanding*, vol. 227, p. 103618, Jan. 2023.

[26] G. R. Leticio, V. A. S. Kawai, L. P. Valem, and D. C. G. Pedronette, "Neighbor embedding projection and graph convolutional networks for image classification," *Proceedings Copyright*, vol. 511, p. 518, 2025.

[27] L. C. S. Afonso, D. C. G. Pedronette, A. N. de Souza, and J. P. Papa, " Improving Optimum- Path Forest Classification Using Unsupervised Manifold Learning ," in *2018 24th International Conference on Pattern Recognition (ICPR)*. Los Alamitos, CA, USA: IEEE Computer Society, Aug. 2018, pp. 560–565.

[28] F. A. Breve and D. C. G. Pedronette, "Combined unsupervised and semi-supervised learning for data classification," in *2016 IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP)*, 2016, pp. 1–6.

[29] F. Breve, L. Zhao, M. Quiles, W. Pedrycz, and J. Liu, "Particle competition and cooperation in networks for semi-supervised learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 24, no. 9, pp. 1686–1698, 2012.

[30] B. Rozin, "Machine learning and information retrieval techniques for time series analysis," Dissertação de Mestrado, Universidade Estadual Paulista "Júlio de Mesquita Filho", Rio Claro, 2024.

[31] D. C. G. Pedronette and L. J. Latecki, "Rank-based self-training for graph convolutional networks," *Information Processing & Management*, vol. 58, no. 2, p. 102443, 2021.

[32] B. Rozin, V. H. Pereira-Ferrero, L. T. Lopes, and D. C. G. Pedronette, "A rank-based framework through manifold learning for improved clustering tasks," *Information Sciences*, vol. 580, pp. 202–220, 2021.

[33] L. T. Lopes and D. C. G. Pedronette, "Self-supervised clustering based on manifold learning and graph convolutional networks," in *2023 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, 2023, pp. 5623–5632.