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Incomplete Multi-View Clustering based on Semi-Definite Constraint and Tensor Low-Rank Learning

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Abstract

Incomplete Multi-View Clustering (IMVC) faces significant challenges in preserving high-order correlations and the Positive Semi-Definite (PSD) property of missing kernels. This paper proposes a novel approach, a unified framework that simultaneously performs kernel completion and consensus graph learning. The method leverages tensor low-rank constraints to capture global consistency across views and explicitly enforces a strict PSD constraint to ensure kernel validity. An efficient Augmented Lagrangian Multiplier (ALM)-based algorithm is developed to solve the optimization problem. Experimental results demonstrate the superiority of the method over state-of-the-art methods.

Keywords

Incomplete views; Tensor Low-Rank Learning; Semi-Definite Constraint

1. Introduction

Multi-view clustering (MVC) has emerged as a fundamental research topic in machine learning, aiming to partition data by fusing complementary information from heterogeneous representations, such as visual signals, audio tracks, or text[1][2][3]. Conventional MVC approaches typically rely on the strict assumption that all instances are fully observed across all views, establishing a one-to-one correspondence that facilitates information alignment[1]. However, in practical applications, this assumption is frequently violated due to sensor failures, transmission errors, or privacy restrictions[10]. This scenario, known as IMVC, poses a significant challenge: the absence of sample correspondence in missing views makes it difficult to directly measure consensus across views[4][15][17]. Simple imputation methods like zero-filling often introduce noise, necessitating more robust solutions[21].

To tackle the IMVC problem, numerous algorithms have been proposed, broadly categorized into subspace-based[8] and matrix-completion-based methods[5][16]. While effective, most existing approaches rely on pairwise correlations or treat views independently, failing to fully exploit the high-order correlations embedded in multi-view data. Recently, tensor-based learning has shown promise in modeling such high-order structures by stacking similarity matrices into a tensor and leveraging tensor norms[6]. However, applying tensor completion to kernel-based clustering introduces a critical bottleneck: the PSD property. A valid kernel matrix must be positive semi-definite. Standard tensor completion methods typically relax this constraint or rely on post-processing projections, which destroy the theoretical validity of the kernels and lead to suboptimal clustering performance.

To address the neglect of high-order information in matrix-based methods and the difficulty of maintaining the PSD property in tensor-based approaches, this paper proposes a unified framework named Incomplete Multi-View Clustering based on Semi-Definite Constraint and Tensor Low-Rank Learning (SDC-TLR).

Unlike methods that treat completion as a preprocessing step, SDC-TLR seamlessly integrates kernel completion and consensus graph learning into a single objective function. We impose tensor low-rank constraints on both the stacked similarity graphs and the kernel tensor to capture global consistency across all views. Crucially, to overcome the limitations of existing relaxations, we introduce a rigorous optimization strategy based on eigen-decomposition. This ensures that the recovered kernels strictly satisfy the semi-definite constraint during the iterative updates, thereby preserving the geometric interpretation of the kernel space.

In summary, the main contributions of this paper are as follows:

(1) We propose a novel framework, for incomplete multi-view clustering that simultaneously performs kernel completion and consensus graph learning. This unified approach prevents error propagation from separate completion steps.

(2) We incorporate tensor low-rank constraints on both the similarity graphs and the kernel tensor to fully exploit high-order consensus information among views, which significantly enhances the recovery of missing data.

(3) We derive an efficient optimization algorithm based on the ALM method. A key feature of our algorithm is a specific solver for the kernel update that strictly satisfies the positive semi-definite constraint without resorting to loose relaxations.

(4) Extensive experiments on benchmark datasets demonstrate that our method outperforms state-of-the-art IMVC methods, verifying the effectiveness of preserving the PSD property and leveraging tensor structures.

2. Proposed Method

2.1. Notations

Let V be the number of views. For the v-th view, let $K^v \in \mathbb{R}^{n\times n}$ denote the kernel matrix, which corresponds precisely to the v-th frontal slice of the kernel tensor $\mathcal{K}$. In the incomplete setting, only a subset of entries in K^v are observed. Let Ω denote the set of indices for observed entries. We aim to learn a similarity graph S^v for each view and a consensus indicator matrix $F \in \mathbb{R}^{n\times c}$.

2.2. Model Formulation

First, for each view v, we aim to learn a similarity graph S^v that best approximates the intrinsic structure of the kernel matrix K^v. Following standard graph learning principles, we minimize the reconstruction error. To automatically weigh the importance of different views, we introduce a weighting parameter ω_v. The basic loss function is formulated as:

$$\min_{S^v,\omega} \sum_{v=1}^{V} \omega_v^{-1} \mathrm{Tr}(K^v - 2K^v S^v + S^{vT} K^v S^v), \tag{0.1}$$

where $\sum \omega_v = 1$. This term ensures that the learned graph S^v captures the local geometry of the data in the v-th view.

In multi-view clustering, different views share a common underlying structure. To exploit global consistency and capture the high-order correlations among views, we stack the similarity graphs $\{S^1,\dots,S^V\}$ into a 3rd-order tensor $\mathcal{S} \in \mathbb{R}^{n\times n\times V}$ [23]. We impose the Tensor Nuclear Norm (TNN)[19] constraint on $\mathcal{S}$. TNN serves as a convex surrogate for the tensor tubal rank, effectively enforcing the low-rank structure across views, which leads to the following model:

$$\min_{S^v,\omega} \sum_{v=1}^{V} \omega_v^{-1} \mathrm{Tr}(K^v - 2K^v S^v + S^{vT} K^v S^v) + \alpha \|\mathcal{S}\|_*, \tag{0.2}$$

where $\|\mathcal{S}\|_*$ denotes the Tensor Nuclear Norm of tensor $\mathcal{S}$.

Specifically, the TNN is defined based on the t-product framework and Tensor Singular Value Decomposition (t-SVD)[19]. Let $\overline{\mathcal{S}} \in \mathbb{R}^{n\times n\times V}$ denote the tensor obtained by applying the Discrete Fourier Transform (DFT) to $\mathcal{S}$ along the third dimension, i.e., $\overline{\mathcal{S}} = \mathrm{fft}(\mathcal{S},[],3)$. The TNN of $\mathcal{S}$ is defined as the average sum of the nuclear norms of all frontal slices of $\overline{\mathcal{S}}$ in the Fourier domain: $\|\mathcal{S}\|_* = \frac{1}{V}\sum_{k=1}^{V} \|\overline{S}^{(k)}\|_*$ where $\overline{S}^{(k)}$ represents the k-th frontal slice of $\overline{\mathcal{S}}$, and $\|\cdot\|_*$ denotes the standard matrix nuclear norm.

To obtain the final clustering result directly from the learned graphs, we incorporate the spectral clustering objective. We seek a unified cluster indicator matrix $F \in \mathbb{R}^{n\times c}$ that minimizes the spectral cut:

$$\begin{aligned} \min_{S^v,\omega} & \sum_{v=1}^{V} \omega_v^{-1} \mathrm{Tr}(K^v - 2K^v S^v + S^{vT} K^v S^v) + \alpha \|\mathcal{S}\|_* + \lambda \mathrm{Tr}(F^T \sum_{v=1}^{V} L_{S^v} F), \\ s.t.\ & F^T F = I_c \end{aligned} \tag{0.3}$$

where $L_{S^v} = D_{S^v} - \frac{S^v + (S^v)^T}{2}$ is the Laplacian matrix of the v-th graph.

A core challenge in incomplete multi-view clustering is that the kernel matrix K^v contains unobserved entries[20]. We treat the kernel matrices as a tensor $\mathcal{K}$ and utilize tensor low-rank learning to recover missing values[8]. To ensure the recovered matrices are valid kernels, we strictly enforce the TN constraint. Therefore, we finally develop our objective as:

$$\min_{S^v,\omega,F,\mathcal{K}} \sum_{v=1}^{V} \omega_v^{-1} \mathrm{Tr}(K^v - 2K^vS^v + S^{vT}K^vS^v) + \alpha \|\mathcal{S}\|_* + \lambda \mathrm{Tr}(F^T \sum_{v=1}^{V} L_{S^v} F) \quad ,$$

$$+\beta \|\mathcal{K}\|_* , \quad s.t. \quad S^v \geq 0, \quad \sum_{v=1}^{V} \omega_v = 1, \quad F^TF = I_c, K_\Omega^v = K_c^v, \quad K^v \succeq 0.$$

(0.4)

where α, λ, and β are non-negative balancing parameters that balance the contributions of different terms. For brevity, we refer to our proposed method as SDC-TLR in the subsequent sections.

3. Optimization

In this section, we develop an efficient optimization algorithm for the SDC-TLR using the Augmented Lagrangian Multiplier(ALM)[18] method. We introduce auxiliary variables $\mathcal{Y}$ and $\mathcal{Z}$ to decouple the tensor norms. The augmented Lagrangian function is:

$$\mathcal{L} = \sum_{v=1}^{V} \omega_v^{-1} \mathrm{Tr}(K^v - 2K^vS^v + S^{vT}K^vS^v) + \alpha \|\mathcal{Y}\|_* + \frac{\rho}{2} \sum_{v=1}^{V} \| S^v - Y^v + \frac{E_1}{\rho} \|_F^2$$

$$+\lambda \mathrm{Tr}(F^T \sum L_{S^v} F) + \beta \|\mathcal{Z}\|_* + \frac{\rho}{2} \sum_{v=1}^{V} \| K^v - Z^v + \frac{E_2}{\rho} \|_F^2 ,$$

$$s.t. \quad S^v \geq 0, \quad \sum_{v=1}^{V} \omega_v = 1, \quad F^TF = I_c, K_\Omega^v = K_c^v, \quad K^v \succeq 0.$$

(0.5)

3.1. Update S^v

Fixing other variables, the optimization w.r.t S^v becomes:

$$\min_{S^v} \omega_v^{-1} \mathrm{Tr}(-2K^vS^v + S^{vT}K^vS^v) + \frac{\rho}{2} \| S^v - Y^v + \frac{E_1}{\rho} \|_F^2 + \lambda \mathrm{Tr}(F^T L_{S^v} F),$$

(0.6)

Taking the derivative and setting it to zero leads to the closed-form solution:

$$S^v = \left[\omega_v^{-1}(K^v + K^{vT}) + \rho I \right]^{-1} \left(2\omega_v^{-1} K^{vT} + \rho Y^v - E_1 + \lambda FF^T - \frac{\lambda}{2} \mathcal{A}(FF^T) \right) ,$$

(0.7)

where $\mathcal{A}$ represents the operator related to the Laplacian gradient. We enforce non-negativity via $S^v = \max(S^v, 0)$.

Remark 1. $\mathcal{A}(\cdot)$ is an operator that constructs a matrix from the diagonal elements of the input matrix. Specifically, for a matrix $X \in \mathbb{R}^{n \times n}$, let $\mathbf{d} \in \mathbb{R}^n$ be the vector composed of the diagonal elements of X (i.e., $d_i = X_{ii}$). The operator is defined as: $\mathcal{A}(X) = \mathbf{d}\mathbf{1}^T + \mathbf{1}\mathbf{d}^T$, where $\mathbf{1}$ is a column vector of all ones. Consequently, the (i, j)-th entry of the term $\lambda FF^T - \frac{\lambda}{2}\mathcal{A}(FF^T)$ simplifies to $-\frac{\lambda}{2}\| f_i - f_j \|_2^2$, which intuitively integrates the pair-wise Euclidean distance of the spectral representations into the graph learning process.

3.2. Update F

The optimization of F aims to find a unified low-dimensional embedding that partitions the data into c clusters. By fixing other variables, the sub-problem for F is equivalent to a standard spectral clustering objective on the aggregated graph:

$$\min_F \lambda \mathrm{Tr}\left(F^T \left(\sum_{v=1}^{V} L_{S^v} \right) F \right) \quad s.t. \quad F^T F = I_c , \tag{0.8}$$

where $L_{con} = \sum_{v=1}^{V} L_{S^v}$ can be interpreted as the consensus Laplacian matrix, which integrates the structural information from all views. To minimize this objective under the orthogonality constraint, the optimal solution F is formed by the c eigenvectors corresponding to the c smallest eigenvalues of L_{con}. This step ensures that the final clustering result F is consistent with the learned similarity graphs across all views.

3.3. Update K^v

The update of K^v is the core component of our method, as it facilitates kernel completion while strictly enforcing the PSD constraint ($K^v \succeq 0$). Unlike traditional methods that relax this constraint, we adopt an eigen-decomposition based strategy[22].

Let $K^v = U \Lambda U^T$, where $\Lambda = \mathrm{diag}(\lambda_1, \dots, \lambda_n)$ contains the eigenvalues ($\lambda_i \geq 0$) and $U \in \mathbb{R}^{n \times n}$ contains the eigenvectors ($U^T U = I$). The optimization problem w.r.t K^v is:

$$\min_{K^v \succeq 0} \omega_v^{-1} \mathrm{Tr}(K^v B) + \frac{\rho}{2} \| K^v - M \|_F^2 , \tag{0.9}$$

where $B = I - 2S^v + S^v S^{vT}$ and $M = Z^v - \frac{E_2}{\rho}$. Substituting the decomposition into the objective, we solve for Λ and U alternatingly.

1) Updating Eigenvalues Λ: Fixing the eigenvectors U, let $H = U^T D U$, where

$D = B / \omega_v - \frac{\rho}{2} M$. The problem simplifies to a quadratic minimization w.r.t λ_i:

$$\min_{\lambda_i \geq 0} \sum_{i=1}^{n} \left(\frac{\rho}{2} \lambda_i^2 + \lambda_i H_{ii} \right). \tag{0.10}$$

This problem has a closed-form solution for each eigenvalue, ensuring non-negativity:

$$\lambda_i = \max\left(-\frac{H_{ii}}{\rho}, 0 \right) \ . \tag{0.11}$$

This step effectively filters out negative eigenvalues caused by noise or missing data, strictly maintaining the semi-definite property.

2) Updating Eigenvectors U: Fixing Λ, the problem becomes minimizing the trace term under the orthogonality constraint:

$$\min_U \mathrm{Tr}(\Lambda U^T D U) \quad s.t. \quad U^T U = I \, . \tag{0.12}$$

This is a non-convex problem on the Stiefel manifold. To solve it efficiently, we employ an inner ALM scheme. We introduce an auxiliary variable V (with $V = U$) to decouple the objective. The Lagrangian function for this sub-problem is:

$$\mathcal{L}_U = \mathrm{Tr}(V \Lambda U^T D) + \frac{\mu}{2} \| U - V + \frac{Y_U}{\mu} \|_F^2 , \tag{0.13}$$

where μ is a penalty parameter and Y_U is the multiplier. This leads to the following closed-form update for U using Singular Value Decomposition (SVD): Let $X = \mu(V - \frac{Y_U}{\mu}) - DV\Lambda$. The problem is transformed into $\max_U \mathrm{Tr}(U^T X)$.

By

computing the SVD of X as $X = P \Sigma Q^T$, the optimal update for U is given by:

$$U = PQ^T .$$

This Procrustes-like solution guarantees that U remains strictly orthogonal ($U^T U = I$) throughout the optimization process.

3.4. Update Multipliers and Parameters

The multipliers and penalty parameter are updated in a standard way:

$$E_1^v = E_1^v + \rho(S^v - Y^v), E_2^v = E_2^v + \rho(K^v - Z^v), \rho = \min(\rho_{max}, \kappa\rho), \tag{0.14}$$

where $\kappa > 1$ is a constant scaling factor to accelerate the convergence, and ρ_{max} is a predefined threshold to prevent the penalty parameter from becoming numerically unstable.

4. Experiments

In this section, we conduct extensive experiments to evaluate the effectiveness of the proposed SDC-TLR method. To quantitatively measure the clustering performance, we employ three standard evaluation metrics: Accuracy (ACC), Normalized Mutual Information (NMI), and Purity. For all these metrics, a higher value indicates better clustering quality. Furthermore, to demonstrate the superiority of our approach, we compare SDC-TLR with several baselines, including BSV[11], Concat[12], DAIMC[5], OPIMC[13], PIC[15], IMSC-AGL[14]. We present the details of the experiments in the rest of this section.

4.1. Datasets

We conduct experiments on three multi-view datasets: ORL, WebKB, and BBC-Sport[9]. To simulate the incomplete multi-view setting, we randomly remove 10 percentage of instances from each view, ensuring that every sample is preserved in at least one view[4]. The detailed statistics of these datasets are summarized in Table 1.

1) ORL: This dataset contains 400 face images of 40 distinct subjects (10 images per subject). Three types of features are extracted: 4,096-dimensional intensity features, 3,304-dimensional LBP features, and 6,750-dimensional Gabor features.

2) WebKB: A subset of the WebKB dataset consisting of 1,051 web pages from two categories. It is described by two views with dimensions of 3,304 and 2,949.

3) BBC-Sport: Derived from the BBC Sport news corpus, this dataset includes 544 documents organized into 5 clusters. It features two views with dimensions of 3,183 and 3,203.

Table 1. Statistics of the Datasets

Data sets	Statistics of the benchmark datasets used in experiments.		
	Samples	Classes/Views	Dimensions
ORL	400	40/3	4,096/3,304/6,750
WebKB	1051	2/2	334/2,949
BBC-Sport	544	5/2	3,813/3,203

4.2. Clustering Performance

The clustering results of the proposed SDC-TLR and six baseline methods on the ORL, WebKB, and BBC-Sport datasets are comprehensively reported in Table 2-4. As can be seen, SDC-TLR consistently yields the best performance across all three datasets in terms of Accuracy (ACC), Normalized Mutual Information (NMI), and Purity, significantly outperforming both the single-view strategies and state-of-the-art incomplete multi-view clustering algorithms.

Compared to the simple baselines, SDC-TLR achieves substantial improvements. For example, on the WebKB dataset, our method improves the ACC by approximately 15%-18% over BSV and Concat. This sharp contrast validates that simply concatenating features or relying on a single view is insufficient for handling missing data, whereas our method successfully recovers and fuses the complementary information hidden in incomplete views.

Furthermore, when compared with advanced matrix-factorization and graph-learning methods, SDC-TLR demonstrates remarkable superiority. A striking observation is on the WebKB dataset, where existing methods struggle to capture the underlying cluster structure (with NMIs generally below 23%), while our model achieves a dominant NMI of 78.01%. Similarly, on the ORL and BBC-Sport datasets, SDC-TLR achieves near-perfect Purity scores (99.08%), outperforming the second-best method by a large margin of over 20% on ORL. At the same time, a more intuitive clustering performance is presented in Figure 1.

These significant performance gains can be attributed to the unified learning framework of SDC-TLR. Unlike previous approaches that often relax constraints or rely solely on pairwise view correlations, our method imposes a TNN constraint to capture high-order consensus among views and strictly enforces the PSD property during kernel completion. This ensures that the recovered data structure is not only globally consistent but also geometrically valid, leading to more accurate and robust clustering results.

Table 2. Comparison of different methods in three metrics on ORL data set.

ORL	Clustering Metrics		
	ACC	NMI	Purity
BSV	49.68	66.76	54.83
Concat	45.68	59.47	51.68
DAIMC	71.93	85.21	75.70
OPIMC	43.20	65.86	46.00
PIC	68.00	84.36	74.00
IMSC-AGL	74.35	86.64	77.05
Our Model	**82.75**	**93.11**	**99.08**

Table 3. Comparison of different methods in three metrics on WebKB data set.

WebKB	Clustering Metrics		
	ACC	NMI	Purity
BSV	78.71	09.33	80.77
Concat	82.03	13.35	82.18
DAIMC	83.63	16.54	83.63
OPIMC	78.30	07.61	78.30
PIC	78.02	04.47	78.11
IMSC-AGL	76.65	22.63	80.01
Our Model	**97.24**	**78.01**	**97.24**

Table 4. Comparison of different methods in three metrics on BBC-Sport data set.

BBC-Sport	Clustering Metrics		
	ACC	NMI	Purity
BSV	55.95	37.18	61.74
Concat	55.11	34.19	58.34

BBC-Sport	Clustering Metrics		
	ACC	NMI	Purity
DAIMC	75.47	66.63	80.90
OPIMC	73.89	57.41	73.90
PIC	85.11	73.83	85.11
IMSC-AGL	80.35	70.79	83.30
Our Model	**99.08**	**93.11**	**99.08**

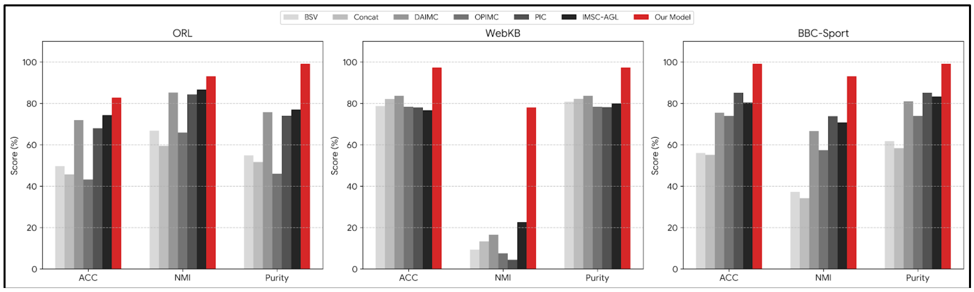

Figure 1. Clustering performance comparison on three datasets.

5. Conclusion

In this paper, we proposed a novel framework named SDC-TLR for incomplete multi-view clustering. By integrating kernel completion and consensus graph learning into a unified objective, our method effectively captures high-order correlations across different views via tensor low-rank constraints. A key contribution of this work is the strict enforcement of the positive semi-definite constraint during the optimization process, which ensures the theoretical validity and geometric integrity of the recovered kernels. Extensive experiments on the ORL, WebKB, and BBC-Sport datasets demonstrate that SDC-TLR consistently outperforms state-of-the-art baselines and exhibits strong robustness in handling missing data. Future work will focus on improving the computational efficiency of the algorithm for large-scale applications.

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