Novelty Assessment Report

Paper: Unified and Efficient Multi-view Clustering from Probabilistic Perspective

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Abstract

Multi-view clustering aims to segment the view-specific data into the corresponding clusters. There have been a large number of works for multi-view clustering in recent years. As representive methods in multi-view clustering, works built on the graph make use of a view-consistent and discriminative graph while utilizing graph partitioning for the final clustering results. Despite the achieved significant success, these methods usually construct full graphs and the efficiency is not well guaranteed for the multi-view datasets with large scales. To handle the large-scale data, multi-view clustering methods based on anchor have been developed by learning the anchor graph with smaller size. However, the existing works neglect the interpretability of multi-view clustering based on anchor from the probabilistic perspective. These methods also ignore analyzing the relationship between the input data and the final clustering results based on the assigned meaningful probability associations in a unified manner. In this work, we propose a novel method termed Unified and Efficient Multi-view Clustering from Probabilistic perspective(UEMCP). It aims to improve the explanation ability of multi-view clustering based on anchor from the probabilistic perspective in an end-to-end manner. It ensures the consistent inherent structures among these views by learning the common transition probability from data points to categories in one step. With the guidance of the common transition probability matrix from data points to categories, the soft label of data points can be achieved based on the common transition probability matrix from anchor points to categories in the learning framework. Experiments on different challenging multi-view datasets confirm the superiority of UEMCP compared with the representative ones.

Core Task Landscape

This paper addresses: **Multi-View Clustering with Anchor-Based Probabilistic Transition Matrices**

A total of **5 papers** were analyzed and organized into a taxonomy with **5 categories**.

Taxonomy Overview

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

- **Unified Probabilistic Framework Methods**
- **Anchor Enhancement and Alignment Methods**
- **Incomplete Multi-View Clustering with Anchors**

Complete Taxonomy Tree

- Multi-View Clustering with Anchor-Based Probabilistic Transition Matrices Survey Taxonomy
- Unified Probabilistic Framework Methods
  - Direct Transition Probability Learning ★ (2 papers)
  - [0] Unified and Efficient Multi-view Clustering from Probabilistic Perspective (Anon et al., 2026) View paper
  - [3] One-Step Multi-View Clustering Based on Transition Probability (Zhao Wenhui, 2024) View paper
  - Tensor-Based Probability Aggregation (1 papers)
  - [4] Fast Tensor-Based Multi-View Clustering with Anchor Probability Transition Matrix (W Feng, n.d.) View paper
- Anchor Enhancement and Alignment Methods
  - Cross-View Anchor Alignment (1 papers)
  - [1] Scalable multi-view graph clustering with cross-view corresponding anchor alignment (Siwei Wang, 2025) View paper
  - Adaptive Anchor-Guided Subspace Learning (1 papers)
  - [5] Adaptive Anchor-Guided Representation Learning for Efficient Multi-View Subspace Clustering. (Meng-Jiao Zhang, n.d.) View paper
- Incomplete Multi-View Clustering with Anchors
  - Anchor-Shift Mitigation with Cross-View Reconstruction (1 papers)
  - [2] Alleviate anchor-shift: Explore blind spots with cross-view reconstruction for incomplete multi-view clustering (Zhibin Dong, 2024) View paper

Narrative

Core task: multi-view clustering with anchor-based probabilistic transition matrices. This field addresses the challenge of integrating information from multiple data views while maintaining computational efficiency through anchor-based representations. The taxonomy reveals three main branches that capture distinct methodological emphases. Unified Probabilistic Framework Methods focus on learning transition probabilities that connect data points to anchors in a principled probabilistic manner, often optimizing joint objectives that balance clustering quality and cross-view consistency. Anchor Enhancement and Alignment Methods concentrate on refining anchor selection and ensuring that anchors from different views correspond meaningfully, addressing issues such as anchor shift and cross-view alignment to improve the reliability of the learned representations. Incomplete Multi-View Clustering with Anchors tackles scenarios where some views are partially observed, developing strategies to handle missing data while still leveraging anchor-based efficiency. Representative works such as Transition Probability Clustering[3] and Alleviate Anchor Shift[2] illustrate how these branches operationalize their respective priorities.

Several active lines of work highlight key trade-offs in the field. One central tension involves balancing the expressiveness of probabilistic models against the computational savings that anchors provide, with some methods pursuing more flexible transition structures while others prioritize scalability through simpler anchor schemes. Another recurring theme concerns the robustness of anchor-based representations when views are misaligned or incomplete, prompting research into adaptive anchor selection and alignment mechanisms as seen in Scalable Anchor Alignment[1] and Adaptive Anchor Subspace[5]. The original paper, Unified Probabilistic Multiview[0], sits within the Direct Transition Probability Learning cluster of the Unified Probabilistic Framework branch. Compared to Transition Probability Clustering[3], which also emphasizes direct learning of transition probabilities, Unified Probabilistic Multiview[0] appears to pursue a more integrated probabilistic treatment that unifies multiple views under a single coherent framework, rather than treating each view's transitions independently before fusion.

Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

1. One-Step Multi-View Clustering Based on Transition Probability

Authors: Zhao Wenhui, Wenhui Zhao, Gao, Quanxue, Quanxue Gao, et al. (11 authors total) | **Year/Venue**: 2024 • arXiv.org | **URL**: View paper

Abstract

The large-scale multi-view clustering algorithms, based on the anchor graph, have shown promising performance and efficiency and have been extensively explored in recent years. Despite their successes, current methods lack interpretability in the clustering process and do not sufficiently consider the complementary information across different views. To address these shortcomings, we introduce the One-Step Multi-View Clustering Based on Transition Probability (OSMVC-TP). This method adopts a pro...

Relationship Analysis

Both papers belong to the Direct Transition Probability Learning category, sharing the approach of learning transition probabilities from data to categories in one step without intermediate graph construction. They overlap in using anchor-based probabilistic frameworks for multi-view clustering, learning common transition probabilities across views, and employing soft label matrices for interpretability. The key difference is that OSMVC-TP emphasizes Schatten p-norm constraints on tensors to capture complementary information across views, while UEMCP focuses on unified probabilistic framework with adaptive view weighting and orthogonality constraints on the label matrix.

Contributions Analysis

Overall novelty summary. The paper proposes UEMCP, a unified probabilistic framework for anchor-based multi-view clustering that aims to improve interpretability by establishing explicit probabilistic connections between data and cluster assignments. It resides in the 'Direct Transition Probability Learning' leaf of the taxonomy, which contains only two papers total. This leaf sits within the 'Unified Probabilistic Framework Methods' branch, indicating the paper addresses a relatively focused research direction rather than a densely populated area. The small number of sibling papers suggests this specific approach to unified probabilistic modeling remains underexplored compared to other multi-view clustering paradigms.

The taxonomy reveals that anchor-based multi-view clustering research divides into three main branches: unified probabilistic frameworks, anchor enhancement techniques, and incomplete data handling. The paper's leaf neighbors a 'Tensor-Based Probability Aggregation' approach, suggesting alternative strategies for combining view-specific information exist nearby. The broader 'Anchor Enhancement and Alignment Methods' branch addresses complementary concerns like cross-view anchor correspondence and adaptive subspace learning, which the paper does not emphasize. The taxonomy structure indicates the field balances trade-offs between probabilistic expressiveness, computational efficiency, and robustness to data irregularities, with this work prioritizing the first two aspects.

Among 20 candidates examined, all three core contributions show evidence of prior work overlap. The unified probabilistic framework contribution examined 6 candidates with 3 appearing refutable, while common transition probability learning examined 10 candidates with 6 showing overlap. The soft label derivation mechanism examined 4 candidates with 2 refutable. These statistics suggest that within the limited search scope, each contribution encounters substantial related work, though the analysis does not claim exhaustive coverage. The relatively high proportion of refutable candidates across contributions indicates the core ideas have precedents in the examined literature, though the specific integration and formulation may differ.

Based on the top-20 semantic matches examined, the work appears to build on established concepts in anchor-based probabilistic clustering, with multiple contributions showing overlap with prior methods. The taxonomy placement in a sparsely populated leaf suggests the specific unified formulation may offer a distinct perspective, but the contribution-level analysis reveals that individual technical components have been explored previously. The limited search scope means additional relevant work may exist beyond the candidates examined, particularly in adjacent research areas not fully captured by semantic similarity.

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

Contribution 1: Unified and Efficient Multi-view Clustering from Probabilistic perspective (UEMCP)

Description: The authors introduce UEMCP, a new multi-view clustering method that assigns probabilistic interpretations to anchor graphs and soft labels. This approach enhances the interpretability of anchor-based multi-view clustering by providing meaningful probability associations between input data and clustering results in a unified framework.

This contribution was assessed against **6 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. Efficient Anchor Graph Factorization for Multi-View Clustering

URL: View paper

Brief Assessment

Anchor Graph Factorization[9] focuses on anchor graph factorization with orthogonal NMF and tensor low-rank constraints, not on probabilistic interpretations of anchor graphs and soft labels as transition probability matrices.

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2. Dual-Constraint Multi-view Fuzzy Clustering with Scalable Anchor Graph Learning

URL: View paper

Brief Assessment

Dual Constraint Fuzzy[6] focuses on fuzzy clustering with dual constraints and scalable anchor graph learning, which is a different technical approach from UEMCP's probabilistic interpretation of anchor graphs and transition probability matrices for multi-view clustering.

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3. Multi-view Clustering Based on Probabilistic Tensor Regression

URL: View paper

Prior Art Analysis

Probabilistic Tensor Regression[8] demonstrates that assigning probabilistic interpretations to anchor graphs in multi-view clustering was proposed prior to the original paper. Both papers reinterpret anchor graphs from a probabilistic perspective, with the candidate explicitly stating they 'reinterpret the regression process of the anchor graph from the perspective of probability' and model 'the anchor graph as the transition probability from samples to anchors.' This directly challenges the novelty claim that UEMCP was the first to assign probabilistic meaning to anchor graphs and soft labels in multi-view clustering.

Evidence

Evidence 1 - **Rationale**: Both papers claim to introduce probabilistic perspectives to anchor-based multi-view clustering. The candidate explicitly reinterprets anchor graphs from a probabilistic viewpoint, which directly overlaps with the original's core contribution. - **Original**: we propose a novel method termed unified and efficient multi-view clustering from probabilistic perspective(uemcp). it aims to improve the explanation ability of multi-view clustering based on anchor from the probabilistic perspective in an end-to-end manner. - **Candidate**: we propose a multi-view clustering method based on probabilistic tensor regression (mvcptr). specifically, we reinterpret the regression process of the anchor graph from the perspective of probability.

Evidence 2 - **Rationale**: The candidate models anchor graphs as transition probabilities, which is the same probabilistic interpretation claimed as novel by the original paper. This shows prior work exists with the same probabilistic framework. - **Original**: we propose a novel method termed unified and efficient multi-view clustering from probabilistic perspective (uemcp), which assigns the probabilistic meaning to the anchor graph and soft label of data points to increase the explanation ability of multi-view clustering model in an end-to-end manner. - **Candidate**: by modeling the anchor graph as the transition probability from samples to anchors, we construct the implicit relationship between labels of samples and anchors.

Evidence 3 - **Rationale**: Both papers identify the same gap in existing literature - that prior methods ignore probabilistic characteristics of anchor graphs. This suggests they are addressing the same problem space, with the candidate having done so earlier. - **Original**: however, the existing works neglect the interpretability of multi-view clustering based on anchor from the probabilistic perspective. these methods also ignore analyzing the relationship between the input data and the final clustering results based on the assigned meaningful probability associations... - **Candidate**: multi-view clustering based on anchor graph and regression is widely used to deal with high dimensional and redundant data. however, most of these methods ignore the probabilistic characteristics of anchor graph

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4. One-Step Multi-View Clustering Based on Transition Probability

URL: View paper

Prior Art Analysis

Transition Probability Clustering[3] demonstrates that prior work exists on probabilistic interpretations of anchor graphs and soft labels in multi-view clustering. Both papers adopt a probabilistic approach where anchor graphs represent transition probabilities, and both derive soft label matrices for samples and anchor points to enhance interpretability. The candidate paper explicitly states it 'adopts a probabilistic approach, which leverages the anchor graph, representing the transition probabilities from samples to anchor points' and 'directly learns the transition probabilities from anchor points to categories, and calculates the transition probabilities from samples to categories, thus obtaining soft label matrices for samples and anchor points, enhancing the interpretability of clustering.' This directly parallels the original paper's claim of assigning 'probabilistic meaning to the anchor graph and soft label of data points to increase the explanation ability.'

Evidence

Evidence 1 - **Rationale**: Both papers introduce methods that adopt a probabilistic perspective for anchor-based multi-view clustering, with the candidate explicitly describing transition probabilities from samples to anchor points, which is the same conceptual framework as the original's probabilistic interpretation of anchor graphs. - **Original**: we propose a novel method termed unified and efficient multi-view clustering from probabilistic perspective(uemcp). it aims to improve the explanation ability of multi-view clustering based on anchor from the probabilistic perspective in an end-to-end manner. - **Candidate**: we introduce the one-step multi-view clustering based on transition probability (osmvc-tp). this method adopts a probabilistic approach, which leverages the anchor graph, representing the transition probabilities from samples to anchor points.

Evidence 2 - **Rationale**: Both papers claim to enhance interpretability by assigning probabilistic meanings to anchor graphs and soft labels. The candidate's 'soft label matrices for samples and anchor points, enhancing the interpretability' directly corresponds to the original's claim of assigning 'probabilistic meaning to the anchor graph and soft label of data points to increase the explanation ability.' - **Original**: uemcp assigns the probabilistic meaning to the anchor graph and soft label of data points to increase the explanation ability of multi-view clustering model in an end-to-end manner. - **Candidate**: our method directly learns the transition probabilities from anchor points to categories, and calculates the transition probabilities from samples to categories, thus obtaining soft label matrices for samples and anchor points, enhancing the interpretability of clustering.

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5. Priori Anchor Labels Supervised Scalable Multi-View Bipartite Graph Clustering

URL: View paper

Brief Assessment

Priori Anchor Labels[10] focuses on supervised anchor selection using predefined labels for bipartite graph clustering, while UEMCP addresses probabilistic interpretations of anchor graphs and soft labels in an unsupervised framework. The technical approaches and objectives differ fundamentally.

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6. Image Clustering With Transition Probabilities Learning

URL: View paper

Prior Art Analysis

Image Transition Probabilities[7] demonstrates that the concept of assigning probabilistic interpretations to anchor graphs and soft labels in multi-view clustering was previously explored. The candidate paper explicitly constructs an anchor graph factorization model from the perspective of transition probabilities, learning transition probability matrices from samples to clusters and from anchor points to clusters. This directly challenges the novelty claim of UEMCP, as both papers address the same fundamental problem: providing probabilistic interpretations to anchor-based multi-view clustering with soft labels. The candidate's approach of 'simultaneously learning transition probability matrices from samples to clusters and from anchor points to clusters, serving as soft label matrices' is conceptually identical to UEMCP's claim of assigning 'probabilistic meaning to the anchor graph and soft label of data points.'

Evidence

Evidence 1 - **Rationale**: Both papers propose methods that provide probabilistic interpretations to anchor-based multi-view clustering. The candidate explicitly constructs an anchor graph factorization model from the perspective of transition probabilities, which directly refutes the novelty of UEMCP's probabilistic perspective approach. - **Original**: we propose a novel method termed unified and efficient multi-view clustering from probabilistic perspective(uemcp). it aims to improve the explanation ability of multi-view clustering based on anchor from the probabilistic perspective in an end-to-end manner. - **Candidate**: we introduce multi-view clustering with transition probabilities learning (mvc-tpl). specifically, we construct an anchor graph factorization model from the perspective of transition probabilities, while simultaneously learning transition probability matrices from samples to clusters and from anchor...

Evidence 2 - **Rationale**: Both papers emphasize providing probabilistic interpretations to enhance the interpretability of multi-view clustering. The candidate's 'sound probability interpretation' and 'one-step label acquisition' directly parallels UEMCP's claim of assigning 'probabilistic meaning' to improve 'explanation ability.' - **Original**: uemcp assigns the probabilistic meaning to the anchor graph and soft label of data points to increase the explanation ability of multi-view clustering model in an end-to-end manner. - **Candidate**: this model enables one-step label acquisition and provides the model with a sound probability interpretation.

Evidence 3 - **Rationale**: Both papers identify the same research gap: lack of interpretability in anchor-based multi-view clustering. The candidate's observation that 'most methods lack interpretability in clustering' directly addresses the same problem that UEMCP claims to be the first to solve. - **Original**: however, the existing works neglect the interpretability of multi-view clustering based on anchor from the probabilistic perspective. these methods also ignore analyzing the relationship between the input data and the final clustering results based on the assigned meaningful probability associations... - **Candidate**: large-scale multi-view clustering for image data has achieved impressive clustering performance and efficiency. however, most methods lack interpretability in clustering and do not fully consider the complementarity of distributions between different views.

Contribution 2: Common transition probability learning across views

Description: The method learns a shared transition probability matrix from data points to categories across all views in a single step. This ensures that the inherent data structures remain consistent across different views, addressing the challenge of maintaining view consistency in multi-view clustering.

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.

1. Multi-view Clustering Based on Probabilistic Tensor Regression

URL: View paper

Brief Assessment

Probabilistic Tensor Regression[8] uses tensor regression for multi-level information fusion but does not explicitly describe learning a single shared transition probability matrix from data points to categories across all views in one step as the original paper does.

2. nmODE-MVC: Neural Memory ODE-Based Multi-View Clustering

URL: View paper

Brief Assessment

Neural Memory ODE[19] focuses on dynamic feature refinement using neural ODEs for multi-view clustering, not on learning common transition probability matrices across views as the original paper does.

3. One-Step Multi-View Clustering Based on Transition Probability

URL: View paper

Prior Art Analysis

Transition Probability Clustering[3] demonstrates prior work on learning consistent transition probabilities across views. The candidate paper explicitly addresses view consistency by applying constraints to maintain consistency in labels across different views, stating 'to maintain consistency in labels across different views, we apply a schatten p-norm constraint on the tensor composed of the soft labels. This approach effectively harnesses the complementary information among the views.' This directly parallels the original paper's claim of learning 'the common transition probability from data points to categories shared by different views' to ensure 'the consistent inherent structures among these views.'

Evidence

Evidence 1 - **Rationale**: Both papers address the challenge of maintaining consistency across views in multi-view clustering. The candidate's approach to 'maintain consistency in labels across different views' using tensor constraints directly corresponds to the original's claim of ensuring 'consistent inherent structures among these views' through common transition probability learning. - **Original**: it ensures the consistent inherent structures among these views by learning the common transition probability from data points to categories in one step. - **Candidate**: to maintain consistency in labels across different views, we apply a schatten p-norm constraint on the tensor composed of the soft labels. this approach effectively harnesses the complementary information among the views.

4. Consensus representation-driven structured graph learning for multi-view clustering

URL: View paper

Prior Art Analysis

Consensus Structured Graph[14] demonstrates that learning a consensus transition probability matrix across multiple views was proposed prior to the original paper. The candidate explicitly describes recovering a 'consensus low-rank transition probability matrix' from multiple views and using it to promote 'clustering consistency across multiple views via co-regularization.' This directly parallels the original paper's claim of learning 'the common transition probability from data points to categories shared by different views' to ensure 'consistency of inherent structures for these views.' Both methods address the same fundamental problem of maintaining view consistency through shared probabilistic representations.

Evidence

Evidence 1 - **Rationale**: Both papers describe learning a consensus/common transition probability matrix across views. The candidate's 'consensus low-rank transition probability matrix' directly corresponds to the original's 'common transition probability from data points to categories shared by different views.' - **Original**: it is able to learn the common transition probability from data points to categories shared by different views with one step, which guarantees the consistent inherent structures among these views - **Candidate**: consensus low-rank transition probability matrix recovered from multiple pre-specified affinity

Evidence 2 - **Rationale**: Both methods aim to ensure consistency across views. The candidate's approach of 'promoting clustering consistency across multiple views' aligns with the original's goal to 'ensure the consistency of inherent structures for these views' through shared transition probabilities. - **Original**: uemcp learns the common transition probability from data points to categories shared by multiple views with one step, which is able to ensure the consistency of inherent structures for these views - **Candidate**: data and then promoting clustering consistency across multiple views via co-regularization

Evidence 3 - **Rationale**: The candidate's recovery of a 'consensus' transition probability matrix demonstrates the same core concept as the original's learning of a 'common' transition probability to maintain structural consistency across views. - **Original**: it ensures the consistent inherent structures among these views by learning the common transition probability from data points to categories in one step - **Candidate**: consensus low-rank transition probability matrix recovered from multiple pre-specified affinity

5. Understanding InfoNCE: Transition Probability Matrix Induced Feature Clustering

URL: View paper

Brief Assessment

InfoNCE Feature Clustering[16] focuses on contrastive learning with a transition probability matrix for data augmentation dynamics in single-view settings, not multi-view clustering with shared transition probabilities across views.

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6. Self-learning symmetric multi-view probabilistic clustering

URL: View paper

Brief Assessment

Symmetric Probabilistic Clustering[13] focuses on learning individual view distributions through self-learning probability functions and symmetric probability estimation, rather than learning a shared transition probability matrix from data points to categories in a single step as described in the original paper.

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7. Error-robust multi-view clustering

URL: View paper

Prior Art Analysis

Error Robust Multiview[18] demonstrates prior work on learning shared transition probability matrices across multiple views for clustering. The candidate paper explicitly decomposes each view into 'a shared transition probability matrix and error matrix' and states that this shared matrix is learned across all views. This directly addresses the same technical challenge of maintaining view consistency through common transition probabilities that the original paper claims as novel. Both papers use transition probability matrices in the context of multi-view clustering and aim to ensure consistency across views through a shared/common probability structure.

Evidence

Evidence 1 - **Rationale**: Both papers explicitly describe learning a shared/common transition probability matrix across views. The candidate's 'shared transition probability matrix' serves the same purpose as the original's 'common transition probability' - ensuring consistency across views. - **Original**: it is able to learn the common transition probability from data points to categories shared by different views with one step, which guarantees the consistent inherent structures among these views - **Candidate**: by decomposing each view into a shared transition probability matrix and error matrix and imposing structured sparsity-inducing norms on error matrices, we characterize and handle typical types of errors explicitly

Evidence 2 - **Rationale**: The candidate paper describes decomposing views into a shared transition probability matrix that is common across all views, which is the same technical approach as learning a 'common transition probability' across views. Both aim to ensure view consistency through this shared structure. - **Original**: uemcp learns the common transition probability from data points to categories shared by multiple views with one step, which is able to ensure the consistency of inherent structures for these views - **Candidate**: this approach decomposes a transition probability matrix of each view into two parts: a shared transition probability matrix across all views and an error matrix which encodes the noise in the transition probability matrix in each view. the error matrix of each view captures the difference between t...

Evidence 3 - **Rationale**: Both papers use the same mathematical framework of decomposing view-specific transition probabilities into a shared/common component. The candidate's formulation 'p(k) = ˆp + e(k)' where ˆp is shared across views directly implements the concept of common transition probabilities across views. - **Original**: it ensures the consistent inherent structures among these views by learning the common transition probability from data points to categories in one step - **Candidate**: assuming that each individual view might be erroneous so that it causes wrong assignment of data points to clusters, each transition probability matrix p(k) can be decomposed into two terms: a shared transition probability matrix ˆp and the error matrix e(k) that indicates the error in the transitio...

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8. Adaptive transition probability matrix learning for multiview spectral clustering

URL: View paper

Prior Art Analysis

Adaptive Transition Matrix[15] demonstrates that learning a shared transition probability matrix across multiple views was proposed prior to the original paper. The candidate paper explicitly describes learning 'an adaptive transition probability matrix (MCA2M)' that is 'shared by all views' and directly learns this matrix 'in one step' rather than through separate representation learning followed by matrix construction. Both papers address the same core challenge: learning a common/shared transition probability structure across views to maintain consistency, with the candidate paper published in 2022 (appearing in IEEE TNNLS, Vol. 33, No. 9, September 2022) before the original submission.

Evidence

Evidence 1 - **Rationale**: Both papers explicitly describe learning a 'common' or 'shared' transition probability matrix across all views, demonstrating that this concept existed in prior work. - **Original**: it ensures the consistent inherent structures among these views by learning the common transition probability from data points to categories in one step. - **Candidate**: rmsc [29] learns only the shared common transition probability matrix ˆp among all views.

Evidence 2 - **Rationale**: The candidate paper describes learning the transition probability matrix 'directly' in contrast to two-step methods, which parallels the original paper's claim of learning 'in one step'. - **Original**: uemcp learns the common transition probability from data points to categories shared by multiple views with one step, which is able to ensure the consistency of inherent structures for these views. - **Candidate**: different from the existing methods [1], [7], [9], which construct the transition probability matrix s by two separate steps, we select to directly learn an adaptive s.

Evidence 3 - **Rationale**: Both papers emphasize learning a unified/common transition probability structure across views rather than separate per-view representations, addressing view consistency. - **Original**: it is able to learn the common transition probability from data points to categories shared by different views with one step, which guarantees the consistent inherent structures among these views. - **Candidate**: we propose a unified model for multiview spectral clustering by directly learning an adaptive transition probability matrix (mca 2m), rather than an individual representation matrix of each view.

Evidence 4 - **Rationale**: Both papers describe learning transition probability matrices with specific properties (common/shared, nonnegative, symmetric) as part of their unified learning framework. - **Original**: based on the common transition probability matrix from anchor points to categories, the soft labels of data points can be achieved with the guidance of the common transition probability matrix from data points to categories in the learning procedure. - **Candidate**: the main idea of mca 2mi st h a tw ew a n t to learn a nonnegative and symmetric transition probability matrix without any postprocessing.

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9. Image Clustering With Transition Probabilities Learning

URL: View paper

Prior Art Analysis

Image Transition Probabilities[7] demonstrates prior work on learning consistent transition probabilities across multiple views. The candidate paper explicitly addresses the problem of ensuring 'clusters of samples and anchor points should be consistent across all views' by employing Schatten p-norm regularization on transition probability matrices. This approach of 'aligning the labels across views more consistently' and 'mining the complementary information distributed among the views' directly challenges UEMCP's novelty claim of learning a shared transition probability matrix to ensure consistency across views. Both papers recognize and address the same fundamental challenge of maintaining view consistency through transition probability learning.

Evidence

Evidence 1 - **Rationale**: Both papers address the same problem of ensuring consistency across views through transition probability learning. The candidate's approach of using Schatten p-norm regularization to align labels across views is functionally equivalent to UEMCP's learning of common transition probabilities to guarantee consistent structures. - **Original**: it is able to learn the common transition probability from data points to categories shared by different views with one step, which guarantees the consistent inherent structures among these views. - **Candidate**: since the clusters of samples and anchor points should be consistent across all views, we employ schatten p-norm regularization on the two matrices, effectively mining the complementary information distributed among the views, thereby aligning the labels across views more consistently.

Evidence 2 - **Rationale**: The candidate paper demonstrates a method for ensuring view consistency through regularization on transition probability matrices, which directly refutes the novelty of UEMCP's common transition probability learning approach. - **Original**: uemcp learns the common transition probability from data points to categories shared by multiple views with one step, which is able to ensure the consistency of inherent structures for these views. - **Candidate**: we employ schatten p-norm regularization on the two matrices, effectively mining the complementary information distributed among the views, thereby aligning the labels across views more consistently.

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10. Consensus Low-Rank Multi-View Subspace Clustering With Cross-View Diversity Preserving

URL: View paper

Prior Art Analysis

Consensus Lowrank Diversity[17] demonstrates prior work on learning consensus representations through transition probability matrix fusion across multiple views. The candidate paper explicitly describes 'auto-weighted local neighboring transition probability matrix fusion' for achieving consensus representation, which directly addresses the same technical challenge of maintaining view consistency through shared probability structures. Both papers tackle the fundamental problem of learning common probability-based representations across views, with the candidate providing evidence that this approach existed before the original paper's submission.

Evidence

Evidence 1 - **Rationale**: Both papers describe learning consensus/common representations through transition probability mechanisms across views. The candidate's 'transition probability matrix fusion' directly parallels the original's 'common transition probability' learning, demonstrating that this probabilistic approach to view consistency was previously proposed. - **Original**: it aims to improve the explanation ability of multi-view clustering based on anchor from the probabilistic perspective in an end-to-end manner. it ensures the consistent inherent structures among these views by learning the common transition probability from data points to categories in one step. - **Candidate**: we propose a novel multi-view subspace clustering method, which learns a consensus representation with auto-weighted local neighboring transition probability matrix fusion and preserves cross-view diversity with a matrix-induced term.

Evidence 2 - **Rationale**: The original claims learning 'common transition probability' shared across views as a novel contribution. The candidate explicitly describes learning consensus representations through 'transition probability matrix fusion', showing this concept of shared probability structures across views existed in prior work. - **Original**: uemcp learns the common transition probability from data points to categories shared by different views with one step, which guarantees the consistent inherent structures among these views. - **Candidate**: learns a consensus representation with auto-weighted local neighboring transition probability matrix fusion

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Contribution 3: Soft label derivation via anchor-to-category transition probabilities

Description: The authors develop a mechanism to derive soft labels for data points by introducing a transition probability matrix from anchor points to categories. This is guided by the common transition probability from data points to categories, enabling a unified learning procedure that connects anchors, data points, and final cluster assignments.

This contribution was assessed against **4 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. One-Step Multi-View Clustering Based on Transition Probability

URL: View paper

Prior Art Analysis

Transition Probability Clustering[3] demonstrates prior work on deriving soft labels through transition probabilities from anchor points to categories. The candidate paper explicitly states it 'directly learns the transition probabilities from anchor points to categories, and calculates the transition probabilities from samples to categories, thus obtaining soft label matrices for samples and anchor points.' This mechanism of learning transition probabilities from anchors to categories to derive soft labels is the same conceptual approach claimed as novel by the original paper.

Evidence

Evidence 1 - **Rationale**: Both papers describe a mechanism for deriving soft labels by learning transition probabilities from anchor points to categories. The candidate's approach of learning 'transition probabilities from anchor points to categories' to obtain 'soft label matrices' directly corresponds to the original's claim of achieving 'soft labels of data points' based on 'transition probability matrix from anchor points to categories.' - **Original**: based on the common transition probability matrix from anchor points to categories, the soft labels of data points can be achieved with the guidance of the common transition probability matrix from data points to categories in the learning framework. - **Candidate**: our method directly learns the transition probabilities from anchor points to categories, and calculates the transition probabilities from samples to categories, thus obtaining soft label matrices for samples and anchor points, enhancing the interpretability of clustering.

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2. Efficient Co-clustering via Anchor-refined Label Spreading

URL: View paper

Brief Assessment

Cannot assess refutation potential as the candidate paper's full text context is not available (marked as 'n/a'). Without access to Anchor Refined Coclustering[12]'s methodology and technical details, it is impossible to determine whether it demonstrates prior work on anchor-to-category transition probabilities for soft label derivation.

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3. State aggregation learning from markov transition data

URL: View paper

Brief Assessment

State Aggregation Learning[11] focuses on Markov state aggregation with anchor states for dimensionality reduction in control systems, not multi-view clustering with soft labels derived from anchor-to-category transitions for cluster assignments.

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4. Image Clustering With Transition Probabilities Learning

URL: View paper

Prior Art Analysis

Image Transition Probabilities[7] explicitly demonstrates prior work on deriving soft labels through transition probability matrices from anchor points to clusters. The candidate paper states it learns 'transition probability matrices from samples to clusters and from anchor points to clusters, serving as soft label matrices for samples and anchor points, respectively.' This directly refutes UEMCP's novelty claim, as the candidate already implements the mechanism of deriving soft labels via anchor-to-category transition probabilities. The candidate's approach of 'simultaneously learning' these matrices and using them as 'soft label matrices' is conceptually identical to UEMCP's claimed contribution.

Evidence

Evidence 1 - **Rationale**: Both papers derive soft labels using transition probability matrices from anchor points to categories. The candidate explicitly states these matrices serve as 'soft label matrices,' which is the same mechanism UEMCP claims as novel. - **Original**: based on the common transition probability matrix from anchor points to categories, the soft labels of data points can be achieved with the guidance of the common transition probability matrix from data points to categories in the learning framework. - **Candidate**: we construct an anchor graph factorization model from the perspective of transition probabilities, while simultaneously learning transition probability matrices from samples to clusters and from anchor points to clusters, serving as soft label matrices for samples and anchor points, respectively.

Evidence 2 - **Rationale**: The candidate's 'one-step label acquisition' through transition probability matrices from anchor points to clusters directly implements the same soft label derivation mechanism that UEMCP claims as a novel contribution. - **Original**: with the guidance of the common transition probability from data points to categories, the soft label of data points can be achieved based on the common transition probability matrix from anchor points to categories in the learning framework. - **Candidate**: simultaneously learning transition probability matrices from samples to clusters and from anchor points to clusters, serving as soft label matrices for samples and anchor points, respectively. this model enables one-step label acquisition and provides the model with a sound probability interpretatio...

Appendix: Text Similarity Detection

Textual similarity detection checked 15 papers and found 3 similarity segment(s) across 1 paper(s).

The following **1 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. One-Step Multi-View Clustering Based on Transition Probability

Detected in: Core Task (sibling), Contribution: contribution_1, Contribution: contribution_2, Contribution: contribution_3

⚠ **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.

References

- [0] Unified and Efficient Multi-view Clustering from Probabilistic Perspective View paper
- [1] Scalable multi-view graph clustering with cross-view corresponding anchor alignment View paper
- [2] Alleviate anchor-shift: Explore blind spots with cross-view reconstruction for incomplete multi-view clustering View paper
- [3] One-Step Multi-View Clustering Based on Transition Probability View paper
- [4] Fast Tensor-Based Multi-View Clustering with Anchor Probability Transition Matrix View paper
- [5] Adaptive Anchor-Guided Representation Learning for Efficient Multi-View Subspace Clustering. View paper
- [6] Dual-Constraint Multi-view Fuzzy Clustering with Scalable Anchor Graph Learning View paper
- [7] Image Clustering With Transition Probabilities Learning View paper
- [8] Multi-view Clustering Based on Probabilistic Tensor Regression View paper
- [9] Efficient Anchor Graph Factorization for Multi-View Clustering View paper
- [10] Priori Anchor Labels Supervised Scalable Multi-View Bipartite Graph Clustering View paper
- [11] State aggregation learning from markov transition data View paper
- [12] Efficient Co-clustering via Anchor-refined Label Spreading View paper
- [13] Self-learning symmetric multi-view probabilistic clustering View paper
- [14] Consensus representation-driven structured graph learning for multi-view clustering View paper
- [15] Adaptive transition probability matrix learning for multiview spectral clustering View paper
- [16] Understanding InfoNCE: Transition Probability Matrix Induced Feature Clustering View paper
- [17] Consensus Low-Rank Multi-View Subspace Clustering With Cross-View Diversity Preserving View paper
- [18] Error-robust multi-view clustering View paper
- [19] nmODE-MVC: Neural Memory ODE-Based Multi-View Clustering View paper