

Intra-view and Inter-view Correlation Guided Multi-view Novel Class Discovery

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Abstract

In this paper, we address the problem of novel class discovery (NCD), which aims to cluster novel classes by leveraging knowledge from disjoint known classes. While recent advances have made significant progress in this area, existing NCD methods face two major limitations. First, they primarily focus on single-view data (e.g., images), overlooking the increasingly common multi-view data, such as multi-omics datasets used in disease diagnosis. Second, their reliance on pseudo-labels to supervise novel class clustering often results in unstable performance, as pseudo-label quality is highly sensitive to factors such as data noise and feature dimensionality. To address these challenges, we propose a novel framework named Intra-view and Inter-view Correlation Guided Multi-view Novel Class Discovery (IICMVNCD), which is the first attempt to explore NCD in multi-view setting so far. Specifically, at the intra-view level, leveraging the distributional similarity between known and novel classes, we employ matrix factorization to decompose features into view-specific shared base matrices and factor matrices. The base matrices capture distributional consistency among the two datasets, while the factor matrices model pairwise relationships between samples. At the inter-view level, we utilize view relationships among known classes to guide the clustering of novel classes. This includes generating predicted labels through the weighted fusion of factor matrices and dynamically adjusting view weights of known classes based on the supervision loss, which are then transferred to novel class learning. Experimental results validate the effectiveness of our proposed approach.

1. Introduction

Clustering, which aims to partition samples into groups based on their similarities [1, 3, 8, 9, 26, 34, 34, 35, 37, 40, 42, 44–47, 56–58, 60], is a fundamental task in unsupervised learning and data mining. Traditional clustering methods, however, often assume no prior information and rely solely on sample similarities for partitioning [14, 17, 38, 54, 65, 67]. This assumption significantly diverges from human learning processes, where prior knowledge is commonly utilized to understand and classify new concepts. For example, a child familiar with phones and tablets can correctly distinguish new electronic devices, such as computers and smartwatches, by leveraging existing knowledge. Inspired by this cognitive ability, a novel learning paradigm, Novel Class Discovery (NCD), has been proposed to address this limitation [6, 19, 69, 70].

NCD focuses on transferring knowledge from a labeled dataset to cluster an unlabeled dataset with non-overlapping categories [13, 41]. This paradigm has shown great potential in applications such as disease discovery and face recognition. To the best of our knowledge, existing NCD methods can be broadly categorized into two types [10]: two-stage and one-stage methods. Two-stage methods train a model on known classes and then fine-tune it for novel classes, while one-stage methods simultaneously learn representations for both classes and conduct the clustering process. One-stage methods generally achieve better performance because they can capture distributional relationships between the two datasets [24].

Despite significant advances, existing NCD methods face two major challenges that limit their practical application and performance: 1) Ignoring multi-view data: Most existing methods assume data comes from a single view, neglecting the increasingly common multi-view data. For example, in clinical diagnosis, accurately identifying new diseases (e.g., COVID-19) often requires multi-omics features, such as gene expression and imaging data,

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to work together for precise classification. Single-view data may not provide sufficient information for decision-making. Unlike single-view learning, multi-view settings [4, 5, 18, 32, 33, 36, 49, 55, 61, 68] require mining information from each view while effectively leveraging inter-view relationships to achieve consistent results. This limitation renders existing NCD methods unsuitable for handling multi-view data. 2) Dependency on pseudo-labels: Existing NCD methods often rely on pseudo-labels to supervise the learning of novel classes. However, the quality of pseudo-labels is easily affected by factors such as data distribution and feature space dimensionality, which can lead to unstable or even failed performance. Notably, these two issues are not independent. For instance, due to the diversity and complexity of multi-view data, generating pseudo-labels becomes more challenging and unreliable.

A key aspect of handling multi-view data is learning high-quality feature representations within each view while fusing information across views to achieve consistent results [21, 22, 39, 50, 53, 59, 63, 64]. Inspired by this, we argue that NCD in multi-view settings can be addressed from two perspectives: From an intra-view perspective, it is essential to learn high-quality view-specific features by leveraging the data distributions of both known and novel sets. From an inter-view perspective, it is crucial to exploit correlations between views from known classes for feature fusion to obtain consistent representations for clustering. Fortunately, unlike traditional multi-view clustering that lacks prior information, the supervision signals from known classes can guide the learning of view weights for novel classes, making the weight assignment more reasonable and interpretable.

In light of this, we propose Intra-view and Inter-view Correlation Guided Multi-view Novel Class Discovery (IICMVNCD). Unlike existing one-stage NCD paradigms, our approach relies solely on the true labels of known classes for supervision, without involving the unreliable supervision of pseudo-labels. At the intra-view level, since the data distributions of both sets are similar, we learn a shared view-specific basis matrix via matrix factorization to capture the relationships between samples from known and novel classes, thereby obtaining better feature representations. At the inter-view level, we introduce two designs: 1) We optimize the view weights of novel classes based on the classification performance of known classes, enabling the model to dynamically adjust the importance of different views. 2) We directly guide the learning of view-consistent predicted labels using the relationships and data distributions of known and novel classes, rather than relying on pseudo-label supervision. The mutual guidance between the predicted labels of the two sets further boosts performance. Experimental results validate the effectiveness of our proposed method. Our contributions are summarized as

follows:

- To the best of our knowledge, this is the first attempt to address novel class discovery in the multi-view setting. Unlike existing pseudo-labeling methods, we predict the label by exploiting data distributions and class relationships across both novel and known categories.
- We exploit intra-view and inter-view correlations to transfer knowledge from known classes to novel classes. The intra-view shared basis matrix facilitates view-specific feature representation, while inter-view guidance helps capture the relationships between view weights and fusion strategies.
- Extensive experiments on diverse datasets demonstrate the effectiveness of our approach, achieving significant improvements over existing multi-view clustering and NCD methods.

2. Related Work

In this section, we briefly introduce the most related research, including novel class discovery and multi-view clustering.

2.1. Novel Class Discovery

The primary goal of NCD is to transfer knowledge from known disjoint classes to cluster a novel unlabeled dataset. To the best of our knowledge, NCD was first studied in [15, 16], and later formally defined by Han et al. in [11], which spurred its rapid development. Unlike traditional clustering methods, NCD utilizes a labeled dataset as a reference for prior information when performing clustering. Furthermore, unlike semi-supervised learning, the labeled and unlabeled sets in NCD are disjoint in terms of classes.

As previously mentioned, NCD methods are mainly divided into two categories: two-stage and one-stage methods. Most early work focused on the two-stage framework. For example, [15] first trains a prediction network on the labeled dataset and then applies it to the unlabeled dataset to calculate sample similarities, followed by clustering based on these similarities. In contrast, one-stage methods simultaneously learn from both labeled and unlabeled data through a joint optimization objective. For instance, the authors of [12] first pre-train feature representations via self-supervised learning on two datasets, then generate pseudo-labels using ranking statistics, and design a joint optimization objective to classify labeled data and cluster unlabeled data simultaneously.

2.2. Matrix Factorization-based Multi-view Clustering

Multi-view clustering aims to partition samples by leveraging information from multiple views of data. With the increasing prevalence of multi-view data, this field has received significant attention in recent years [2, 23, 28, 29, 54,

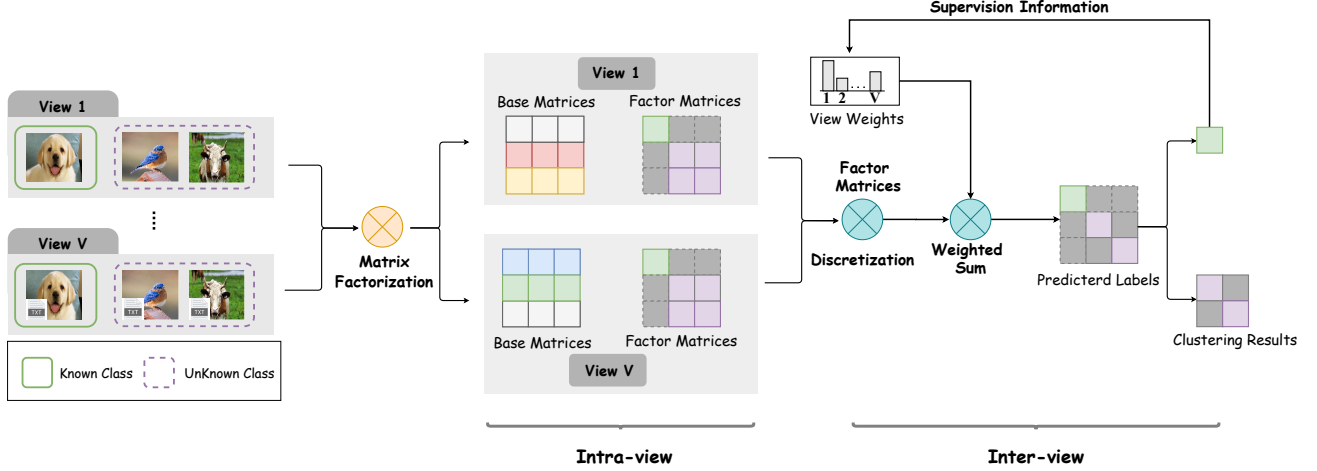


Figure 1. Framework of the proposed algorithm: We first apply matrix factorization to decompose the features of the two sets into set-shared base matrices and factor matrices. The shared basis matrices effectively capture the intra-view distributional consistency between the two sets. Next, the factor matrices are further decomposed and discretized into predicted labels with the incorporation of view weights. The discrepancy between the predicted and true labels of known classes is used to adjust the learning of view weights, enabling the guidance of inter-view relationships for unknown classes and facilitating cross-view fusion.

62, 66]. Among various approaches, matrix factorization-based multi-view clustering (MFMVC) [7, 25] has gained popularity due to its low computational complexity and ability to preserve essential multi-view information. This method typically decomposes features from all views into view-specific base matrices and a consensus factor matrix. The consensus matrix is then used for clustering to partition the multi-view data. For instance, the authors in [48] proposed a diverse non-negative matrix factorization (NMF) method to enhance the diversity among multi-view representations. Liu et al. observed that separating clustering and multi-view feature learning could lead to suboptimal solutions. To address this, they further decomposed the consensus matrix into a consensus hard partition matrix and view-specific centroid matrices, directly learning the final clustering assignments.

However, existing algorithms often assume the absence of prior knowledge during clustering, which contrasts with human learning, where prior knowledge is crucial. Additionally, current NCD methods overlook the challenges of multi-view data, failing to effectively leverage information across views. Our work aims to develop a novel approach for multi-view novel class discovery (MVNCD) to address these limitations.

3. Method

3.1. Overview

In the MVNCD setting, we are given a labeled dataset $\mathcal{D}_l = \left\{ \left\{ \mathbf{x}_v^i \right\}_{v=1}^V, \mathbf{g}^i \right\}_{i=1}^{n_l}$ and an unlabeled dataset $\mathcal{D}_u =$

$\left\{ \left\{ \mathbf{x}_v^j \right\}_{v=1}^V \right\}_{j=1}^{n_u}$, where $\mathbf{x}_v^i$ and $\mathbf{x}_v^j$ denote samples from the v -th view with feature dimension d_v . The categories in $\mathcal{D}_l$ and $\mathcal{D}_u$ are disjoint. The goal is to partition the samples in $\mathcal{D}_u$ into k_u clusters by leveraging the knowledge extracted from $\mathcal{D}_l$ with k_l categories. Consistent with most existing NCD settings, the number of clusters k_u is assumed to be known a priori. At test time, we evaluate the clustering performance on the unlabeled dataset $\mathcal{D}_u$.

To address this issue, we utilize intra-view and inter-view correlations between known and novel classes to better partition the unlabeled dataset. From the intra-view perspective, we perform matrix factorization on the feature matrix of each view to learn a shared view-specific basis matrix for both datasets, which effectively enhances the quality of feature representations (see Sec. 3.2). From the inter-view perspective, we leverage the relationships between views in the known classes to guide the learning of view relationships for the novel classes. Specifically, based on the factor matrices obtained in the intra-view step, we predict view-consistent labels by considering the data distribution and correlation across views. To improve clustering performance, we dynamically adjust view weights by combining the loss between the predicted and true labels of the known classes. The learned view weights are then applied to the novel classes, ensuring a more effective partitioning of the unlabeled dataset (see Sec. 3.3). Finally, we provide the final loss function to jointly optimize intra-view and inter-view objectives (see Sec. 3.4). The basic framework of our method is given in Fig. 1.

3.2. Intra-view Information Extraction

In this section, we discuss how to utilize the intra-view relationships to extract higher-quality features, which facilitates subsequent cross-view feature fusion. Traditional NCD algorithms often focus solely on the relationships within each dataset, neglecting the core assumption of NCD: the data distributions of the labeled and unlabeled datasets are similar. Based on this assumption, we propose to decompose the feature matrix of each view into a view-specific shared basis matrix $\mathbf{W}_v \in \mathbf{R}^{d_v \times k}$ and a factor matrix $\mathbf{Z}_v \in \mathbf{R}^{k \times n}$, where $k = k_l + k_u$ and $n = n_l + n_u$.

The shared basis matrix $\mathbf{W}_v$ is designed to capture the distributional consistency across the labeled and unlabeled datasets, effectively modeling the common feature space shared by the two datasets. This ensures that the representation is not biased towards the labeled data while still being generalizable to the unlabeled data. On the other hand, the factor matrix $\mathbf{Z}_v$ models the relationships among individual samples. The formulation is provided as follows:

$$\min_{\mathbf{W}_v, \mathbf{Z}_v} \|\mathbf{X}_v - \mathbf{W}_v \mathbf{Z}_v\|_F^2 \text{ s.t. } \mathbf{W}_v^\top \mathbf{W}_v = \mathbf{I}_k. \quad (1)$$

where $\mathbf{X}_v = [\mathbf{X}_v^l, \mathbf{X}_v^u] \in \mathbf{R}^{d_v \times n}$ is the feature matrix concatenated of the two sets in v -th view.

This formulation ensures that the basis matrix $\mathbf{W}_v$ remains orthonormal, which not only stabilizes the optimization process but also prevents redundancy.

3.3. Inter-view Information Extraction

Unlike traditional NCD methods that consider single-source data only, MVNCD requires effectively leveraging multi-view information for fusion and decision-making. In practical applications, the quality and importance of different views often vary. For example, in medical diagnosis, multi-view data such as imaging and ultrasound information may both contribute to decision-making, but their importance differs depending on the disease being detected. Therefore, how to utilize the relationships between views for fusion is a critical aspect of MVNCD. Fortunately, with the presence of the labeled dataset, we can leverage supervised learning to capture view relationships in the known classes and transfer this knowledge to the learning of the unlabeled data.

Specifically, we first utilize the factor matrices obtained in Sec. 3.2 to derive the view-specific centroid matrix $\mathbf{A}_v$ and consistent predicted labels $\mathbf{Y}$ based on the k-means idea. Considering that the importance of each view varies, we assign a learnable weight to different views when generating consistent labels. The learning of view weights is constrained by the supervised loss on the known classes. In particular, we dynamically adjust the view weights α by incorporating the difference between the predicted labels $\mathbf{Y}_l$ and the ground truth $\mathbf{G}_l$ of the known classes, and then apply this optimization strategy to the view weight learning

for the novel classes. The overall optimization objective is as follows:

$$\begin{aligned} & \min_{\alpha, \mathbf{W}_v, \mathbf{A}_v, \mathbf{Y}} \sum_{v=1}^V \alpha_v^2 \|\mathbf{X}_v - \mathbf{W}_v \mathbf{A}_v \mathbf{Y}\|_F^2 + \lambda_1 \|\mathbf{Y}_l - \mathbf{G}_l\|_F^2 \\ & \text{s.t. } \alpha^\top \mathbf{1} = 1, \alpha \geq \mathbf{0}, \mathbf{W}_v^\top \mathbf{W}_v = \mathbf{I}_k, \mathbf{Y} \in \Phi^{k \times n}. \end{aligned} \quad (2)$$

where $\mathbf{Y} = [\mathbf{Y}_l, \mathbf{Y}_u] \in \mathbf{R}^{k \times n}$ denotes the matrix of predicted labels, where each column is a k -dimensional one-hot vector representing the predicted label of a corresponding sample.

Through this design, the supervised loss on the known classes not only regulates the generation of $\mathbf{Y}_l$ but also contributes to the learning of view weights.

3.4. Loss Function

Due to the similarity in data distributions between the known and novel classes, there is a risk that novel class samples may be misclassified into the known classes during the joint learning process. To address this issue, we impose constraints on the labels of the novel classes to ensure label disjointness between the two sets. Building upon Eq. (2), we propose the final objective function as follows:

$$\begin{aligned} & \min_{\alpha, \mathbf{W}_v, \mathbf{A}_v, \mathbf{Y}} \sum_{v=1}^V \alpha_v^2 \|\mathbf{X}_v - \mathbf{W}_v \mathbf{A}_v \mathbf{Y}\|_F^2 + \\ & \lambda_1 \|\mathbf{Y}_l - \mathbf{G}_l\|_F^2 - \lambda_2 \sum_{\mathbf{g}^i \in \mathbf{G}^l} \sum_{\mathbf{y}^j \in \mathbf{Y}^u} \|\mathbf{g}^i - \mathbf{y}^j\|_F^2 \\ & \text{s.t. } \alpha^\top \mathbf{1} = 1, \alpha \geq \mathbf{0}, \mathbf{W}_v^\top \mathbf{W}_v = \mathbf{I}_k, \mathbf{Y} \in \Phi^{k \times n}, \end{aligned} \quad (3)$$

where λ_1 and λ_2 are hyperparameters that control the trade-offs among the terms.

Through this design, the loss function not only optimizes intra-view and inter-view feature representations but also ensures the separation of labels between known and novel classes, thereby improving the clustering performance on unlabeled data.

4. Optimization

We develop a four-step alternating optimization algorithm to solve the resultant problem in Eq. (3). In each step, we optimize one variable while keeping the others fixed.

4.1. $\mathbf{W}_v$ Subproblem

With the other variables fixed in Eq. (3), $\mathbf{W}_v$ can be updated by solving the following formula:

$$\max_{\mathbf{W}_v} \text{Tr}(\mathbf{W}_v^\top \mathbf{B}_v), \quad \text{s.t. } \mathbf{W}_v^\top \mathbf{W}_v = \mathbf{I}_k, \quad (4)$$

where $\mathbf{B}_v = \mathbf{X}_v \mathbf{Y}^\top \mathbf{A}_v^\top$.

Suppose the matrix $\mathbf{B}_v$ has the singular value decomposition (SVD) form as $\mathbf{B}_v = \mathbf{S}_v \mathbf{\Sigma}_v \mathbf{V}_v^\top$. The optimization problem in Eq. (4) can then be solved by the closed-form solution given in [51] as:

$$\mathbf{W}_v = \mathbf{S}_v \mathbf{V}_v^\top. \quad (5)$$

4.2. $\mathbf{A}_v$ Subproblem

Fixing other variables, the formula in Eq. (3) can be reduced to:

$$\min_{\mathbf{A}_v} \|\mathbf{X}_v - \mathbf{W}_v \mathbf{A}_v \mathbf{Y}\|_F^2. \quad (6)$$

By setting the derivative to zero, the solution is:

$$\mathbf{A}_v = \mathbf{W}_v^\top \mathbf{X}_v \mathbf{Y}^\top (\mathbf{Y} \mathbf{Y}^\top)^{-1}. \quad (7)$$

4.3. $\mathbf{Y}$ Subproblem

Since $\mathbf{Y}_l$ and $\mathbf{Y}_u$ are independent of each other for optimization, we further divide the problem into two subproblems.

4.3.1. $\mathbf{Y}_l$ Subproblem

Fixing the other variables, the optimization problem for $\mathbf{Y}_l$ can be rewritten as:

$$\begin{aligned} \min_{\mathbf{Y}_l} \sum_{v=1}^V \alpha_v^2 \|\mathbf{X}_v^l - \mathbf{M}_v \mathbf{Y}_l\|_F^2 + \lambda_1 \|\mathbf{Y}_l - \mathbf{G}_l\|_F^2, \\ \text{s.t. } \mathbf{Y}_l \in \Phi^{k \times n_l}, \end{aligned} \quad (8)$$

where $\mathbf{M}_v = \mathbf{W}_v \mathbf{A}_v$.

The optimal solution of $\mathbf{y}^i \in \mathbf{Y}_l$ can be obtained by solving:

$$\begin{aligned} \min_{\mathbf{y}^i} \mathbf{y}^{i\top} \left(\sum_{v=1}^V \alpha_v^2 \mathbf{M}_v^\top \mathbf{M}_v \right) \mathbf{y}^i - 2 \sum_{v=1}^V \alpha_v^2 \mathbf{x}_v^{i\top} \mathbf{M}_v \mathbf{y}^i \\ - 2\lambda_1 \mathbf{g}^{i\top} \mathbf{y}^i, \quad \text{s.t. } \mathbf{y}^i \in \{0, 1\}^{k \times 1}, \mathbf{y}^i \mathbf{1} = 1. \end{aligned} \quad (9)$$

Let $\mathbf{b} = \text{diag} \left(\sum_{v=1}^V \alpha_v^2 \mathbf{M}_v^\top \mathbf{M}_v \right)$ and $\mathbf{c} = \sum_{v=1}^V \alpha_v^2 \mathbf{M}_v^\top \mathbf{x}_v^i + \lambda_1 \mathbf{g}^i$. The position of the non-zero element is:

$$\arg \min_l \mathbf{b}_l - 2\mathbf{c}_l. \quad (10)$$

4.3.2. $\mathbf{Y}_u$ Subproblem

Similarly, the optimization problem for $\mathbf{Y}_u$ can be rewritten as:

$$\min_{\mathbf{Y}_u} \sum_{v=1}^V \alpha_v^2 \|\mathbf{X}_v^u - \mathbf{M}_v \mathbf{Y}_u\|_F^2 - \lambda_2 \sum_{\mathbf{g}^i \in \mathbf{G}_l} \sum_{\mathbf{y}^j \in \mathbf{Y}_u} \|\mathbf{g}^i - \mathbf{y}^j\|_F^2,$$

s.t. $\mathbf{Y}_u \in \Phi^{k \times n_u}$.

(11)

The optimal solution of $\mathbf{y}^j \in \mathbf{Y}_u$ can be obtained by solving:

$$\begin{aligned} \min_{\mathbf{y}^j} \mathbf{y}^{j\top} \left(\sum_{v=1}^V \alpha_v^2 \mathbf{M}_v^\top \mathbf{M}_v \right) \mathbf{y}^j - 2 \sum_{v=1}^V \alpha_v^2 \mathbf{x}_v^{j\top} \mathbf{M}_v \mathbf{y}^j \\ + 2\lambda_2 \sum_{\mathbf{g}^i \in \mathbf{G}_l} \mathbf{g}^{i\top} \mathbf{y}^j, \quad \text{s.t. } \mathbf{y}^j \in \{0, 1\}^{k \times 1}, \mathbf{y}^j \mathbf{1} = 1, \end{aligned} \quad (12)$$

which is similar to the optimization problem of $\mathbf{Y}_l$.

4.4. α Subproblem

Finally, given other variables, the formulation about α can be solved via optimizing:

$$\min \sum_{v=1}^V \alpha_v^2 r_v^2, \quad \text{s.t. } \alpha^\top \mathbf{1} = 1, \alpha \geq \mathbf{0}, \quad (13)$$

where

$$r_v^2 = \|\mathbf{X}_v - \mathbf{W}_v \mathbf{A}_v \mathbf{Y}\|_F^2. \quad (14)$$

Based on the Cauchy-Schwarz inequality, α_v is updated as:

$$\alpha_v = \frac{\frac{1}{r_v^2}}{\sum_{v=1}^V \frac{1}{r_v^2}}. \quad (15)$$

The overview of the alternate optimization strategy is outlined in Algorithm 1.

Algorithm 1 IICMVNCD

Input: The labeled dataset $\mathcal{D}_l$, unlabeled dataset $\mathcal{D}_u$ with k_u clusters, hyper-parameters λ_1 and λ_2 .

Output: Cluster partition matrix $\mathbf{Y}_u$.

- 1: Initialize α , $\mathbf{W}_v$, $\mathbf{A}_v$ and $\mathbf{Y}$.
 - 2: **while** not converged **do**
 - 3: Update $\mathbf{W}_v$ by solving Eq. (4);
 - 4: Update $\mathbf{A}_v$ by solving Eq. (6);
 - 5: Update $\mathbf{Y}$ by solving Eq. (8) and (11);
 - 6: Update α by solving Eq. (13);
 - 7: **end while**
-

4.5. Theoretical Analysis

4.5.1. Convergence

Most existing NCD methods fail to provide theoretical guarantees for convergence. In contrast, our method is theoretically proven to converge. For simplicity of expression, we reformulate the objective function in Eq. (3) as:

$$\min_{\mathbf{W}_v, \mathbf{A}_v, \mathbf{Y}, \alpha} \mathcal{J}(\mathbf{W}_v, \mathbf{A}_v, \mathbf{Y}, \alpha). \quad (16)$$

Our optimization process consists of four steps in each iteration. Let the superscript t represent the optimization

variables at the t -th iteration. We have:

$$\begin{aligned} \mathcal{J}(\mathbf{W}_v^{(t+1)}, \mathbf{A}_v^{(t+1)}, \mathbf{Y}^{(t+1)}, \boldsymbol{\alpha}^{(t+1)}) &\leq \\ \mathcal{J}(\mathbf{W}_v^{(t)}, \mathbf{A}_v^{(t)}, \mathbf{Y}^{(t)}, \boldsymbol{\alpha}^{(t)}), \end{aligned} \quad (17)$$

which demonstrates that the loss monotonically decreases during the optimization process.

Furthermore, for the loss function in Eq. (3), we can derive the following inequality:

$$\sum_{\mathbf{g}^i \in \mathbf{G}^l} \sum_{\mathbf{y}^j \in \mathbf{Y}^u} \|\mathbf{g}^i - \mathbf{y}^j\|_F^2 \leq n_l n_u \sqrt{2}. \quad (18)$$

Hence, Eq. (3) has a lower bound satisfying:

$$\mathcal{J}(\mathbf{W}_v, \mathbf{A}_v, \mathbf{Y}, \boldsymbol{\alpha}) \geq -\lambda_2 n_l n_u \sqrt{2}. \quad (19)$$

Therefore, the proposed method is theoretically guaranteed to converge.

4.5.2. Time Complexity

The optimization process comprises four subproblems, and we analyze the time complexity of each subproblem separately per iteration. In the $\mathbf{W}_v$ subproblem, it costs $\mathcal{O}(d_v n k)$ to compute $\mathbf{B}_v$. Then, it requires $\mathcal{O}(d_v k^2)$ to perform SVD on it. Thus, the total cost of updating $\{\mathbf{W}_v\}_{v=1}^V$ is $\mathcal{O}(d(nk + k^2))$, where $d = \sum_{v=1}^V d_v$. In the $\mathbf{A}_v$ subproblem, it takes $\mathcal{O}(d_v n k + d_v k^2 + k^3)$ to solve for $\mathbf{A}_v$ in each view. Therefore, the total complexity of updating $\{\mathbf{A}_v\}_{v=1}^V$ is $\mathcal{O}(dnk + dk^2 + V k^3)$. For the $\mathbf{Y}$ subproblem, the cost of updating $\mathbf{Y}$ is $\mathcal{O}(dnk)$. Finally, for the $\boldsymbol{\alpha}$ subproblem, the update requires $\mathcal{O}(k)$.

Combining all subproblems, the overall time complexity per iteration is:

$$\mathcal{O}(d(nk + k^2) + V k^3), \quad (20)$$

which is linear with respect to the sample number n . This ensures the scalability of the proposed method.

5. Experiment

5.1. Experimental Setting

5.1.1. Datasets

We utilized eight multi-view datasets in our experiments, including BRCA, KIPAN, uci-digit, Cora, Wiki, CCV, STL10, and YTB10. Their information is summarized in Table 1. Among these, BRCA and KIPAN are multi-omics datasets. More detailed information is provided in the Appendix due to space limitations.

For the aforementioned datasets, we divide the known classes and novel classes in a 1:1 ratio. For simplicity, we assume that the first half of the classes are designated as known classes, while the second half are treated as novel classes. If the total number of classes is odd, the number of known classes is set to be one less than that of the unknown classes by default.

Table 1. Datasets used in our experiments.

Dataset	Samples	Views	Clusters
BRCA	511	3	4
KIPAN	707	3	3
uci-digit	2,000	3	10
Cora	2,708	4	7
Wiki	2,866	2	10
CCV	6,773	3	20
STL10	13,000	4	10
YTB10	38,654	4	10

5.1.2. Compared Algorithms and Experimental Setup

We compare our proposed method with the six multi-view clustering and two novel class discovery methods, and they are summarized as follows:

1. **LMVSC**[20]: Performs spectral clustering on the final anchor graph derived for each view, achieving linear computational efficiency for large-scale datasets.
2. **FPMVS**[52]: Introduces a subspace clustering approach that simultaneously performs anchor selection and subspace graph construction, eliminating the need for additional hyper-parameters.
3. **OPMC**[27]: A one-pass approach that seamlessly integrates multi-view matrix factorization and partition generation into a unified framework.
4. **AWMVC**[43]: Learns coefficient matrices from view-specific base matrices. It captures more comprehensive information by projecting original features into distinct low-dimensional spaces.
5. **RCAGL**[31]: Proposes a robust and consistent anchor graph learning method for multi-view clustering. It constructs a consistent anchor graph by simultaneously learning a consistent part to capture inter-view commonality and a view-specific part to filter out noise.
6. **AEVC**[30]: A plug-and-play anchor enhancement strategy for multi-view clustering. By analyzing relationships between anchors and samples across neighboring views, it ensures consistency and alignment across similar views.
7. **IIC**[24]: A novel class discovery (NCD) method that models inter-class and intra-class constraints using symmetric Kullback-Leibler divergence.
8. **CKD**[10]: An NCD method that addresses the information loss of class relations in existing methods by utilizing a knowledge distillation framework.

For our method, λ_1 and λ_2 are tuned from $10.^{-4}[0, 1, \dots, 5]$. As for the compared methods, the parameter settings of all baselines were tuned according to the recommendations provided in their respective papers. For NCD methods, originally designed for image datasets,

Table 2. Comparison of ACC, NMI, and Purity for various MVC and NCD algorithms across eight benchmark datasets. The best results are highlighted in bold, while the second-best results are underlined.

Datasets	MVC Methods						NCD Methods		
	LMVSC	FPMVS	OPMC	AWMVC	RCAGL	AEVC	IIC	CKD	Ours
ACC									
BRCA	98.18	80.61	52.73	51.02	56.36	86.67	56.22	84.32	98.79
KIPAN	87.68	91.58	89.86	80.46	51.95	91.67	83.78	<u>91.73</u>	92.51
uci-digit	89.82	87.40	<u>93.60</u>	57.09	87.50	92.60	77.05	92.50	95.30
Cora	57.36	55.93	42.33	40.58	0.00	<u>63.20</u>	48.56	35.23	76.36
Wiki	<u>64.31</u>	39.70	30.77	21.97	33.93	37.30	32.77	61.05	65.42
CCV	32.17	33.30	31.20	22.55	27.06	<u>33.52</u>	26.09	31.66	34.20
STL10	61.91	85.90	<u>98.95</u>	60.34	80.12	98.74	71.16	96.11	99.02
YTB10	84.31	92.05	79.08	57.98	75.01	91.59	72.84	<u>93.01</u>	94.55
NMI									
BRCA	<u>87.81</u>	37.39	0.01	37.54	6.46	50.05	35.47	86.93	90.45
KIPAN	46.27	58.42	55.00	52.60	0.05	<u>61.08</u>	55.99	58.80	62.02
uci-digit	83.85	79.89	84.99	69.14	74.43	82.21	73.45	<u>85.61</u>	86.59
Cora	25.19	21.97	10.95	16.16	0.00	<u>29.96</u>	24.01	2.12	44.59
Wiki	<u>49.98</u>	14.01	6.06	8.48	9.99	13.95	14.04	35.10	66.44
CCV	17.26	16.62	<u>17.81</u>	16.66	12.62	16.83	16.70	16.83	19.24
STL10	56.90	72.39	<u>96.01</u>	62.45	63.50	95.32	62.37	87.28	96.22
YTB10	75.83	<u>83.08</u>	<u>72.89</u>	71.26	70.66	81.14	77.55	82.84	86.85
Purity									
BRCA	<u>98.18</u>	80.61	67.88	91.64	87.27	86.67	89.78	84.32	98.79
KIPAN	87.68	91.58	89.86	88.89	88.46	91.67	90.80	<u>91.73</u>	92.51
uci-digit	90.65	87.43	<u>93.60</u>	91.34	87.50	92.60	90.80	92.50	95.30
Cora	57.36	55.93	42.40	49.38	0.00	<u>63.20</u>	60.62	35.50	76.36
Wiki	<u>65.11</u>	45.32	37.37	41.17	52.94	43.48	46.53	61.12	75.47
CCV	36.80	35.73	36.35	<u>39.12</u>	38.77	37.31	37.22	36.44	39.95
STL10	64.09	85.91	<u>98.95</u>	82.79	80.12	98.74	83.91	96.11	99.02
YTB10	86.08	92.70	79.08	90.20	82.99	91.60	92.23	<u>93.01</u>	94.55

we adapt them for multi-view datasets by replacing their backbone with V separate 3-layer MLP networks. Each network acts as a feature extractor for one view, and the features from all views are concatenated to form the input for the subsequent NCD algorithms. The clustering performance is evaluated using standard metrics, including clustering accuracy (ACC), normalized mutual information (NMI), and Purity. All experiments were conducted on a machine equipped with an Intel Core i9-10850K CPU @ 3.60GHz, 64GB RAM, and an Nvidia RTX 3090 GPU.

5.2. Experimental Results

To demonstrate the effectiveness of our method, we conducted experiments reporting the results of IICMVNCD on eight widely used benchmark datasets, comparing our algorithm with others. The results are presented in Table 2.

From the table, we observe that our algorithm consistently outperforms both MVC and NCD baselines on every dataset, demonstrating its effectiveness. Relative to MVC methods, our approach exploits prior knowledge from

known classes, enabling a better grasp of the data distribution and inter-view relationships for the unseen classes and thus yielding superior clustering results. Existing NCD methods, on the other hand, are largely designed for single-view data and do not effectively exploit complementary cues across views; as a consequence, their performance is generally inferior—often even worse than MVC baselines. These findings highlight the importance of developing NCD techniques that can fully leverage multi-view information, as accomplished by our proposed framework. These findings highlight the importance of developing NCD techniques that can fully leverage multi-view information, as accomplished by our proposed framework.

5.3. Convergence

As proved above, our proposed algorithm is theoretically convergent. To confirm its practical convergence, we plot the changes in the objective value of our method across iterations on two datasets, as illustrated in Figure 2. From the figure, it is evident that the objective value decreases mono-

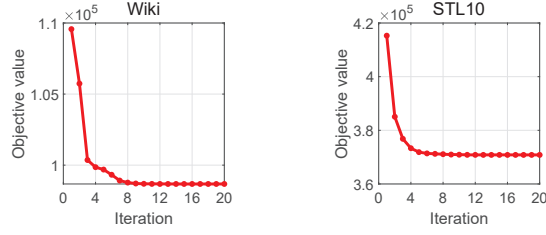


Figure 2. The objective values of our method vary with iterations on two datasets.

Table 3. The ablation study to investigate the effectiveness of main modules of our method in terms of ACC. The best results are marked in bold.

Datasets	w/o α and $\mathcal{D}_l$	w/o α	w/o $\mathcal{D}_l$	Ours
BRCA	52.73	58.79	58.79	98.79
KIPAN	89.86	90.06	90.95	92.51
uci-digit	93.60	95.20	93.80	95.30
Cora	42.33	56.66	42.20	76.36
Wiki	30.77	35.44	64.35	65.42
CCV	31.20	33.41	32.78	34.20
STL10	98.95	99.02	98.95	99.02
YTB10	79.08	94.32	79.08	94.55

tonically and converges within fewer than fifty iterations.

5.4. Ablation Study

In this section, we conduct ablation experiments to validate the effectiveness of the proposed modules. In our framework, we primarily leverage information from known classes to enhance the clustering of novel classes in two key ways. First, we utilize the similarity between the distributions of known and unknown classes at the intra-view level through matrix factorization, allowing us to learn shared view-specific basis matrices and factor matrices that capture the relationships between samples of known and unknown classes. Second, at the inter-view level, we use the view weights learned from known classes to guide the weight learning for unknown classes. To evaluate the contributions of these components, we perform experiments by utilizing only the distribution of novel classes during matrix factorization while retaining the view weight guidance module (w/o $\mathcal{D}_l$). Additionally, we assess the scenario where we use only the information from unknown classes for guiding view weight learning while keeping the intra-view component (w/o α). Finally, we also consider the case where both modules are removed (w/o α and $\mathcal{D}_l$) and report the results in Table 3. From the table, it is evident that removing any one of the modules results in a decline in the performance of our model, thereby showing the usefulness of each module.

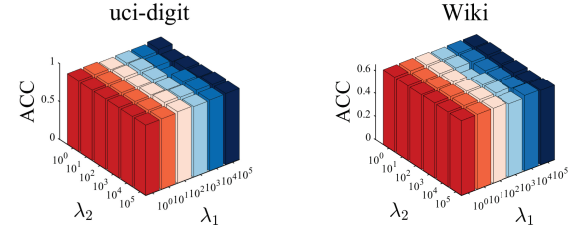


Figure 3. The parameter sensitivity of our method on uci-digit and Wiki.

5.5. Parameter Sensitivity

We employed two hyperparameters to adjust the importance of each term in Eq. (3). To investigate the selection of hyperparameters and their impact on the final results, we plotted the effects of hyperparameter fluctuations on ACC in Fig. 3. It can be observed that our results show minimal variation with changes in hyperparameters, which shows the stability of our method. Moreover, in practical applications, due to the presence of known class label information, we can also adjust the hyperparameters for unknown classes based on the model’s performance on known classes. We will explore how to tune them based on the results of known classes in future research.

6. Conclusion

In this paper, we address two major limitations of existing Novel Class Discovery (NCD) methods: the neglect of multi-view data and the reliance on pseudo-labels. To tackle these issues, we propose an Intra-view and Inter-view Correlation Guided Multi-view Novel Class Discovery method. By leveraging matrix factorization, we effectively capture the distributional consistency between different views and directly fuse the resulting factor matrices to generate class labels. Unlike traditional multi-view clustering methods that lack prior information, our approach utilizes supervision from known classes to guide the learning of view weights for unknown classes, significantly improving performance. Experimental results demonstrate the effectiveness of the proposed algorithm. To the best of our knowledge, this is the first attempt to apply NCD in the multi-view domain, providing valuable insights and inspiration for the future application of NCD methods in multi-view scenarios. In the future, we expect to research how to utilize known class label information to select hyperparameters for novel classes.

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