Efficient Multi-view Clustering via Reinforcement Contrastive Learning

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Abstract

Contrastive multi-view clustering has demonstrated remarkable potential in complex data analysis, yet existing approaches face two critical challenges: difficulty in constructing high-quality positive and negative pairs and high computational overhead due to static optimization strategies. To address these challenges, we propose an innovative **E**fficient **M**ulti-**V**iew **C**lustering framework with **R**einforcement **C**ontrastive **L**earning (EMVC-RCL). Our key innovation is developing a reinforcement contrastive learning paradigm for dynamic clustering optimization. First, we leverage multi-view contrastive learning to obtain latent features, which are then sent to the reinforcement learning module to refine low-quality features. Specifically, it selects high-confident features to guide the positive/negative pair construction of contrastive learning. For the low-confident features, it utilizes the prior balanced distribution to adjust their assignment. Extensive experimental results showcase the effectiveness and superiority of our proposed method on multiple benchmark datasets.

1 Introduction

Multi-view data has become increasingly ubiquitous across diverse real-world applications [Zhan *et al.*, 2018b; Zhang *et al.*, 2016], which describes the same object from multiple perspectives, such as different sensor types [Wang *et al.*, 2015b] and various features [Liu, 2021; Cao *et al.*, 2015b]. Multi-view learning, which can exploit complementary and consistent information across different views, achieves more comprehensive insights than single-view approaches [Li *et al.*, 2019a; Huang *et al.*, 2021; Peng *et al.*, 2022]. As a fundamental multi-view learning paradigm, multi-view clustering (MVC) has emerged as a crucial technique for discovering intrinsic patterns and structures of multi-view data under unsupervised settings [Zhang *et al.*, 2017] and hence receives considerable attention in machine learning and computer vision [Wen *et al.*, 2020; Wang *et al.*, 2018; Zhan *et al.*, 2018a].

Traditional MVC methods primarily obtain consistent latent representation from multi-view data for clustering with linear transformation, which can be roughly categorized into kernel-based methods, subspace-based methods, and nonnegative matrix factorization (NMF) based methods. For example, Gönen and Margolin [2014] proposed a localized data fusion approach for kernel k-means clustering. Liu et al. [2016] introduced matrix-induced regularization to improve the robustness of multiple kernel k-means. Subsequently, Cao et al. [2015a] developed diversity-induced multi-view subspace clustering. Luo et al. [2018] proposed consistent and specific multi-view subspace clustering. However, these traditional approaches rely heavily on predefined kernels or hand-crafted features, which often fail to capture complex semantic relationships and suffer from limited scalability when handling high-dimensional data.

To mitigate these limitations, deep MVC was developed to exploit complex and nonlinear features embedded within multi-view data [Sun *et al.*, 2024]. Typical approaches include autoencoder-based methods, deep CCA, and generative adversarial networks (GAN) based methods [Dong *et al.*, 2020; Andrew *et al.*, 2013; Li *et al.*, 2019b]. Compared to traditional methods, these approaches demonstrate promising clustering performance. However, as unsupervised learning techniques, they lack label guidance and rely solely on feature differences for clustering. This limitation hinders their ability to learn sufficient discriminative information, resulting in suboptimal performance. Some works introduced contrastive learning to enhance discriminative feature by incorporating pseudo labels as guidance [Trosten *et al.*, 2021; Pan and Kang, 2021]. Nevertheless, contrastive MVC methods encounter a situation where the representation quality and clustering accuracy are mutually dependent. Coupled with static and inflexible optimization strategies, these methods incur extensive computational complexity for convergence and limited improvement of clustering performance.

To address the aforementioned challenges, we develop a novel efficient multi-view clustering framework with reinforcement contrastive learning. This framework incorporates a reinforcement learning module to dynamically optimize the clustering process. Specifically, this module select high-quality features for contrastive learning and adaptively refine low-quality features. Then, we propose a memory-enhanced mechanism that leverages historical information,

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which utilizes temporal feature consistency to efficiently refine ambiguous assignments via momentum-based update. To dynamically optimize the memory-enhanced mechanism, we formulate the parameter adaptation as a reinforcement learning problem and solve it with Q-learning. This approach significantly enhances clustering performance while maintaining computational efficiency. Our main contributions are summarized as follows:

- We propose a novel reinforcement contrastive learning framework for deep MVC, which adaptively selects high-confident features to enhance the discriminative feature learned by contrastive learning.
- We design a memory-enhanced mechanism to store high-quality features and refine low-quality feature via momentum-based update, thereby stabilizing the clustering and promoting faster convergence.
- We conduct extensive experiments and comparisons, demonstrating superior clustering performance with only 30% of the traditional computational cost across various benchmark datasets.

2 Related Work

2.1 Deep Multi-view Clustering

Multi-view clustering (MVC) leverages the consistency and complementarity across views, using similarity measures to partition data into clusters and uncover underlying relationships. Due to the inherent challenges of unsupervised learning, many MVC methods design pretext tasks to extract potential low-dimensional features and shared information across views. For instance, autoencoder-based approaches [Zhang *et al.*, 2019; Fan *et al.*, 2020] enhance feature reliability by enforcing consistency between the original inputs and reconstructed outputs. However, such reconstruction constraints typically capture information within individual views, lacking the ability to explore cross-view correlations. To address this, numerous algorithms employ subspace learning to project multi-view data into a unified shared subspace, enabling joint representation learning [Zhang *et al.*, 2018; Wang *et al.*, 2023b; Wang *et al.*, 2023a; Zhang *et al.*, 2023]. Additionally, some methods integrate CCA constraints [Wang *et al.*, 2015a; Gao *et al.*, 2020] or leverage generative adversarial networks [Li *et al.*, 2019b; Xu *et al.*, 2019] to align feature distributions across different views. Recently, the emergence of contrastive learning has revitalized MVC [Xu *et al.*, 2022; Chen *et al.*, 2023; Wang *et al.*, 2025]. By pulling together positive samples and pushing apart negative ones, contrastive objectives implicitly enhance intra-cluster compactness and inter-cluster separability. For example, Cui *et al.* [2024] proposed a dual contrast-driven clustering framework that improves feature discrimination through contrastive learning. Despite these advancements, existing methods still face key limitations, such as static optimization strategies, suboptimal view-weight balancing, and high computational overhead, all of which hinder their scalability and practical deployment.

2.2 Reinforcement Learning for Clustering

Recently, an emerging line of work has started to explore the potential of reinforcement learning (RL) in multi-view clustering (MVC) [Liu *et al.*, 2023]. Dai *et al.* [2025] pioneered a graph-based framework that employs reinforcement learning to infer the number of clusters, using an inter-cluster connectivity reward mechanism to guide the process. Building on this idea, Gu *et al.* [2023] introduced MVCIR-net, which integrates contrastive learning with reinforcement strategies to enhance the recognition of clustering structures. In a different direction, Yang *et al.* [2022] proposed a self-supervised representation learning framework tailored for multi-view reinforcement learning, aiming to improve sample efficiency and representation quality. While these approaches demonstrate the potential of combining RL with MVC, they tend to focus on isolated objectives—such as cluster number estimation or representation learning—without offering a unified solution. Specifically, they fall short in addressing critical challenges such as class imbalance, adaptive optimization, and computational efficiency in a holistic manner. This underscores the need for a more comprehensive framework that can leverage reinforcement learning not only for structural inference or feature learning but also for enhancing the overall robustness and scalability of MVC methods.

3 Methodology

3.1 Notation & Network Architecture

Given a multi-view dataset $\mathcal{X} = \{\mathbf{X}^{(1)}, \mathbf{X}^{(2)}, \ldots, \mathbf{X}^{(V)}\}$ with V views and n samples, where $\mathbf{X}^{(v)} \in \mathbb{R}^{n \times d_v}$ represents the feature matrix of view v, our goal is to partition these samples into K clusters. We denote the latent representations as $\mathbf{Z}^{(v)} \in \mathbb{R}^{n \times d_h}$, enhanced features as $\mathbf{H}^{(v)} \in \mathbb{R}^{n \times d_h}$, and clustering probability distributions as $\mathbf{P}^{(v)} \in \mathbb{R}^{n \times K}$, with its regularized version as $\hat{\mathbf{P}}^{(v)}$.

Our EMVC-RCL framework consists of three key modules: View-specific Encoder-Decoder Module with encoders E_v and decoders D_v that preserve view-specific information; Local-Global Contrastive Module that ensures both sample-level alignment and cluster-level consistency across views; and Dynamic Clustering Refinement Module that employs reinforcement learning with memory bank $\mathbf{M}^{(t,v)} \in \mathbb{R}^{n \times d_h}$ at time step t to stabilize uncertain assignments. These modules work together to achieve consistent and balanced clustering while preserving the unique characteristics of each view.

3.2 View-specific Encoder/Decoder

To learn discriminative representations from multi-view data, we employ view-specific encoders and decoders. For each view v, the encoder E_v projects the input features into a latent space:

$$\mathbf{Z}^{(v)} = E_v(\mathbf{X}^{(v)}) \in \mathbb{R}^{n \times d_h} \tag{1}$$

where E_v is implemented as a Multi-Layer Perception (MLP) that maps features from dimension d_v to d_h. Then, we employ the projected features from other views to refine the v-th view feature as follows:

$$\mathbf{H}^{(v)} = \mathbf{Z}^{(v)} + \alpha_t \cdot \frac{1}{V-1} \sum_{u \neq v} \mathbf{Z}^{(u)} \in \mathbb{R}^{n \times d_h} \tag{2}$$

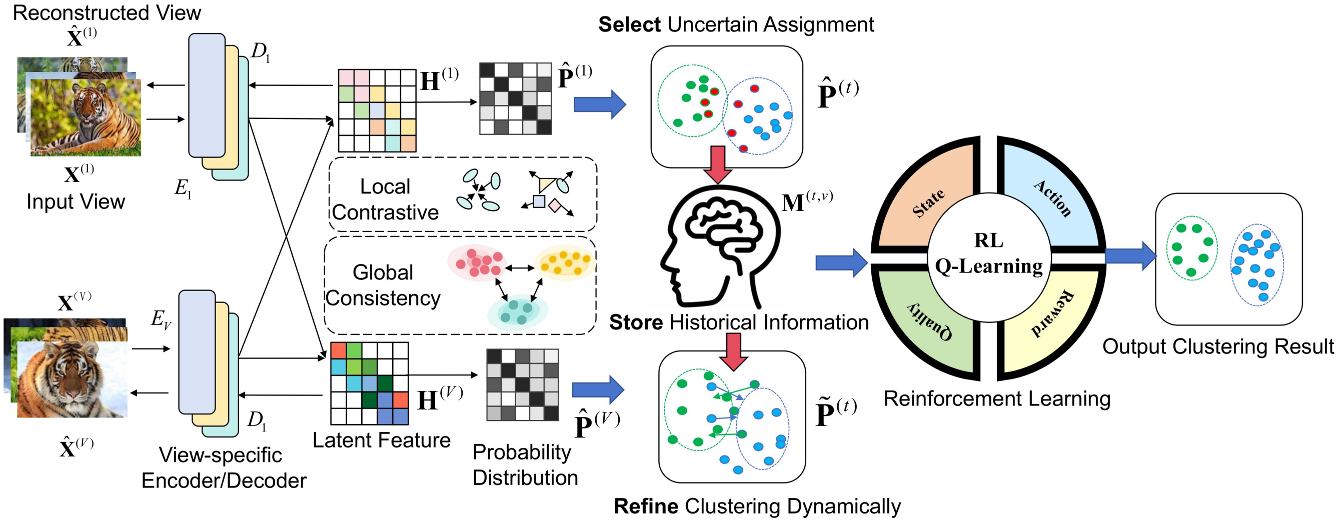


Figure 1: The architecture of our EMVC-RCL framework. The data flow starts from multi-view inputs, which are processed by view-specific encoders and decoders to extract latent features and reconstruct each view. These latent features are used to generate clustering probability distributions, which are further optimized by local contrastive and global consistency objectives. Uncertain assignments are identified and refined using a memory module that stores historical information. Reinforcement learning (Q-Learning) dynamically adjusts clustering strategies by evaluating clustering quality and assignment confidence, ultimately producing clustering results.

where $\alpha_t \in [0, 1]$ controls the intensity of multi-view information integration. To preserve essential view information, we reconstruct the input data through view-specific decoders:

$$\hat{\mathbf{X}}^{(v)} = D_v(\mathbf{H}^{(v)}) \in \mathbb{R}^{n \times d_v} \tag{3}$$

where D_v is also implemented as an MLP. We employ the reconstruction loss to guarantee reconstruction quality:

$$\mathcal{L}_{rec} = \frac{1}{V} \sum_{v=1}^{V} \|\mathbf{X}^{(v)} - \hat{\mathbf{X}}^{(v)}\|_F^2 \tag{4}$$

where $\|\cdot\|_F$ denotes the Frobenius norm. While this reconstruction process helps preserve view-specific information, it primarily focuses on individual view characteristics and may not fully capture the semantic relationships across views.

3.3 Local-Global Contrastive Module

To learn clustering-friendly representations that capture cross-view semantic relationships, we propose a local-global contrastive learning strategy that operates on the enhanced features $\mathbf{H}^{(v)}$ at both sample and cluster levels. The learned features $\mathbf{H}^{(v)}$ are first transformed into clustering probability distributions through a shared network:

$$\mathbf{P}^{(v)} = \varphi(\mathbf{H}^{(v)}) \in \mathbb{R}^{n \times K} \tag{5}$$

where φ consists of two fully-connected layers with softmax activation that map features to probability distributions, and $\mathbf{P}^{(v)}$ represents the probability matrix for view v.

To ensure cross-view consistency at the sample level, we first design a local contrastive loss that operates on individual samples:

$$\mathcal{L}_{local} = \sum_{v=1}^{V} \sum_{u=v+1}^{V} \sum_{i=1}^{n} -\log \frac{\exp(\mathbf{P}_i^{(v)} \cdot \mathbf{P}_i^{(u)} / \tau_1)}{\sum_{j=1}^{n} \exp(\mathbf{P}_i^{(v)} \cdot \mathbf{P}_j^{(u)} / \tau_1)} \tag{6}$$

where $\mathbf{P}_i^{(v)}$ denotes the i-th row of $\mathbf{P}^{(v)}$, representing the clustering probability distribution of sample i in view v, and τ_1 is a temperature parameter controlling the sharpness of the similarity distribution. This local loss treats each sample pair independently, pulling together the same sample's representations across different views while pushing apart different samples.

While the local contrastive loss ensures sample-level alignment, it does not consider the overall cluster distribution, potentially leading to assignment error. To obtain the global cluster distribution structure, we first adjust the cluster distribution to be sharper as follows:

$$\hat{\mathbf{P}}_{ik}^{(v)} = \frac{(\mathbf{P}_{ik}^{(v)})^2 / f_k}{\sum_{k'} (\mathbf{P}_{ik'}^{(v)})^2 / f_{k'}} \tag{7}$$

where $f_k = \sum_{i=1}^{n} \mathbf{P}_{ik}^{(v)}$ represents the size of cluster k, and $\hat{\mathbf{P}}^{(v)}$ is the regularized probability matrix.

Building upon these regularized distributions, we introduce a global consistency loss that aligns the overall cluster structures across views:

$$\mathcal{L}_{global} = \sum_{u \neq v} \mathrm{KL}(\hat{\mathbf{P}}^{(v)} \| \hat{\mathbf{P}}^{(u)}) \tag{8}$$

Unlike the local contrastive loss that focuses on individual samples, the global consistency loss ensures that the entire clustering structure remains consistent across views by minimizing the KL divergence between view-specific cluster distributions. Meanwhile, this loss can avoid sorting most samples assigned into a single cluster. The final local-global contrastive loss combines both local sample-level alignment and global cluster-level consistency:

$$\mathcal{L}_{con} = \mathcal{L}_{local} + \alpha_c \mathcal{L}_{global} \tag{9}$$

where α_c serves as a regularization coefficient controlling the contribution of global cluster structure consistency.

3.4 Dynamic Clustering Refinement Module

We propose a dynamic clustering refinement module with a reinforcement learning framework. Our key insight is that uncertain assignments need special attention and historical information can help stabilize the uncertain assignments and further improve the clustering process.

Selection of Samples with Uncertain Assignment

Definition 1 (Samples with Uncertain Assignment): Given a sample's cluster probability distribution $\hat{\mathbf{P}}_i^{(v)} \in \mathbb{R}^K$, we define the set of uncertain samples as:

$$\mathcal{U}^{(v)} = \{i | \delta_e(\hat{\mathbf{P}}_i^{(v)}) > \eta_e \text{ or } \delta_c(\hat{\mathbf{P}}_i^{(v)}) < \eta_c\} \tag{10}$$

where $\delta_e(\hat{\mathbf{P}}_i^{(v)})$ is the entropy of the assignment $\hat{\mathbf{P}}_i^{(v)}$; $\delta_c(\hat{\mathbf{P}}_i^{(v)})$ is the confidence score; η_e and η_c are thresholds.

To quantify this uncertainty, we evaluate each sample i in view v through two complementary metrics: entropy and confidence score. A sample is considered with an uncertain assignment if it exhibits either high entropy (dispersed distribution) or low confidence (unclear boundary). The entropy of its probability distribution is:

$$\delta_e(\hat{\mathbf{P}}_i^{(v)}) = -\sum_{k=1}^{K} \hat{\mathbf{P}}_{ik}^{(v)} \log \hat{\mathbf{P}}_{ik}^{(v)} \tag{11}$$

where $\hat{\mathbf{P}}_i^{(v)} \in \mathbb{R}^K$ denotes the i-th row of $\hat{\mathbf{P}}^{(v)}$. Additionally, we compute a confidence score as follows:

$$\delta_c(\hat{\mathbf{P}}_i^{(v)}) = \frac{\max_k \hat{\mathbf{P}}_{ik}^{(v)}}{\text{second\_max}_k \hat{\mathbf{P}}_{ik}^{(v)}} \tag{12}$$

A sample with uncertain assignment means its cluster assignments are less reliable. To enhance its clustering quality, we propose to leverage historical information through a memory-based mechanism, as detailed in the next section.

Storage of Historical Information

To stabilize the clustering assignments of samples with uncertain assignments identified in $\mathcal{U}^{(v)}$, we propose a memory-enhanced mechanism for historical information storage, and then, we realize temporal consistency in feature space to refine uncertain assignments through momentum-based updates.

At each time step t, the memory-enhanced mechanism maintains a memory bank $\mathbf{M}^{(t,v)} \in \mathbb{R}^{n \times d_h}$ and updates it through momentum-based dynamics to ensure stable feature patterns:

$$\mathbf{M}^{(t,v)} = \beta \mathbf{M}^{(t-1,v)} + (1-\beta)\mathbf{H}^{(v)} \tag{13}$$

where $\beta \in (0, 1)$ controls the balance between historical memory and current features.

For uncertain samples in $\mathcal{U}^{(v)}$, we establish relationships $\mathcal{S}_{ij}^{(t,v)}$ between i-th current features $\mathbf{H}_i^{(v)}$ and j-th historical memory $\mathbf{M}_j^{(t,v)}$ using cosine similarity:

$$\mathcal{S}_{ij}^{(t,v)} = \frac{\mathbf{H}_i^{(v)} \cdot \mathbf{M}_j^{(t,v)}}{\|\mathbf{H}_i^{(v)}\| \|\mathbf{M}_j^{(t,v)}\|} \tag{14}$$

Then, we compute the contribution weights based on these similarities:

$$\mathbf{w}_{ij} = \frac{\exp(\mathcal{S}_{ij}^{(t,v)}/\tau)}{\sum_{m=1}^{n} \exp(\mathcal{S}_{im}^{(t,v)}/\tau)} \tag{15}$$

where τ is a temperature parameter controlling the sharpness of the weight distribution. The contribution weight $\mathbf{w}_{ij}$ quantifies the influence of historical samples on the current sample's assignment.

Dynamic Clustering Refinement

Definition 2 (Dynamic Sample Assignment): Given the current sample features and historical memory, the adaptive refinement strategy for cluster assignments is defined as:

$$\tilde{\mathbf{P}}_i^{(t)} = \begin{cases} \phi \hat{\mathbf{P}}_i^{(t)} + (1-\phi) \sum_{j=1}^{n} \mathbf{w}_{ij} \hat{\mathbf{P}}_j^{(t-1)}, & \text{if } i \in \mathcal{U}^{(v)} \\ \hat{\mathbf{P}}_i^{(t)}, & \text{otherwise} \end{cases} \tag{16}$$

where $\mathbf{w}_{ij}$ weights the contribution of each memory entry based on its similarity, allowing samples with uncertain assignments to refine their assignments by combining current predictions with reliable historical patterns.

This adaptive refinement strategy stabilizes uncertain assignments but depends on key parameters like τ and β, which need dynamic adjustment during clustering. Thus, we model parameter adaptation as a sequential decision-making problem, explored in the next part.

Parameter Adaptation with Reinforcement Learning

To dynamically update the parameters, we introduce a reinforcement learning (RL) strategy, specifically utilizing Q-learning, which enables an agent to learn optimal decision-making policies by interacting with an environment, where the agent observes **states**, takes **actions**, and receives **rewards** based on those actions.

Definition 3 (State): The state at each time step t is represented as a vector of features:

$$\text{state}^{(t)} = [\Delta_{\text{in}}^{(t)}, \Delta_{\text{out}}^{(t)}, \rho_k^{(t)}] \tag{17}$$

where

$$\begin{cases} \Delta_{\text{in}}^{(t)} = \dfrac{1}{K} \displaystyle\sum_{k=1}^{K} \sum_{i \in \mathcal{C}_k} \|\mathbf{H}_i^{(v)} - \mathbf{c}_k\|_2^2, \\ \Delta_{\text{out}}^{(t)} = \dfrac{1}{K(K-1)} \displaystyle\sum_{k=1}^{K} \sum_{l \neq k} \|\mathbf{c}_k - \mathbf{c}_l\|_2^2, \\ \rho_k^{(t)} = \dfrac{K_{\text{cur}}}{K}. \end{cases}$$

Here, $\Delta_{\text{in}}^{(t)}$ measures the *compactness* of the clusters, where $\mathcal{C}_k$ represents the set of samples in cluster k and $\mathbf{c}_k$ is the corresponding centroid. $\Delta_{\text{out}}^{(t)}$ quantifies the *separation* between clusters, and $\rho_k^{(t)} = \frac{K_{\text{cur}}}{K}$ represents the *progress* of the clustering process, where K_{cur} is the number of completed clusters at time step t, and K is the total number of clusters.

Definition 4 (Action): Based on the observed state, the agent selects parameters for the memory bank as its action, represented as:

$$\text{action}^{(t)} = [\psi, \eta_c, \tau] \tag{18}$$

where ψ controls the balance between current and historical predictions, η_c is the confidence threshold for identifying uncertain samples, and τ is the temperature parameter controlling the sharpness of similarity weights. These parameters govern the memory-based refinement process and influence how uncertain samples utilize historical information.

Definition 5 (Reward): The effectiveness of the selected parameters is evaluated through a reward signal, defined as:

$$\text{reward}^{(t)} = \Delta_{\text{out}}^{(t)} - \sigma_1 \, \Delta_{\text{in}}^{(t)} + \sigma_2 \sum_{i=1}^{n} \mathbf{1}(\delta_c(\hat{\mathbf{P}}_i^{(v)}) > \eta_c) \quad (19)$$

where σ_1 and σ_2 are weighting parameters balancing cluster quality and assignment confidence, and $\mathbf{1}(\cdot)$ is the indicator function that equals 1 when a sample's confidence exceeds the threshold η_c and 0 otherwise, thus counting the total number of confident samples in the summation.

Following the Q-learning framework, we optimize a Q-network that predicts the expected cumulative reward for state-action pairs. Let s, a, and r represent the state, action, and reward, respectively. The Q-network is trained by minimizing the following loss function:

$$\mathcal{L}_{rl} = \mathbb{E}[(r^{(t)} + \gamma \max_a Q(s^{(t+1)}, a) - Q(s^{(t)}, a^{(t)}))^2] \quad (20)$$

where γ is the discount factor. This optimization process enables the agent to learn effective strategies for selecting parameters that refine uncertain samples based on both current and historical clustering information.

3.5 Overall Objective

The overall objective integrates reconstruction, contrastive learning, and reinforcement learning components:

$$\mathcal{L}_{total} = \mathcal{L}_{rec} + \alpha\mathcal{L}_{con} + \lambda\mathcal{L}_{rl} \quad (21)$$

where α and λ are regularization coefficients.

After model convergence, we compute the final clustering assignment using the refined probability distributions $\tilde{\mathbf{P}}^v$ from Eq. (16):

$$y_i = \arg\max_k \left(\frac{1}{V} \sum_{v=1}^{V} \tilde{\mathbf{P}}_{ik}^v \right) \quad (22)$$

This aggregation leverages complementary information from all views to determine the most probable cluster for each sample.

4 Experiment

4.1 Datasets & Metric

We evaluate our method on six real-world multi-view datasets from previous works [Chen *et al.*, 2023; Xu *et al.*, 2023]: COIL-20 with 1,440 grayscale images of 20 objects from different angles, RGB-D containing 1,449 samples with RGB and depth information, BDGP consisting of 2,500 drosophila embryo images with two visual descriptors, Scene-15 including 4,485 scene images with GIST, LBP, and HOG features, MNIST-USPS combining handwritten digit samples from both datasets, and Fashion containing product images with visual, textual, and categorical features. For evaluation, we use three standard metrics: Accuracy (ACC), Normalized Mutual Information (NMI), and Purity (PUR).

4.2 Experiment Setup

To comprehensively evaluate our proposed EMVC-RCL method, we compare it with several state-of-the-art methods: K-means [MacQueen and others, 1967], BSVC, SCAgg [Nie *et al.*, 2014], EE-IMVC [Liu *et al.*, 2020], ASR [Chen *et al.*, 2022], DSIMVC [Tang and Liu, 2022], DSMVC [Tang and Liu, 2022], DCP [Lin *et al.*, 2022], MFLVC [Xu *et al.*, 2022], CVCL [Chen *et al.*, 2023], CMVKL [Wan *et al.*, 2024],ADMC [Zhao *et al.*, 2024]. All experiments were conducted on an NVIDIA GeForce RTX 4090 GPU with CUDA 12.4, implemented using PyTorch (Python 3.10.13).

4.3 Performance Comparison

As shown in Table 1, our EMVC-RCL demonstrates superior performance across all datasets and metrics. On BDGP dataset, our approach achieves 99.64% ACC, 98.65% NMI, and 99.60% PUR, surpassing the second-best method CVCL (99.20% ACC, 97.29% NMI, 99.20% PUR). The performance advantage is particularly evident on challenging datasets like Scene-15, where our method achieves 76.80% ACC, significantly outperforming other competitors. This substantial improvement can be attributed to our reinforcement contrastive learning framework, which effectively selects high-confident features while refining low-quality ones through dynamic clustering optimization. Similar patterns can be observed on MNIST-USPS and Fashion datasets, where our method consistently achieves the best performance (99.98% and 99.58% ACC respectively), demonstrating its robust performance across different data modalities and cluster distributions. These comprehensive results validate the effectiveness of our proposed EMVC-RCL framework in handling diverse multi-view clustering scenarios while maintaining computational efficiency.

4.4 Hyper-parameter Analysis

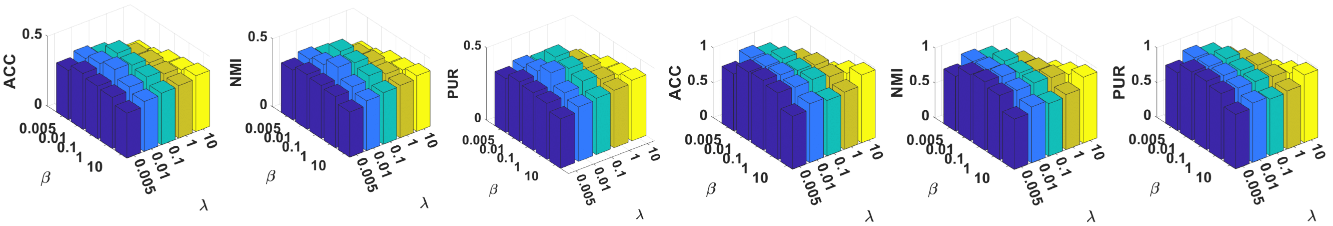
As shown in the Fig. 2, when both λ (geometric relationship consistency) and β (probability distribution consistency) are within the range of [0.01, 1.0], the model exhibits high stability across all three metrics (ACC, NMI, and PUR), indicating that minor perturbations in these hyper-parameters do not significantly affect performance and demonstrating strong generalization ability. When either parameter takes extreme values (such as < 0.005 or > 10), a marked decline in performance is observed, with cluster separation quality being most affected. This pattern is consistent across different datasets, underscoring the critical importance of balancing geometric structure and probability distribution in multi-view clustering. Notably, the performance curves change smoothly with parameter variation, without abrupt fluctuations, further confirming the robustness of our method and its flexibility in practical parameter selection. Moreover, the comparison between the two datasets reflects the universality of our model design and the robustness of its performance.

4.5 Ablation Studies

As shown in Table 2, we conduct comprehensive ablation studies on six benchmark datasets to thoroughly analyze the contribution of each module to the overall performance. The

Methods	COIL-20			RGB-D			BDGP			Scene-15			MNIST-USPS			Fashion		
	ACC	NMI	PUR	ACC	NMI	PUR	ACC	NMI	PUR	ACC	NMI	PUR	ACC	NMI	PUR	ACC	NMI	PUR
K-Means	67.20	78.92	69.72	39.96	36.38	54.11	57.72	47.43	57.72	36.10	36.99	39.40	49.66	44.33	51.70	48.79	48.79	53.66
BSVC	80.21	84.75	80.47	45.34	37.49	51.97	58.05	32.42	54.32	38.05	38.85	42.08	67.98	74.43	72.34	60.32	59.01	63.84
SC$_{Agg}$	73.13	78.46	73.89	44.17	35.10	54.73	38.13	55.71	70.72	39.31	39.31	44.76	89.00	77.12	89.18	98.00	94.80	97.56
EE-IMVC	75.73	83.52	75.76	39.75	27.99	51.62	88.00	71.76	87.76	39.00	33.02	40.27	76.00	68.04	76.48	84.00	79.53	84.45
ASR	80.90	87.60	81.50	23.95	16.94	39.13	97.68	92.63	97.68	42.70	40.17	45.61	97.90	87.72	97.91	96.52	89.94	96.52
CMVKL	32.85	48.00	36.04	21.19	11.20	31.54	77.68	82.99	77.68	31.10	29.31	33.09	50.68	46.04	52.44	57.37	54.50	59.00
DSIMVC	65.55	72.51	66.67	37.13	26.54	40.06	99.04	96.86	99.04	28.27	29.04	29.79	99.34	98.13	99.34	88.21	83.99	88.21
DCP	67.36	78.79	69.86	26.43	22.78	26.43	97.04	92.43	97.04	42.32	40.38	43.85	99.02	97.29	99.02	89.37	88.61	89.37
DSMVC	76.46	84.15	78.19	25.74	14.33	25.17	75.80	61.39	75.80	43.48	41.11	45.92	96.34	94.27	96.34	89.63	86.81	89.63
MFLVC	73.19	81.43	75.07	44.17	25.80	47.55	98.72	96.13	98.72	42.52	40.34	44.53	99.66	99.01	99.66	99.20	98.00	99.20
CVCL	84.65	88.89	85.07	59.52	32.39	48.40	99.20	97.29	99.20	44.59	42.17	47.36	99.70	99.13	99.70	99.31	98.21	99.31
ADMC	77.15	79.43	77.15	75.66	54.27	75.66	96.96	96.12	96.96	43.91	40.57	46.06	91.26	95.50	91.26	89.17	84.92	89.17
Our Method	**95.14**	**98.46**	**95.14**	**80.76**	**71.70**	**80.76**	**99.64**	**98.65**	**99.60**	**44.82**	**47.65**	**48.83**	**99.98**	**99.81**	**99.98**	**99.58**	**96.64**	**99.58**

Table 1: Clustering performance comparison results across all datasets. The optimal result for each metric is presented in boldface, while the second-best result is denoted with an underline.



(a) ACC (b) NMI (c) PUR (d) ACC (e) NMI (f) PUR

Figure 2: Parameter sensitivity analysis on Scene-15 and MNIST-USPS dataset visualized through 3D bar plots. The plots demonstrate how different combinations of λ and β affect the clustering performance metrics.

results clearly demonstrate that all three components $\mathcal{L}_{rec}$, $\mathcal{L}_{con}$, and $\mathcal{L}_{rl}$ are indispensable. With only the reconstruction loss, the model captures basic feature information but achieves limited clustering performance. Introducing the contrastive loss enables the model to better exploit discriminative structures across multiple views, resulting in significant performance gains. Further incorporating the reinforcement learning module leads to optimal results on all metrics, with particularly notable improvements on challenging datasets such as RGB-D and Scene-15. This indicates that the RL module dynamically adjusts clustering strategies and leverages the memory-enhanced mechanism to effectively mitigate the impact of noise and uncertain samples. It is also noteworthy that the contrastive loss plays a pivotal role; its removal causes a substantial drop in performance, underscoring the central importance of multi-view contrastive learning in our framework. Overall, the synergy among these three components not only boosts clustering accuracy but also enhances the model's generalization and robustness, fully validating the rationality and effectiveness of our design.

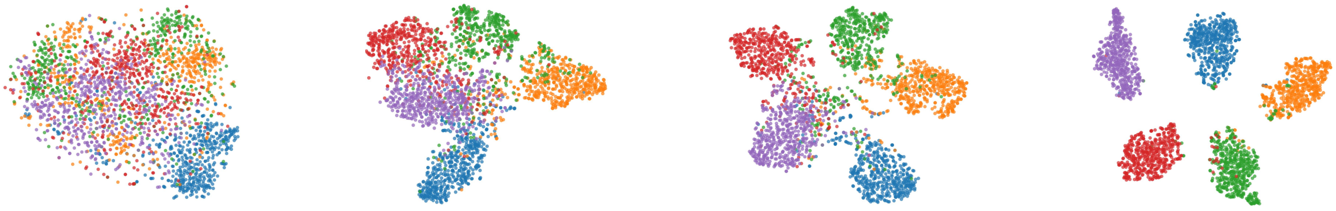
4.6 Visualization Analysis

Fig. 3 illustrates the evolution of feature distributions during the training process using t-SNE visualization. The initial raw features exhibit scattered and mixed clusters with significant overlap. As training progresses, our method gradually refines the feature space: the first stage shows initial cluster formation with reduced inter-cluster overlap, the second stage further enhances cluster separation, and the final stage demonstrates well-defined, compact clusters with clear boundaries. This progressive improvement validates our method's effectiveness in learning discriminative representations through the training process.

Fig. 5 presents a comprehensive comparison between our method and CVCL across six datasets. While maintaining comparable or superior accuracy (represented by bar charts), our method consistently requires significantly less computation time (shown by line plots). For instance, on the MNIST-USPS dataset, our method achieves higher accuracy while reducing the execution time. This substantial improvement in computational efficiency, without compromising clustering performance, demonstrates the practical advantages of our approach.

4.7 Convergence Analysis

Fig. 4 illustrates the convergence behavior of our method. As shown in Fig. 4(a), the training loss exhibits a rapid initial descent and steadily converges after approximately 40 epochs, while the computation time per epoch remains consistently low, demonstrating the computational efficiency of our approach. Notably, the computation time curve shows a slight downward trend, indicating that as the model learns, the reinforcement learning module can more efficiently select samples, reducing the number of uncertain samples that need processing. Fig. 4(b) reveals that both feature quality and class balance metrics improve consistently and stabilize after 60 epochs, validating the effectiveness of our framework in maintaining good feature discrimination while preserving



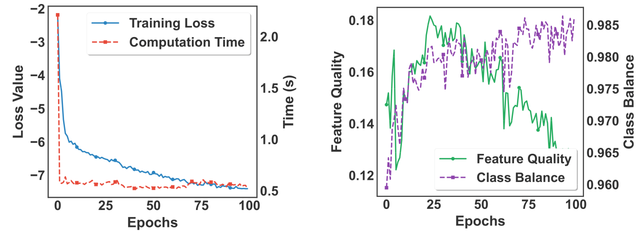
(a) Raw Features (b) 10 Epoch (c) 50 Epoch (d) 100 Epoch

Figure 3: t-SNE visualization of feature evolution on BDGP dataset, demonstrating how features gradually evolve from initial mixed clusters to well-separated final representations through our contrastive learning and feature quality assessment mechanism.

Dataset	$\mathcal{L}_{rec}$	$\mathcal{L}_{con}$	$\mathcal{L}_{rl}$	ACC	NMI	PUR
COIL-20	✓	×	×	73.28	85.15	73.28
	✓	✓	×	83.22	88.04	83.22
	✓	✓	✓	**95.14**	**98.46**	**95.14**
RGB-D	✓	×	×	51.48	23.43	51.48
	✓	✓	×	59.30	32.24	59.30
	✓	✓	✓	**80.76**	**71.70**	**80.76**
BDGP	✓	×	×	74.44	75.30	78.73
	✓	✓	×	97.31	92.65	97.31
	✓	✓	✓	**99.64**	**98.65**	**99.60**
Scene-15	✓	×	×	34.49	38.14	34.49
	✓	✓	×	37.22	40.17	36.58
	✓	✓	✓	**48.82**	**47.65**	**48.83**
MNIST-USPS	✓	×	×	88.01	93.88	88.01
	✓	✓	×	99.12	98.79	99.12
	✓	✓	✓	**99.98**	**99.81**	**99.98**
Fashion	✓	×	×	87.08	84.60	87.08
	✓	✓	×	97.13	94.31	97.13
	✓	✓	✓	**99.58**	**96.64**	**99.58**

Table 2: Ablation study results on six benchmark datasets. The symbols ✓ and × indicate whether each component is enabled: $\mathcal{L}_{rec}$, $\mathcal{L}_{con}$, and $\mathcal{L}_{rl}$.

balanced category distribution. Feature quality and class balance show a slight negative - correlation in fluctuations during optimization, yet both reach high stable levels, evidencing our RL strategy's success in multi - objective optimization.



(a) Loss&Time (b) Quality&Balance

Figure 4: Performance analysis: (a) Convergence of MSE loss during pre-training. (b) Evolution of feature quality and class balance, showing effective learning and balancing.

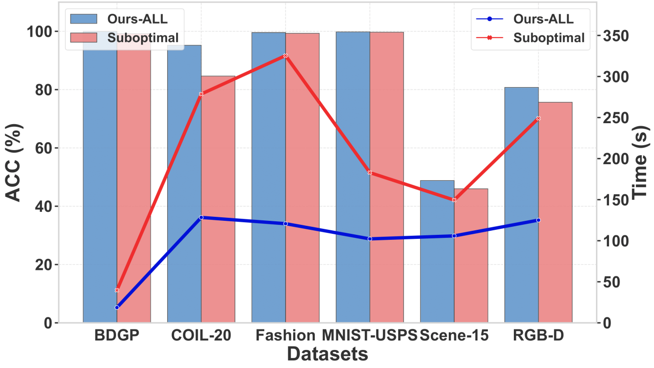


Figure 5: Performance and runtime comparison between our method and the previous best method on each dataset.

5 Conclusions

In this paper, we have presented EMVC-RCL, an innovative efficient multi-view clustering framework with reinforcement contrastive learning, which addresses two critical challenges in contrastive multi-view clustering: the difficulty in constructing high-quality positive and negative pairs, and the high computational overhead caused by static optimization strategies. Our framework introduces a reinforcement contrastive learning paradigm for dynamic clustering optimization, coupled with a memory-enhanced mechanism for efficient feature refinement. Through extensive experiments on six benchmark datasets, we have demonstrated that EMVC-RCL achieves superior clustering performance while requiring only 30% of the traditional training time, validating the effectiveness and efficiency of our approach in complex multi-view data analysis.

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