Learn from View Correlation: An Anchor Enhancement Strategy for Multi-view Clustering

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Overview

Observation:

1. The performances of existing anchor-based methods are significantly affected by the quality of the anchors.
2. The anchors generated by previous works solely rely on single-view information, ignoring the correlation among different views.

Contribution:

1. We propose AEVC, a plug-and-play anchor enhancement strategy for MVC based on view correlation.
2. By learning from the view correlation, AEVC incorporates the anchor distribution information from neighboring views into the process of anchor enhancement.
3. Extensive experiments verify the effectiveness and generalization of the proposed AEVC strategy when integrated with typical anchor-based MVC methods.

Anchor Construction in Multi-View Scenarios

The results of downstream tasks are affected by the quality of the initially fixed anchors.

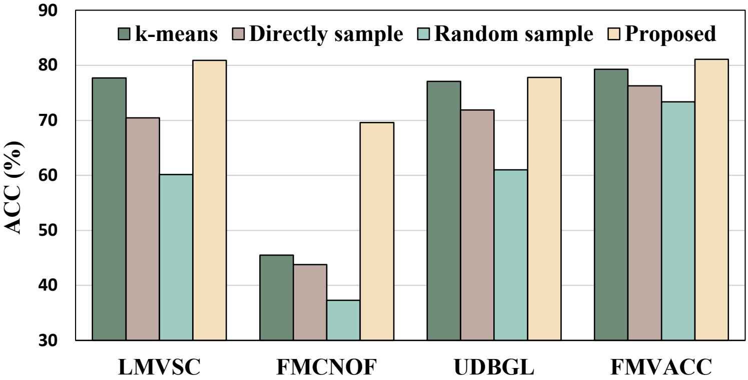

Figure 1: An example illustration of clustering results affected by initial anchors.

Anchor Construction in Multi-View Scenarios

Anchor updating is a strategy to mitigate the impact of initialization.

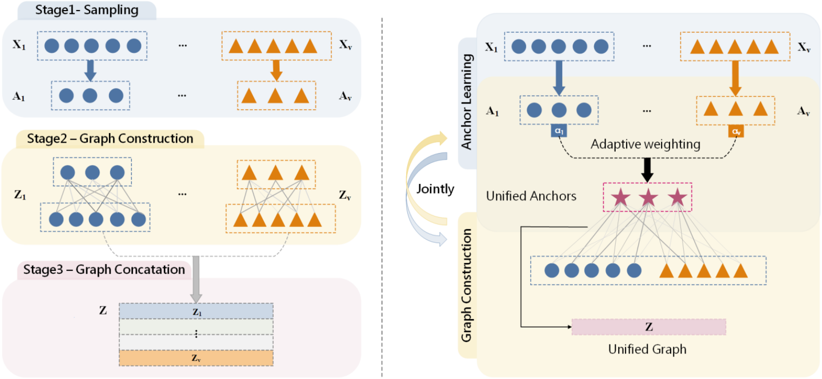

Figure 2: Fixed anchors methods v.s. Updated anchors methods.[1]

[1] Mengjing Sun et al. "Scalable multi-view subspace clustering with unified anchors". In: Proceedings of the 29th ACM International Conference on Multimedia. 2021, pp. 3528–3536.

Anchor Construction in Multi-View Scenarios

Heuristic sampling strategies for single-view scenarios are not suitable for anchor construction in multi-view scenarios:

- Ignoring inter-view relationships and constructing anchors independently leads to inconsistencies in downstream fusion tasks.
- Anchor updating strategy integrates multi-view information into the anchors through alternating optimization between views, yet optimization is inevitably influenced by initialization.

These inspire us to enhance the anchors with view correlations.

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Anchor-based Multi-View Clustering

Anchor-based methods are widely regarded as an effective strategy for handling large-scale datasets. The main idea of the anchor-based methods is to select or sample a small number of representative anchors and explore their relationships with the original samples.[2][3][4]

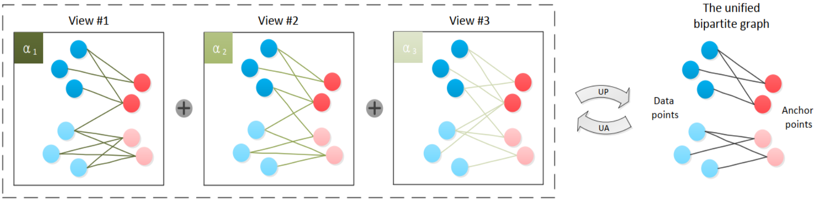

Figure 3: Framework of the anchor-based multi-view clustering method.

[2] Yeqing Li et al. "Large-scale multi-view spectral clustering via bipartite graph". In: Twenty-Ninth AAAI Conference on Artificial Intelligence. 2015.

[3] Zhao Kang et al. "Large-scale multi-view subspace clustering in linear time". In: Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. 04. 2020, pp. 4412–4419.

[4] Xuelong Li et al. "Multi-view clustering: A scalable and parameter-free bipartite graph fusion method". In: IEEE Transactions on Pattern Analysis and Machine Intelligence (2020).

Anchor-based Multi-View Clustering

Anchor-based MVC methods typically consist of three procedures, including:

1.Anchor generation:

Independently select fixed anchors to represent all samples in each view, such as using k-means or random sampling.

2.Anchor graph construction:

$$\min_{\mathbf{Z}_i} \|\mathbf{X}_i - \mathbf{A}_i\mathbf{Z}_i\|_{\mathbf{F}}^2 + \Omega(\mathbf{Z}_i), \text{s.t. } \mathbf{Z}_i \geq 0, \mathbf{Z}_i^\top \mathbf{1} = \mathbf{1}. \tag{1}$$

3.Multi-view fusion:

$$\min_{\boldsymbol{\alpha}^\top \mathbf{1}=\mathbf{1}, \boldsymbol{\alpha}\geq\mathbf{0}, \mathbf{P}} \left\| \sum_{i=1}^{v} \alpha_i \mathbf{Z}_i - \mathbf{P} \right\|_{\mathbf{F}}^2, \text{s.t. } \mathbf{P}^\top \mathbf{1} = \mathbf{1}, \boldsymbol{\alpha} \geq \mathbf{0}. \tag{2}$$

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Anchor Enhancement Strategy with View Correlation

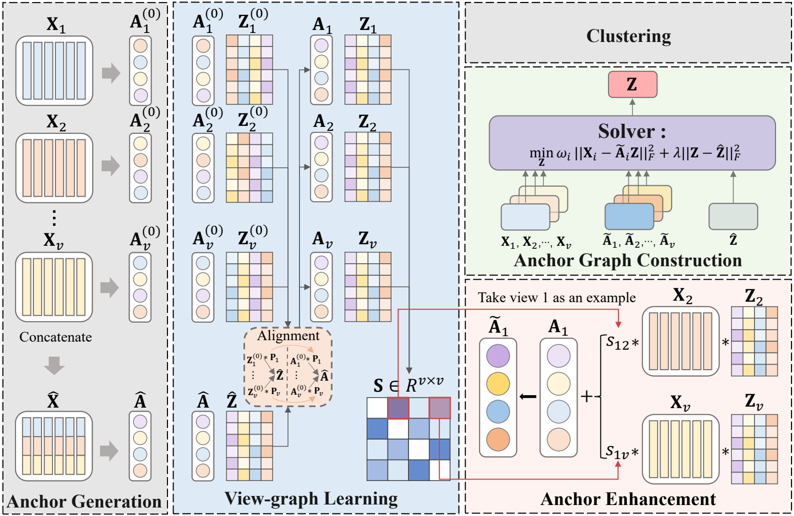

Figure 4: The framework of our proposed AEVC.

View-graph Learning

Firstly, align the anchor graphs and anchors with a common anchor graph.

$$\begin{aligned} &\min_{\mathbf{P}_i} \left\| \hat{\mathbf{Z}} - \mathbf{P}_i \mathbf{Z}_i^{(0)} \right\|_{\mathbf{F}}^2, \\ \text{s.t. } & \mathbf{P}_i \mathbf{1} = \mathbf{1}, \mathbf{P}_i^\top \mathbf{1} = \mathbf{1}, \mathbf{P}_i \in \{0,1\}^{m \times m}. \end{aligned} \tag{3}$$

Then, compute the inter-view correlations based on the anchor graphs.

$$\begin{cases} \mathbf{s}_{ij} = \frac{1}{\|\mathbf{Z}_i - \mathbf{Z}_j\|_{\mathbf{F}}^2}, & i \neq j, \\ \mathbf{s}_{ij} = 0, & i = j. \end{cases} \tag{4}$$

Anchor Enhancement Strategy

Due to the varying dimensions of anchors across views, we enhance the anchors of the current view with the anchor graph of neighboring views.

$$\tilde{\mathbf{A}}_i = \frac{1}{\mu}(\mathbf{A}_i + \gamma \sum_{\mathbf{X}_j \in \Omega_\zeta(\mathbf{X}_i)} \hat{s}_{ij} \mathbf{X}_i \mathbf{Z}_j^\top), \tag{5}$$

where $\mu = 1 + \gamma \sum_{\mathbf{X}_j \in \Omega_\zeta(\mathbf{X}_i)} \hat{s}_{ij}$.

Anchor Graph Construction

Construct a unified anchor graph with the enhanced anchors from each view.

$$\min_{\mathbf{Z}} \omega_i \left\| \mathbf{X}_i - \tilde{\mathbf{A}}_i \mathbf{Z} \right\|_{\mathbf{F}}^2 + \lambda \left\| \mathbf{Z} - \hat{\mathbf{Z}} \right\|_{\mathbf{F}}^2, \quad \text{s.t. } \mathbf{Z} \geq 0, \mathbf{Z}^\top \mathbf{1} = \mathbf{1}, \tag{6}$$

where $\omega_i = \sum_{j=1}^{v} s_{ij}$ is the contribution weight computed with the view-graph.

Two Property of Enhanced Anchors

Property 1. *The disparity among the anchor graphs on each view is reduced after anchor enhancement. Mathematically,*

$$\left\|\tilde{\mathbf{Z}}_1 - \tilde{\mathbf{Z}}_2\right\|_{\mathbf{F}} < \|\mathbf{Z}_1 - \mathbf{Z}_2\|_{\mathbf{F}}. \tag{7}$$

Property 2. *Assuming there exists a value $\beta \in (0, 1)$ such that $\mathbf{Z} = \beta\mathbf{Z}_1 + (1 - \beta)\mathbf{Z}_2$ is the optimal consistent anchor graph among all views, the enhanced anchor graph is closer to the optimal version after enhancement than before for all $\alpha \in (2\beta - 1, 1) \cap (0, 1)$. Mathematically,*

$$\left\|\tilde{\mathbf{Z}}_1 - \mathbf{Z}\right\|_{\mathbf{F}} < \|\mathbf{Z}_1 - \mathbf{Z}\|_{\mathbf{F}}. \tag{8}$$

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Performance on Downstream Tasks

Datasets	LMVSC	SMVSC	FMCNOF	FPMVS-CAG	UDBGL	FastMICE	FDAGF	FMVACC	Proposed
					ACC				
Dermatology	79.02±0.07	78.64±0.05	62.01±0.00	82.96±0.07	84.08±0.00	87.15±0.00	84.41±7.90	84.39±4.34	**93.20±4.50**
ForestTypes	77.68±0.04	72.82±0.01	45.51±0.00	72.22±0.05	77.06±0.00	77.06±0.00	76.40±7.13	79.29±0.23	**82.53±0.09**
BDGP	49.52±0.02	37.22±0.02	31.08±0.00	32.62±0.01	39.28±0.00	49.00±0.00	47.30±3.16	59.51±4.00	**60.65±0.62**
Reuters	27.19±0.01	24.41±0.01	19.25±0.00	17.33±0.00	22.32±0.00	26.00±0.00	25.04±0.50	27.22±0.24	**29.91±0.02**
Hdigit	86.87±0.08	65.99±0.03	32.84±0.00	64.22±0.05	31.39±0.00	85.13±0.00	77.69±7.83	86.55±4.08	**88.01±2.97**
VGGFace	6.09±0.00	7.21±0.00	3.47±0.00	6.02±0.00	5.39±0.00	5.26±0.00	6.50±0.33	6.68±0.16	**8.35±0.07**
CIFAR100	8.92±0.00	8.48±0.00	4.40±0.00	7.46±0.00	7.83±0.00	9.81±0.00	7.47±0.13	7.04±0.12	**10.74±0.08**

Figure 5: Clustering performance comparison of existing anchor-based methods.

Methods	Dermatology	ForestTypes	BDGP	Reuters	Hdigit	VGGFace	CIFAR100
			Fixed Anchors Methods				
FMCNOF	62.01±0.00	45.51±0.00	31.08±0.00	19.25±0.00	32.84±0.00	3.47±0.00	4.40±0.00
FMCNOF-AE	**73.18±0.00**	**69.60±0.00**	**37.64±0.00**	**22.79±0.00**	**34.31±0.00**	3.21±0.00	**5.05±0.00**
LMVSC	79.02±0.07	77.68±0.04	49.52±0.02	27.19±0.01	86.87±0.08	6.09±0.00	8.92±0.00
LMVSC-AE	**88.23±7.80**	**80.90±5.49**	**52.13±0.34**	**28.84±0.67**	85.74±5.72	**6.83±0.16**	8.81±0.16
			Updated Anchors Methods				
UDBGL	84.08±0.00	77.06±0.00	39.28±0.00	22.32±0.00	31.39±0.00	5.39±0.00	7.83±0.00
UDBGL-AE	81.01±0.00	**77.82±0.00**	**46.92±0.00**	**28.53±0.00**	**44.60±0.00**	**5.65±0.00**	**8.57±0.00**
FMVACC	84.39±4.34	79.29±0.23	59.51±4.00	27.22±0.24	86.55±4.08	6.68±0.16	7.04±0.12
FMVACC-AE	**88.41±3.13**	**81.08±0.23**	59.36±3.03	**33.12±2.49**	**88.42±2.93**	**7.13±0.17**	**7.28±0.15**

Figure 6: Comparison between anchor-based MVC w./w.o. our AEVC strategy.

Validation of Anchor Enhancement

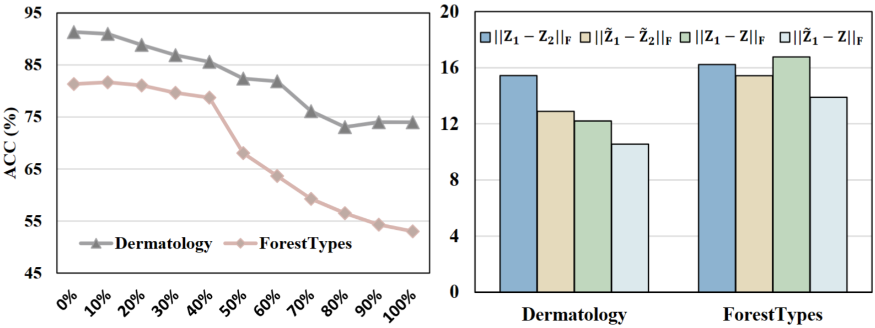

Figure 7: Left: As the proportion of randomly generated anchors increases, the corresponding clustering performance decreases monotonically. Right: After anchor enhancement, the differences in anchor graphs between different views are reduced, and the enhanced anchor graph is closer to the optimal consensus anchor graph.

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