

# Novelty Assessment Report

**Paper:** Aligning Collaborative View Recovery and Tensorial Subspace Learning via Latent Representation for Incomplete Multi-View Clustering

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## Abstract

Multi-view data usually suffer from partially missing views in open scenarios, which inevitably degrades clustering performance. The incomplete multi-view clustering (IMVC) has attracted increasing attention and achieved significant success. Although existing imputation-based IMVC methods perform well, they still face one crucial limitation, i.e., view recovery and subspace representation lack explicit alignment and collaborative interaction in exploring complementarity and consistency across multiple views. To this end, this study proposes a novel IMVC method to Align collaborative view Recovery and tensorial Subspace Learning via latent representation (ARSL-IMVC). Specifically, the ARSL-IMVC infers the complete view from view-shared latent representation and view-specific estimator with Hilbert-Schmidt Independence Criterion regularizer, reshaping the consistent and diverse information intrinsically embedded in original multi-view data. Then, the ARSL-IMVC learns the view-shared and view-specific subspace representations from latent feature and recovered views, and models high-order correlations at the global and local levels in the unified low-rank tensor space. Thus, leveraging the latent representation as a bridge in a unified framework, the ARSL-IMVC seamlessly aligns the complementarity and consistency exploration across view recovery and subspace representation learning, negotiating with each other to promote clustering. Extensive experimental results on seven datasets demonstrate the powerful capacity of ARSL-IMVC in complex incomplete multi-view clustering tasks under various view missing scenarios.

### Disclaimer

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

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

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## Core Task Landscape

This paper addresses: **Incomplete multi-view clustering with missing views**

A total of **50 papers** were analyzed and organized into a taxonomy with **22 categories**.

### Taxonomy Overview

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

- **View Recovery and Imputation Approaches**
- **Imputation-Free Approaches**
- **Deep Learning Architectures**
- **Specialized Problem Settings**
- **Optimization and Efficiency Enhancements**

### Complete Taxonomy Tree

- Incomplete multi-view clustering with missing views Survey Taxonomy
- View Recovery and Imputation Approaches
  - Generative Model-Based Recovery
  - Diffusion-Based View Generation (3 papers)
    - [21] Incomplete multi-view clustering via diffusion completion (Sifan Fang, 2023) [View paper](#)
    - [25] Incomplete Multi-view Clustering via Diffusion Contrastive Generation (Ke, 2025) [View paper](#)
    - [40] Diffusion-based missing-view generation with the application on incomplete multi-view clustering (J Wen, 2024) [View paper](#)
  - GAN and VAE-Based Recovery (3 papers)
    - [9] Deep variational incomplete multi-view clustering: Exploring shared clustering structures (Gehui Xu, 2024) [View paper](#)
    - [18] Adversarial incomplete multi-view clustering. (Cai, 2019) [View paper](#)
    - [43] Partial multi-view clustering via consistent GAN (Qianqian Wang, 2018) [View paper](#)
  - Matrix Factorization and Subspace Learning
  - Latent Representation Alignment ★ (3 papers)
    - [0] Aligning Collaborative View Recovery and Tensorial Subspace Learning via Latent Representation for Incomplete Multi-View Clustering (Anon et al., 2026) [View paper](#)
    - [33] Unified tensor framework for incomplete multi-view clustering and missing-view inferring (Fei Lunke, 2021) [View paper](#)
    - [50] Unified embedding alignment with missing views inferring for incomplete multi-view clustering (Jie Wen, 2019) [View paper](#)
  - Direct Matrix Factorization (4 papers)
    - [1] Incomplete multi-view clustering with cosine similarity (J. Yin, 2022) [View paper](#)
    - [11] Incomplete multi-view clustering (Hang Gao, 2016) [View paper](#)
    - [23] Projective incomplete multi-view clustering (Shijie Deng, 2023) [View paper](#)
    - [44] Incomplete Multi-View Clustering With Reconstructed Views (J. Yin, 2021) [View paper](#)
  - Prototype-Based Recovery (2 papers)
  - [30] Robust prototype completion for incomplete multi-view clustering (Honglin Yuan, 2024) [View paper](#)
  - [49] Prototype Matching Learning for Incomplete Multi-View Clustering (Honglin Yuan, 2025) [View paper](#)
  - Multiple Imputation and Ensemble Strategies (1 papers)

- [10] Incomplete multi-view clustering with multiple imputation and ensemble clustering (Guoqing Chao, 2022) [View paper](#)
- Imputation-Free Approaches
  - Contrastive Learning-Based Methods (3 papers)
  - [2] Incomplete contrastive multi-view clustering with high-confidence guiding (Guoqing Chao, 2024) [View paper](#)
  - [4] Completer: Incomplete multi-view clustering via contrastive prediction (Yijie Lin, 2021) [View paper](#)
  - [13] Deep incomplete multi-view clustering with cross-view partial sample and prototype alignment (Jiaqi Jin, 2023) [View paper](#)
  - Graph-Based Fusion Methods
  - Anchor-Based Graph Learning (4 papers)
    - [3] Fast incomplete multi-view clustering with view-independent anchors (Suyuan Liu, 2022) [View paper](#)
    - [24] Scalable incomplete multi-view clustering with structure alignment (Wen Yi, 2023) [View paper](#)
    - [27] Incomplete multi-view clustering via efficient anchor tensor recovery framework. (Jintian Ji, 2025) [View paper](#)
    - [31] Incomplete Multi-View Clustering With Paired and Balanced Dynamic Anchor Learning (Xingfeng Li, 2025) [View paper](#)
  - Direct Graph Fusion (7 papers)
    - [14] Incomplete Multi-View Clustering With Sample-Level Auto-Weighted Graph Fusion (Naiyao Liang, 2023) [View paper](#)
    - [15] Incomplete multi-view clustering based on hypergraph (Jin Chen, 2024) [View paper](#)
    - [17] Partial multi-view clustering (Shao-Yuan Li, 2014) [View paper](#)
    - [26] Deep multi-view graph clustering with incomplete views (Kerou Chang, 2024) [View paper](#)
    - [35] Adaptive graph completion based incomplete multi-view clustering (Jie Wen, 2020) [View paper](#)
    - [39] Self-Completed Bipartite Graph Learning for Fast Incomplete Multi-View Clustering (Xiaojia Zhao, 2024) [View paper](#)
    - [46] Incomplete Multi-View Clustering with Regularized Hierarchical Graph (Shuping Zhao, 2023) [View paper](#)
  - Manifold and Structural Learning (2 papers)
  - [5] Manifold-based incomplete multi-view clustering via bi-consistency guidance (Wang Hui-bing, 2024) [View paper](#)
  - [20] Structural deep incomplete multi-view clustering network (Jie Wen, 2021) [View paper](#)
  - Mutual Information and Consistency Maximization (1 papers)
  - [34] Incomplete Multi-View Clustering via Mutual Information (Xuejiao Yu, 2025) [View paper](#)
- Deep Learning Architectures
  - View-Specific Encoder Architectures (2 papers)
  - [6] Deep safe incomplete multi-view clustering: Theorem and algorithm (H Tang, 2022) [View paper](#)
  - [12] Dimc-net: Deep incomplete multi-view clustering network (Jie Wen, 2020) [View paper](#)
  - Shared Representation Learning (2 papers)
  - [22] Partial Multi-View Clustering via Self-Supervised Network (Wei Feng, 2024) [View paper](#)
  - [38] Incomplete Multi-View Clustering Via Inference and Evaluation (Binqiang Huang, 2024) [View paper](#)
  - Distribution and Consistency Guidance (2 papers)
  - [29] Incomplete Multi-View Clustering With Complete View Guidance (Zhikui Chen, 2023) [View paper](#)
  - [32] Deep Incomplete Multi-view Clustering with Distribution Dual-Consistency Recovery Guidance (Jin Jiaqi, 2025) [View paper](#)
- Specialized Problem Settings
  - Fully Incomplete Information (3 papers)
  - [7] Robust multi-view clustering with incomplete information (Mouxing Yang, 2022) [View paper](#)
  - [16] Semantic invariant multi-view clustering with fully incomplete information (Pengxin Zeng, 2023) [View paper](#)
  - [48] Robust Multi-View Clustering With Noisy Correspondence (Yuan Sun, 2024) [View paper](#)
  - Continual and Streaming Data (1 papers)
  - [8] Fast continual multi-view clustering with incomplete views (Xinhang Wan, 2024) [View paper](#)
  - Federated and Distributed Settings (1 papers)
  - [19] A novel federated multi-view clustering method for unaligned and incomplete data fusion (Yazhou Ren, 2024) [View paper](#)
  - Evidential and Uncertainty-Aware Clustering (1 papers)
  - [41] Self-filling evidential clustering for partial multi-view data (Chaoyu Gong, 2023) [View paper](#)
  - Synthetic and Relational Data (1 papers)
  - [45] Synthetic multi-view clustering with missing relationships and instances (Jing Zhang, 2023) [View paper](#)
- Optimization and Efficiency Enhancements
  - Late Fusion Strategies (2 papers)
  - [37] Late fusion incomplete multi-view clustering (Xinwang Liu, 2018) [View paper](#)
  - [42] Latent structure-aware view recovery for incomplete multi-view clustering (Cheng Liu, 2024) [View paper](#)
  - Tensor-Based Optimization (1 papers)
  - [28] Between/within view information completing for tensorial incomplete multi-view clustering (Mingze Yao, 2024) [View paper](#)
  - Sample-Level Weighting and Adaptation (2 papers)
  - [36] Incomplete multi-view clustering via structure exploration and missing-view inference (Ziyu Wang, 2023) [View paper](#)
  - [47] From incompleteness to unity: A framework for multi-view clustering with missing values (Fangchen Yu, 2023) [View paper](#)

## Narrative

Core task: Incomplete multi-view clustering with missing views addresses the challenge of grouping data when some views are unavailable for certain samples. The field has evolved along several major branches that reflect different philosophies for handling missingness. View Recovery and Imputation Approaches attempt to reconstruct or fill in absent views through matrix factorization, subspace learning, or generative models, enabling downstream clustering on completed data. Imputation-Free Approaches sidestep explicit reconstruction by learning consensus representations directly from available views, often leveraging graph-based or anchor-based methods. Deep Learning Architectures introduce neural encoders and autoencoders to capture complex nonlinear patterns, while Specialized Problem Settings extend the core task to scenarios involving noisy correspondences, federated learning, or unaligned samples. Finally, Optimization and Efficiency Enhancements focus on scalable algorithms and continual learning strategies to handle large-scale or streaming data.

Within the View Recovery branch, a particularly active line of work centers on aligning latent representations across views to ensure that imputed features preserve semantic consistency. Collaborative View Recovery[0] exemplifies this direction by jointly learning view-specific embeddings and enforcing alignment constraints, aiming to produce coherent reconstructions even when missingness patterns are severe. This contrasts with earlier methods like Unified Embedding Alignment[50], which directly aligns embeddings without explicit imputation, and Unified Tensor Framework[33], which leverages tensor decomposition to capture higher-order correlations. A key trade-off in this space is between the fidelity of recovered views and the risk of propagating noise or artifacts into the clustering stage. Recent

efforts such as High-Confidence Guiding[2] and Bi-Consistency Guidance[5] address this by selectively weighting reliable samples during alignment, while View-Independent Anchors[3] offers a complementary strategy that reduces dependence on view-specific reconstructions altogether. Collaborative View Recovery[0] sits naturally among these latent alignment techniques, emphasizing cross-view collaboration to improve imputation quality while maintaining computational tractability.

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## Related Works in Same Category

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The following **2 sibling papers** share the same taxonomy leaf node with the original paper:

### 1. Unified tensor framework for incomplete multi-view clustering and missing-view inferring

**Authors:** Fei Lunke, Wen Jie, Xu Yong, Zhang Zheng, Zhang Zhao, et al. (7 authors total) | **Year/Venue:** 2021 | **URL:** [View paper](#)

#### Abstract

In this paper, we propose a novel method, referred to as incomplete multi-view tensor spectral clustering with missing-view inferring (IMVTS-CMVI) to address the challenging multi-view clustering problem with missing views. Different from the existing methods which commonly focus on exploring the certain information of the available views while ignoring both of the hidden information of the missing views and the intra-view information of data, IMVTS-CMVI seeks to recover the missing views and ex...

#### Relationship Analysis

Both papers belong to the Latent Representation Alignment category, unifying view recovery with subspace/latent representation learning in integrated frameworks. They overlap in using latent representations as bridges between view imputation and clustering, and both employ tensor-based methods to capture high-order correlations across views. The key difference is that the original paper (ARSL-IMVC) emphasizes collaborative interaction through HSIC-regularized view-specific estimators and tensorial subspace learning with explicit alignment via shared latent representation, while the candidate paper (IMVTS-CMVI) focuses on simultaneous feature-space missing-view inferring and manifold-space similarity graph learning unified through low-rank tensor constraints on multiple similarity graphs rather than subspace coefficients.

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### 2. Unified embedding alignment with missing views inferring for incomplete multi-view clustering

**Authors:** Jie Wen, Zheng Zhang, Yong Xu, Bob Zhang, Lunke Fei, et al. (6 authors total) | **Year/Venue:** 2019 | **URL:** [View paper](#)

#### Abstract

Multi-view clustering aims to partition data collected from diverse sources based on the assumption that all views are complete. However, such prior assumption is hardly satisfied in many real-world applications, resulting in the incomplete multi-view learning problem. The existing attempts on this problem still have the following limitations: 1) the underlying semantic information of the missing views is commonly ignored; 2) The local structure of data is not well explored; 3) The importance of...

#### Relationship Analysis

Both papers belong to the Latent Representation Alignment category, using latent representations to bridge view recovery and subspace learning in unified frameworks. The original paper (ARSL-IMVC) aligns collaborative view recovery with tensorial subspace learning through a shared latent representation, incorporating HSIC regularization for diversity and low-rank tensor constraints for high-order correlations. The candidate paper (UEAF) differs by focusing on locality-preserved reconstruction with Laplacian regularization for missing view inference and employs reverse graph regularization to guarantee consensus local structure, rather than tensor-based high-order modeling.

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## Contributions Analysis

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**Overall novelty summary.** The paper proposes a unified framework that aligns view recovery with tensorial subspace learning through shared latent representations, aiming to capture both consistency and diversity across incomplete views. It resides in the 'Latent Representation Alignment' leaf under 'Matrix Factorization and Subspace Learning', which contains only three papers total (including this one). This leaf represents a relatively focused research direction within the broader 'View Recovery and Imputation Approaches' branch, suggesting the paper targets a specific methodological niche rather than a densely populated area.

The taxonomy reveals that neighboring leaves include 'Direct Matrix Factorization' (four papers) and 'Prototype-Based Recovery' (two papers), both under the same parent node. Adjacent branches explore 'Generative Model-Based Recovery' (six papers across GAN/VAE and diffusion methods) and 'Multiple Imputation' strategies. The paper's emphasis on explicit alignment distinguishes it from direct factorization methods, while its reliance on latent representations rather than generative models or prototypes positions it at the intersection of subspace learning and collaborative imputation, a boundary clarified by the taxonomy's scope notes.

Among 29 candidates examined, the contribution-level analysis indicates substantial prior work overlap. The unified alignment framework (10 candidates examined, 3 refutable) and collaborative recovery mechanism (10 candidates, 2 refutable) both show evidence of overlapping ideas in the limited search scope. The tensorial subspace component (9 candidates, 4 refutable) appears to have the most prior work addressing high-order correlation modeling. These statistics suggest that within the examined literature, each core contribution encounters at least some papers proposing similar alignment, recovery, or tensor-based strategies.

Given the limited search scope of 29 candidates drawn from semantic similarity and citation expansion, the analysis captures a snapshot rather than an exhaustive field survey. The paper's position in a small taxonomy leaf with two siblings suggests it refines an established alignment paradigm rather than opening an entirely new direction. The refutability counts indicate that among the examined candidates, multiple works address overlapping subproblems, though the specific combination of alignment, collaborative recovery, and tensorial modeling may still offer incremental distinctions not fully captured by top-K retrieval.

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

### Contribution 1: Unified framework aligning view recovery and subspace learning via latent representation

**Description:** The method introduces a unified framework that explicitly aligns collaborative view recovery and tensorial subspace learning through a shared latent representation. This latent representation serves as a bridge to enable coherent cross-view semantic correlation exploration, facilitating interaction between view completion and clustering structure learning.

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

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#### 1. Tensorized multi-view subspace representation learning

**URL:** [View paper](#)

#### Brief Assessment

Tensorized Subspace[51] focuses on tensorized multi-view subspace representation learning without incomplete views, using low-rank tensor constraints to model high-order correlations. It does not address view recovery or missing data scenarios that are central to the original paper's contribution.

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## 2. A survey of multi-view representation learning

URL: [View paper](#)

### Brief Assessment

Survey Representation Learning[52] is a survey paper that reviews existing multi-view representation learning methods. It does not propose a novel unified framework for aligning view recovery and subspace learning. The survey discusses general alignment and fusion paradigms but does not present a specific method that would refute the original paper's novelty claim of explicitly aligning collaborative view recovery with tensorial subspace learning through shared latent representation.

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## 3. Fast Incomplete Multi-view Clustering with Adaptive Similarity Completion and Reconstruction

URL: [View paper](#)

### Brief Assessment

Adaptive Similarity Completion[58] focuses on anchor-based clustering with similarity graph completion, not on aligning view recovery and subspace learning through a shared latent representation as the bridge mechanism described in the original paper.

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## 4. Deep subspace clustering via latent representation learning

URL: [View paper](#)

### Brief Assessment

Cannot assess refutation as the candidate paper's full text context is marked as 'n/a', making comparison impossible.

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## 5. Latent multi-view subspace clustering

URL: [View paper](#)

### Prior Art Analysis

Latent Subspace[53] demonstrates that a unified framework aligning view recovery and subspace learning through latent representation was already proposed prior to the original paper. The candidate paper explicitly introduces a latent representation that serves as a bridge between multiple views and subspace clustering, learning both the latent representation from multi-view features and generating subspace representations simultaneously. The candidate integrates latent representation learning and multi-view subspace clustering in a unified optimization framework, where the latent representation facilitates data reconstruction and directly contributes to subspace learning - the same core mechanism claimed as novel in the original paper.

### Evidence

Evidence 1 - **Rationale:** Both papers describe learning latent representations from multi-view features and using them to generate subspace representations in a unified framework, demonstrating the same core approach. - **Original:** the arsl-imvc infers the complete view from view-shared latent representation and view-specific estimator with hilbert-schmidt independence criterion regularizer, reshaping the consistent and diverse information intrinsically embedded in original multi-view data. then, the arsl-imvc learns the view-... - **Candidate:** we propose the latent multi-view subspace clustering (lmsc) method. our proposed method learns the latent representation based on multi-view features, and generates a common subspace representation rather than that of individual view. moreover, our method integrates the latent representation learnin...

Evidence 2 - **Rationale:** The candidate paper explicitly describes using latent representation as a bridge to align view recovery and subspace learning in a unified framework, which is the exact mechanism claimed as novel in the original paper. - **Original:** leveraging the latent representation as a bridge in a unified framework, the arsl-imvc seamlessly aligns the complementarity and consistency exploration across view recovery and subspace representation learning, negotiating with each other to promote clustering - **Candidate:** based on this assumption, we propose the latent multi-view subspace clustering (lmsc) method. our proposed method learns the latent representation based on multi-view features, and generates a common subspace representation rather than that of individual view. moreover, our method integrates the lat...

Evidence 3 - **Rationale:** Both papers describe the dual role of latent representation: serving view reconstruction while contributing to subspace learning, demonstrating the same architectural principle. - **Original:** the latent representation not only serves as fictitious transitional factor for view reconstruction but also directly contributes to the subspace learning with structural awareness - **Candidate:** with the complementarity of multiple views, the latent representation could depict data themselves more comprehensively than each single view individually, accordingly makes subspace representation more accurate and robust as well

Evidence 4 - **Rationale:** The candidate paper's unified objective function explicitly shows the joint optimization of view recovery (lh term) and subspace learning (lr term) through shared latent representation h, demonstrating the same alignment mechanism claimed in the original paper. - **Original:** in eq.(6), the shared latent representationhnot only facilitates the joint optimization and collaborative interaction between view recovery and subspace learning but also serves as a semantic anchor that aligns the reconstructed views with corresponding subspace representations in capturing cross-vi... - **Candidate:** we integrate the latent representation learning in eq. (3) and subspace clustering in eq. (4) into one unified objective function, shown as follows  $\min p, h, z \text{ lh}(x, ph) + \lambda_1 \text{lr}(h, hz) + \lambda_2 \omega(z)$ , (5) where  $\lambda_1 > 0$  and  $\lambda_2 > 0$  balance the three terms. the subspace clustering is guaranteed by the reasona...

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## 6. Flexible multi-view representation learning for subspace clustering.

URL: [View paper](#)

### Prior Art Analysis

Flexible Representation[55] demonstrates that prior work exists on using latent representations to bridge view recovery and subspace learning. The candidate paper proposes a flexible multi-view representation (FMR) learning method that constructs a latent representation to facilitate subspace clustering, explicitly stating that this latent representation serves as a bridge between multiple views and subspace representation. The candidate uses HSIC (Hilbert-Schmidt Independence Criterion) to drive the latent representation to be close to different views, and then conducts subspace clustering on this latent representation. This approach directly addresses the alignment of view information and subspace learning through a shared latent representation, which is the core claim of the original paper's contribution.

### Evidence

Evidence 1 - **Rationale:** Both papers use a latent representation as a bridge to connect multiple views with subspace learning. The candidate explicitly describes constructing a latent representation that is close to different views and well-adapted to subspace clustering, which parallels the original's claim of using latent representation to align view recovery and subspace learning. - **Original:** the arsl-imvc infers the complete view from view-shared latent representation and view-specific estimator with hilbert-schmidt independence criterion regularizer, reshaping the consistent and diverse information intrinsically embedded in original multi-view data. then, the arsl-imvc learns the view-... - **Candidate:** we propose to conduct subspace clustering based on flexible multi-view representation (fmr) learning, which avoids using partial information for data reconstruction. the latent representation is flexibly constructed by enforcing it to be close to different views, which implicitly makes it more compre...

Evidence 2 - **Rationale:** Both papers formulate unified objective functions where the latent representation h serves as the bridge between view information (through HSIC terms) and subspace representation (through the constraint  $h = hz + e$ ). This demonstrates prior work on aligning view recovery and subspace learning through latent representation. - **Original:** the information flow propagation

enables coherent cross-view semantic correlation exploration, promoting the clustering quality for complex imvc task - **Candidate:** the latent representation is more comprehensive than any single view due to the encoded complementary information. we conduct subspace clustering on it and obtain the total objective function as follows:  $\min_{h,z,e} \sum_v \sum_{v=1} \text{vhsic}(x(v);h) + 1jzjj + 2jjejj; 1 \text{ s:t:h} = hz + e$

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## 7. Incomplete Multi-view Clustering via Hierarchical Semantic Alignment and Cooperative Completion

URL: [View paper](#)

### Brief Assessment

Hierarchical Semantic Alignment[54] focuses on hierarchical semantic alignment with dual-level semantic spaces and dynamic weighted fusion for incomplete multi-view clustering, rather than explicitly aligning view recovery and tensorial subspace learning through a shared latent representation as described in the original paper.

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## 8. A Novel Approach for Effective Partially View-Aligned Clustering with Triple-Consistency

URL: [View paper](#)

### Brief Assessment

Triple-Consistency[59] focuses on partially view-aligned clustering without view recovery or imputation, using structural consistency features and contrastive learning. The original paper's unified framework for aligning view recovery with subspace learning via latent representation addresses a different problem (incomplete multi-view clustering with missing views).

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## 9. Robust tensor subspace learning for incomplete multi-view clustering

URL: [View paper](#)

### Prior Art Analysis

Robust Tensor Subspace[56] demonstrates that the concept of using latent representations to bridge view recovery and subspace learning was already established in prior work. The candidate paper explicitly describes recovering missing samples through matrix factorization, then using this recovered information for latent representation learning, which is subsequently organized into tensors for subspace learning. This shows that the alignment of view recovery and subspace learning through latent representations is not novel to the original paper.

### Evidence

Evidence 1 - **Rationale:** Both papers describe a sequential process where view recovery is followed by latent representation learning, which then feeds into subspace learning. The candidate explicitly states that recovered information is used for latent representation learning, demonstrating the same bridging concept claimed as novel in the original paper. - **Original:** the arsl-imvc infers the complete view from view-shared latent representation and view-specific estimator with hilbert-schmidt independence criterion regularizer, reshaping the consistent and diverse information intrinsically embedded in original multi-view data. then, the arsl-imvc learns the view-... - **Candidate:** the missing samples within views are first recovered by matrix factorization. the recovered information is utilized for latent representations learning. and then, the obtained latent representations are organized from all views into a third-order tensor and the intrinsic sample relations are capture...

Evidence 2 - **Rationale:** Both papers describe a unified framework where view recovery and subspace learning interact to improve clustering performance. The candidate's statement about simultaneously handling missing samples and exploiting correlations demonstrates the same alignment concept. - **Original:** leveraging the latent representation as a bridge in a unified framework, the arsl-imvc seamlessly aligns the complementarity and consistency exploration across view recovery and subspace representation learning, negotiating with each other to promote clustering. - **Candidate:** our model can simultaneously handle the missing samples and exploit the intrinsic correlations, leading to enhanced representation capability and better quality of the recovered data.

Evidence 3 - **Rationale:** The candidate paper demonstrates that latent representations serve as an intermediary between view recovery and tensor-based subspace learning, showing the same bridging mechanism claimed in the original paper. - **Original:** the shared latent representation not only facilitates the joint optimization and collaborative interaction between view recovery and subspace learning but also serves as a semantic anchor that aligns the reconstructed views with corresponding subspace representations in capturing cross-view compleme... - **Candidate:** the missing samples within views are first recovered by matrix factorization. the recovered information is utilized for latent representations learning. and then, the obtained latent representations are organized from all views into a third-order tensor

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## 10. Low-rank kernel tensor learning for incomplete multi-view clustering

URL: [View paper](#)

### Brief Assessment

Low-Rank Kernel Tensor[60] focuses on kernel-based incomplete multi-view clustering using tensor nuclear norm constraints for kernel imputation, not on aligning view recovery and subspace learning through latent representations in feature space.

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## Contribution 2: Collaborative view recovery with consistency-diversity modeling

**Description:** The method infers complete views from a view-shared latent representation and view-specific estimators with HSIC regularization, reshaping consistent and diverse information across multiple views. This approach ensures reconstruction fidelity while encouraging diversity among recovered views.

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

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### 1. Soft label collaborative view consistency enhancement with application to incomplete multi-view clustering

URL: [View paper](#)

#### Brief Assessment

Soft Label Consistency[67] focuses on soft-label based view information interaction and collaborative imputation using transformer encoders, rather than the HSIC-regularized view-shared latent representation with view-specific estimators proposed in the original paper.

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### 2. Deep Incomplete Multi-view Clustering with Distribution Dual-Consistency Recovery Guidance

URL: [View paper](#)

#### Brief Assessment

Distribution Dual-Consistency[32] focuses on cross-view distribution transfer using flow-based models for incomplete multi-view clustering, not on collaborative view recovery with HSIC-based consistency-diversity modeling as in the original paper.

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### 3. UMCGL: Universal multi-view consensus graph learning with consistency and diversity

URL: [View paper](#)

#### Brief Assessment

UMCGL[65] focuses on graph learning with original and generative graphs for multi-view clustering, not on view recovery from missing data. The original paper addresses incomplete multi-view clustering with missing samples, while UMCGL[65] handles diversity challenges in complete multi-view graph data.

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#### 4. Incremental multi-view clustering: Exploring stream-view correlations to learn consistency and diversity

URL: [View paper](#)

##### Brief Assessment

Incremental Stream-View[62] addresses incremental multi-view clustering with streaming views, focusing on preserving consistency and diversity information across sequentially arriving views. The original paper addresses incomplete multi-view clustering where views are partially missing, using HSIC regularization for diversity in view recovery. These are fundamentally different problem settings and technical approaches.

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#### 5. Manifold-based incomplete multi-view clustering via bi-consistency guidance

URL: [View paper](#)

##### Prior Art Analysis

Bi-Consistency Guidance[5] demonstrates that prior work exists on collaborative view recovery with consistency-diversity modeling in incomplete multi-view clustering. Both papers propose methods that recover missing views from a shared latent representation while explicitly modeling consistency and diversity across views. The original paper uses HSIC regularization to encourage diversity among recovered views, while Bi-Consistency Guidance[5] employs reverse regularization and manifold embedding to balance consistency and diversity. Both methods integrate view recovery with representation learning in a unified framework, showing that the core concept of collaborative view recovery with consistency-diversity modeling was not first introduced by the original paper.

##### Evidence

Evidence 1 - **Rationale:** Both papers recover missing views from a shared/consensus representation while explicitly modeling consistency information across views, demonstrating prior work on this concept. - **Original:** the arsl-ilmv infers the complete view from view-shared latent representation and view-specific estimator with hilbert-schmidt independence criterion regularizer, reshaping the consistent and diverse information intrinsically embedded in original multi-view data. - **Candidate:** mimb first recovers the missing instances for all the views. then, mimb utilizes biconsistency guidance for the consensus representation, which can explore the latent consistency from the recovered data.

Evidence 2 - **Rationale:** Both methods introduce specific regularization terms (HSIC vs. inverse regularization) to ensure recovered views maintain both consistency and diversity/complementary information during the recovery process. - **Original:** to improve the freedom of view recovery, view-specific feature estimator  $v_1$  is introduced and thus the view reconstruction is formulated, i.e.,  $p_{vh+e} v_1$  (1) further, to ensure that the various recovered views retain sufficient complementary information, the hilbert-schmidt independence criterion (... - **Candidate:** mimb proposes a unique recovery-based incomplete multi-view clustering framework that utilizes consensus representation learning and inverse regularization as biconsistency guidance to recover incomplete views and to explore more consistent information. in addition, mimb also embeds the manifold str...

Evidence 3 - **Rationale:** Both papers explicitly address the consistency-diversity trade-off in view recovery through specialized regularization terms, showing this is not a novel contribution of the original paper. - **Original:** the hsic term penalize the dependence between the various reconstruction views, thereby encouraging diversity and informativeness among them in the feature level. to explore the consistency-diversity and ensure the reconstruction quality, the cvr module is formulated - **Candidate:** Different from the existing methods, mimb takes the disparity in distributions between the recovered missing data and existing data into consideration to ensure the effectiveness of the recovered data, and explores the consistency information from multiple views with reverse regularization.

Evidence 4 - **Rationale:** Both papers propose unified frameworks that simultaneously perform view recovery and representation learning while explicitly modeling consistency across views through shared representations. - **Original:** this study unifies collaborative view completion and tensorial subspace learning, and breaks the gap between them in complementarity and consistency modeling by shared latent representation. - **Candidate:** mimb first utilizes a recovery-based matrix factorization approach to simultaneously recover the incomplete instances and learn a consensus representation. then, mimb takes the correction between the recovered data and original data into consideration through reverse representation regularization of...

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#### 6. Balancing Complementarity and Consistency via Delayed Activation in Incomplete Multi-view Clustering

URL: [View paper](#)

##### Brief Assessment

Delayed Activation[66] focuses on balancing complementarity and consistency through delayed activation mechanisms in dual networks, while the original paper uses HSIC regularization with view-shared latent representations and view-specific estimators for collaborative view recovery.

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#### 7. MCoCo: Multi-level Consistency Collaborative Multi-view Clustering

URL: [View paper](#)

##### Brief Assessment

MCoCo[64] focuses on multi-level consistency in semantic and feature spaces for complete multi-view clustering, not on view recovery from incomplete data with consistency-diversity modeling via HSIC regularization.

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#### 8. Latent structure-aware view recovery for incomplete multi-view clustering

URL: [View paper](#)

##### Brief Assessment

Latent Structure-Aware[42] focuses on view recovery through discriminative latent representations with graph-based structural information and consistency diffusion, rather than the HSIC-regularized diversity modeling approach used in the original paper.

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#### 9. Collaborative Similarity Fusion and Consistency Recovery for Incomplete Multi-view Clustering

URL: [View paper](#)

##### Brief Assessment

Collaborative Similarity Fusion[61] focuses on similarity graph learning and sample-level recovery guided by fused graphs, not on view recovery from latent representations with HSIC-based diversity regularization as in the original paper.

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#### 10. Feature Space Recovery for Efficient Incomplete Multi-View Clustering

URL: [View paper](#)

##### Prior Art Analysis

Feature Space Recovery[63] demonstrates prior work on view recovery with consistency-diversity modeling in incomplete multi-view clustering. Both papers employ similar mechanisms: inferring complete views from latent representations with view-specific estimators

while enforcing diversity constraints. The candidate uses low-rank feature space recovery with projection matrices and Frobenius norm minimization, while the original uses HSIC regularization. Both methods explicitly model consistency through shared latent representations and diversity through view-specific components, with the candidate's approach predating or being contemporaneous with the original's submission.

#### Evidence

Evidence 1 - **Rationale:** Both papers propose unified frameworks for view recovery with consistency learning, demonstrating that the concept of integrating view recovery with consistency modeling was already established in Feature Space Recovery[63]. - **Original:** the arsl-imvc infers the complete view from view-shared latent representation and view-specific estimator with hilbert-schmidt independence criterion regularizer, reshaping the consistent and diverse information intrinsically embedded in original multi-view data - **Candidate:** we first propose a feature space recovery based imvc (fsr-imvc) method, where low-rank feature space recovery and low-rank tensor ring based consistency learning are considered into a unified framework

Evidence 2 - **Rationale:** Both formulations show view recovery from latent representations ( $h, hv$ ) using projection matrices ( $pv$ ) with orthogonality constraints. The candidate's formulation demonstrates that this approach to collaborative view recovery existed prior to the original paper. - **Original:** the cvr module is formulated as follows:  $\min_{h,p} \sum_v \sum_x w=1; \hat{w}=v \text{hsic}(ev \ 1, e \ w \ 1) \text{ s.t. } xv = (pvh + e \ v \ 1)wv, (p \ v)t \ pv = i$  - **Candidate:**  $\min \{ev, zv, pv, hv, xv\} v=1 \varphi(z) + \sum_v \sum_x \gamma \ 2 \|hv\|_2^2 f + \lambda \|ev\|_1 \text{ s. t. } xv = pvhv + ex \ v, hv = hvzv + eh \ v, pt \ v \ pv = ik$

Evidence 3 - **Rationale:** Both methods explicitly model view recovery quality through constraints on reconstruction. The candidate's approach to ensuring reconstruction quality through low-rank constraints demonstrates prior work on this concept. - **Original:** to explore the consistency-diversity and ensure the reconstruction quality, the cvr module is formulated as follows:  $\min_{h,p} \sum_v \sum_x w=1; \hat{w}=v \text{hsic}(ev \ 1, e \ w \ 1) \text{ s.t. } xv = (pvh + e \ v \ 1)wv$  - **Candidate:** according to corollary 1,  $\min \{hv, pv\} v=1 \gamma \ 2 \|hv\|_2^2 f, \text{ s. t. } xv = pvhv + ex \ v, pt \ v \ pv = ik$  depicts the low-rank property of the recovered feature spaces  $xv, pt \ v \ pv = ik$  means the feature spaces are projected onto discriminating subspaces

Evidence 4 - **Rationale:** While the specific diversity regularization differs (HSIC vs. low-rank constraints), both papers demonstrate the concept of enforcing diversity among recovered views through regularization terms, with the candidate showing this approach was already established. - **Original:** the hilbert-schmidt independence criterion (hsic) is introduced as diversity regularizer between any estimator pair  $v \ 1$  and  $w \ 1$  - **Candidate:** the latent feature subspace  $hv$  simultaneously learns the correlations of inter/intra-view and sample features through the updated  $cv$  and the lowrank structure of  $xv$ , for recovering the feature space  $xv$ . in turn, the anchor graph tensor  $c$  is adaptively updated from  $hv, v=1, \dots, v$ , and low-rank  $tr \dots$

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### Contribution 3: Tensorial subspace learning with high-order correlation modeling

**Description:** The method learns view-shared and view-specific subspace representations from latent features and recovered views, organizing them into a unified low-rank tensor space. This enables modeling of high-order correlations at both global and local levels, facilitating multi-level structural information interaction.

This contribution was assessed against **9 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### 1. Tensor-based adaptive consensus graph learning for multi-view clustering

URL: [View paper](#)

##### Prior Art Analysis

Adaptive Consensus Graph[69] demonstrates that tensorial approaches for modeling high-order correlations across multiple views were already established prior to the original paper. Both papers stack view-specific representations into a unified tensor structure to capture high-order correlations. The candidate explicitly states that representation matrices from multiple views are stacked into a representation tensor to reveal high-order connections, and applies tensor nuclear norm constraints to maintain low-rank properties—techniques that directly parallel the original paper's claimed novel contribution of organizing view-shared and view-specific representations into a unified low-rank tensor space for high-order correlation modeling.

#### Evidence

Evidence 1 - **Rationale:** Both papers use the same fundamental approach: stacking multiple view representations into a tensor structure and applying low-rank constraints to model high-order correlations. The candidate's method of stacking representation matrices into a tensor to reveal high-order connections directly corresponds to the original's claim of organizing representations into a unified low-rank tensor space. - **Original:** the arsl-imvc learns the view-shared and view-specific subspace representations from latent feature and recovered views, and models high-order correlations at the global and local levels in the unified low-rank tensor space - **Candidate:** all representation matrices of multiple views are stacked into a representation tensor to reveal high-order connections among multiple views. a weighted tensor nuclear norm is imposed on representation tensor to maintain property of low-rank

Evidence 2 - **Rationale:** The candidate explicitly describes stacking multiple view representations into a tensor to capture high-order connections, which is the core mechanism claimed as novel in the original paper for modeling high-order correlations through tensorial subspace learning. - **Original:** the arsl-imvc learns the view-shared and view-specific subspace representations from latent feature and recovered views, and models high-order correlations at the global and local levels in the unified low-rank tensor space - **Candidate:** specifically, all representation matrices of multiple views are stacked into a representation tensor to reveal high-order connections among multiple views

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#### 2. Hyperspectral images super-resolution via learning high-order coupled tensor ring representation

URL: [View paper](#)

##### Brief Assessment

Coupled Tensor Ring[75] focuses on hyperspectral image super-resolution by fusing low-resolution HSI with high-resolution MSI through shared latent core tensors, not on multi-view clustering with view-shared and view-specific subspace representations for incomplete data scenarios.

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#### 3. Multiview tensor spectral clustering via co-regularization

URL: [View paper](#)

##### Brief Assessment

Co-Regularization[74] focuses on graph-based multi-view clustering with high-order affinities for HDLSS data, not on tensorial subspace learning with latent representation for incomplete multi-view clustering. The technical approaches and problem settings differ fundamentally.

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#### 4. Robust Multi-view Clustering via Graph-oriented High-order Correlations Learning

URL: [View paper](#)

##### Brief Assessment

Graph-Oriented High-Order[76] focuses on graph-based clustering with Tucker decomposition for denoising similarity matrices, not on subspace representation learning from latent features and recovered views as in the original paper's incomplete multi-view clustering framework.

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## 5. Robust tensor subspace learning for incomplete multi-view clustering

URL: [View paper](#)

### Prior Art Analysis

Robust Tensor Subspace[56] explicitly describes organizing latent representations from all views into a third-order tensor and using tensor nuclear norm to capture high-order connections among views. This demonstrates that tensorial subspace learning with high-order correlation modeling across views was already established in prior work, refuting the novelty claim of the original paper.

### Evidence

Evidence 1 - **Rationale:** Both papers describe organizing representations into tensors and using low-rank tensor constraints to model high-order correlations across views. The candidate explicitly mentions capturing high-order connections among views through tensor nuclear norm. - **Original:** the arsl-imvc learns the view-shared and view-specific subspace representations from latent feature and recovered views, and models high-order correlations at the global and local levels in the unified low-rank tensor space. - **Candidate:** the obtained latent representations are organized from all views into a third-order tensor and the intrinsic sample relations are captured with tensor linear representation. moreover, a low-rank sample coefficient tensor is sought to capture high-order connections among views by imposing the tensor ...

Evidence 2 - **Rationale:** Both papers use tensor nuclear norm (denoted as  $\|z\|_{\otimes}$  in the original) to enforce low-rank structure on tensors constructed from multiple views, demonstrating the same approach to high-order correlation modeling. - **Original:** both shared and specific subspace representations into a unified low-rank tensor. thus, the tsl module is formulated as follows:  $\min_{z, z_v, e_h, e_v} \|z\|_{\otimes} + \lambda \sum_{h,p} (\|e_h\|_{2,1} + \sum_{v=1}^p \|e_v\|_{2,1})$  s.t.  $h = hz + e_h, p \quad v_h + e_v \quad 1 = (p v_h + e_v \quad 1) z v + e_v \quad 2, z = \varphi(z \quad 1, z \quad 2, \dots, z \quad v, z)$  - **Candidate:** the obtained latent representations are organized from all views into a third-order tensor and the intrinsic sample relations are captured with tensor linear representation. moreover, a low-rank sample coefficient tensor is sought to capture high-order connections among views by imposing the tensor ...

Evidence 3 - **Rationale:** Both papers emphasize that tensor-based approaches can capture correlations both within and across views, demonstrating the same multi-level structural information modeling claimed in the original paper. - **Original:** in the low-rank tensor space, the high-order cross-view correlations at different levels be effectively captured, facilitating semantic alignment across diverse views and achieving collaborative interaction between local and global structural information. - **Candidate:** compared with traditional learning paradigms in the vector space, the sample relations within each view as well as across views could be preserved with the aid of robust tensor subspace learning.

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## 6. Essential tensor learning for multi-view spectral clustering

URL: [View paper](#)

### Brief Assessment

Essential Tensor[73] focuses on spectral clustering via Markov chain transition probability matrices organized into tensors, not on subspace learning from latent features and recovered views for incomplete multi-view clustering as in the original paper.

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## 7. Low-rank tensor based proximity learning for multi-view clustering

URL: [View paper](#)

### Prior Art Analysis

Proximity Learning[68] demonstrates that tensorial approaches for modeling high-order correlations across multiple views existed prior to the original paper. Both papers organize view-specific representations into a unified low-rank tensor space to capture higher-order correlations. The candidate explicitly states it addresses 'neglecting the comprehensiveness and deeper higher-order correlations among multiple views' by stacking 'multiple affinity representations in a low-rank constrained tensor to recover their comprehensiveness and higher-order correlations.' This directly parallels the original paper's claim of learning 'view-shared and view-specific subspace representations' and modeling 'high-order correlations at the global and local levels in the unified low-rank tensor space.'

### Evidence

Evidence 1 - **Rationale:** Both papers use low-rank tensor structures to model higher-order correlations across views. The candidate explicitly addresses the same technical challenge of capturing 'higher-order correlations' through tensor-based methods, demonstrating prior work in this area. - **Original:** the arsl-imvc learns the view-shared and view-specific subspace representations from latent feature and recovered views, and models high-order correlations at the global and local levels in the unified low-rank tensor space. - **Candidate:** multiple affinity representations are stacked in a low-rank constrained tensor to recover their comprehensiveness and higher-order correlations.

Evidence 2 - **Rationale:** The candidate paper identifies the problem of neglecting higher-order correlations as a gap in existing work, then proposes tensor-based solutions. This shows the concept of using tensors for higher-order correlation modeling was already established in the field before the original paper. - **Original:** the view-shared and view-specific subspace representations from latent feature and recovered views, and models high-order correlations at the global and local levels in the unified low-rank tensor space. - **Candidate:** they target at studying a common representation or pairwise correlations between views, neglecting the comprehensiveness and deeper higher-order correlations among multiple views.

Evidence 3 - **Rationale:** Both papers employ unified low-rank tensor frameworks to capture multi-level structural information. The candidate's approach of jointly studying multiple representations in a unified tensor framework demonstrates the same core methodology claimed as novel by the original paper. - **Original:** both shared and specific subspace representations into a unified low-rank tensor. thus, the high-order cross-view correlations at different levels be effectively captured, facilitating semantic alignment across diverse views and achieving collaborative interaction between local and global structural... - **Candidate:** we propose a novel low-rank tensor based proximity learning (ltbpl) approach for multi-view clustering, where multiple low-rank probability affinity matrices and consensus indicator graph reflecting the final performances are jointly studied in a unified framework.

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## 8. Tensorial multi-view clustering via low-rank constrained high-order graph learning

URL: [View paper](#)

### Brief Assessment

High-Order Graph Learning[70] focuses on learning Laplacian graphs and stacking them into tensors for graph-based clustering, while the original paper learns view-shared and view-specific subspace representations from latent features and recovered views in incomplete multi-view scenarios. The technical approaches and problem settings differ fundamentally.

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## 9. Elastic multi-view subspace clustering with pairwise and high-order correlations

URL: [View paper](#)

### Prior Art Analysis

Elastic Pairwise[71] demonstrates that tensorial subspace learning with high-order correlation modeling was proposed prior to the original paper. Both papers organize multi-view representations into a unified low-rank tensor space to model high-order correlations. The candidate explicitly states it 'collects multi-view similarity matrices into a tensor and utilizes the low-rank tensor norm to exploit the high-order correlation among different views,' which directly parallels the original paper's claim of organizing 'view-shared and view-specific subspace representations' into 'a unified low-rank tensor space' to model 'high-order correlations at both global and local levels.'

#### Evidence

Evidence 1 - **Rationale:** Both papers describe organizing multi-view representations into a unified low-rank tensor structure to model high-order correlations, demonstrating that this approach existed in prior work. - **Original:** the arsl-imvc learns the view-shared and view-specific subspace representations from latent feature and recovered views, and models high-order correlations at the global and local levels in the unified low-rank tensor space. - **Candidate:** e-escs collects multi-view similarity matrices into a tensor and utilizes the low-rank tensor norm to exploit the high-order correlation among different views.

Evidence 2 - **Rationale:** Both papers formulate the problem of learning shared and specific representations in a unified framework using tensor-based optimization, showing the candidate proposed this methodology earlier. - **Original:** both shared and specific subspace representations into a unified low-rank tensor. thus, the tsl module is formulated as follows:  $\min_{z, z_v, e_h, e_v} \|z\|_{\otimes} + \lambda_1 (\|e_h\|_{2,1} + \|e_v\|_{2,1})$  s.t.  $h = z + e_h$ ,  $p = z + e_v$ ,  $1 = (p + e_v)z$ ,  $z = \phi(z_1, z_2, \dots, z_v, z)$  - **Candidate:** escs simultaneously explores the pairwise and high-order correlations among different views, resulting in a more comprehensive shared representation. escs formulates these two kinds of correlations into a unified objective framework, which are able to be jointly optimized to refine each other.

Evidence 3 - **Rationale:** The candidate explicitly identifies the problem of modeling high-order correlations and proposes a solution, establishing prior work in this area before the original paper. - **Original:** in the low-rank tensor space, the high-order cross-view correlations at different levels be effectively captured, facilitating semantic alignment across diverse views and achieving collaborative interaction between local and global structural information. - **Candidate:** however, the existing multi-view clustering methods fail to simultaneously consider the pairwise and high-order correlations among different views in the process of obtaining the final results. in this article, we propose the elastic multi-view subspace clustering with pairwise and high-order correl...

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## Appendix: Text Similarity Detection

Textual similarity detection checked 31 papers and found 2 similarity segment(s) across 2 paper(s).

The following **2 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

### 1. Unified embedding alignment with missing views inferring for incomplete multi-view clustering

**Detected in:** Core Task (sibling)

△ **Note:** This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

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### 2. Tensorized multi-view subspace representation learning

**Detected in:** Contribution: contribution\_1

△ **Note:** This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

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- [1] Incomplete multi-view clustering with cosine similarity [View paper](#)
- [2] Incomplete contrastive multi-view clustering with high-confidence guiding [View paper](#)
- [3] Fast incomplete multi-view clustering with view-independent anchors [View paper](#)
- [4] Completer: Incomplete multi-view clustering via contrastive prediction [View paper](#)
- [5] Manifold-based incomplete multi-view clustering via bi-consistency guidance [View paper](#)
- [6] Deep safe incomplete multi-view clustering: Theorem and algorithm [View paper](#)
- [7] Robust multi-view clustering with incomplete information [View paper](#)
- [8] Fast continual multi-view clustering with incomplete views [View paper](#)
- [9] Deep variational incomplete multi-view clustering: Exploring shared clustering structures [View paper](#)
- [10] Incomplete multi-view clustering with multiple imputation and ensemble clustering [View paper](#)
- [11] Incomplete multi-view clustering [View paper](#)
- [12] Dimc-net: Deep incomplete multi-view clustering network [View paper](#)
- [13] Deep incomplete multi-view clustering with cross-view partial sample and prototype alignment [View paper](#)
- [14] Incomplete Multi-View Clustering With Sample-Level Auto-Weighted Graph Fusion [View paper](#)
- [15] Incomplete multi-view clustering based on hypergraph [View paper](#)
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- [32] Deep Incomplete Multi-view Clustering with Distribution Dual-Consistency Recovery Guidance [View paper](#)

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