Dual-Topology Learning with Adaptive Anchors for Multi-View Clustering

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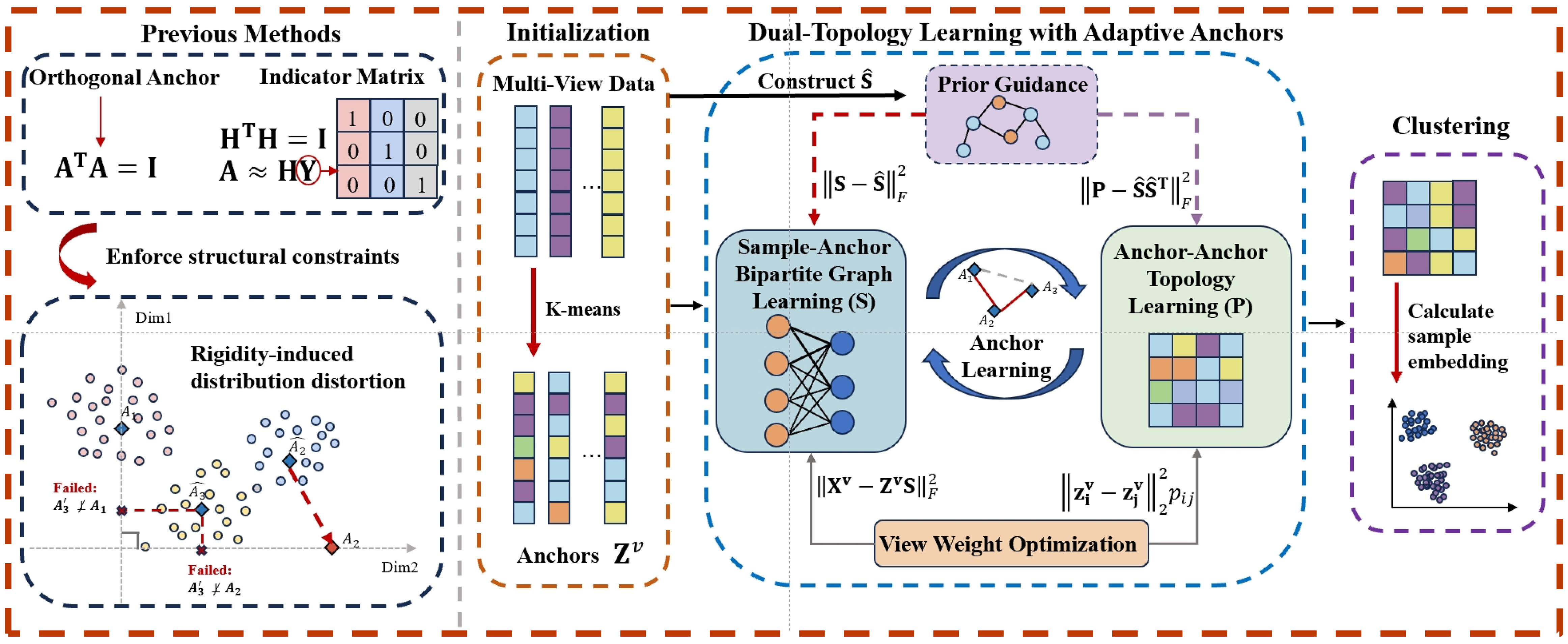
Background

- A multi-view sample is represented by multiple types of data, often collected from different sources, such as various sensors. Multi-view clustering (MVC) is to divide the multi-view data into disjoint groups.
- Traditional MVC methods construct sample-level graphs to capture data relationships, but suffer from high computational costs due to quadratic complexity.
- Existing methods often ignore anchor topology and impose rigid constraints, which may distort intrinsic structures.

Motivation

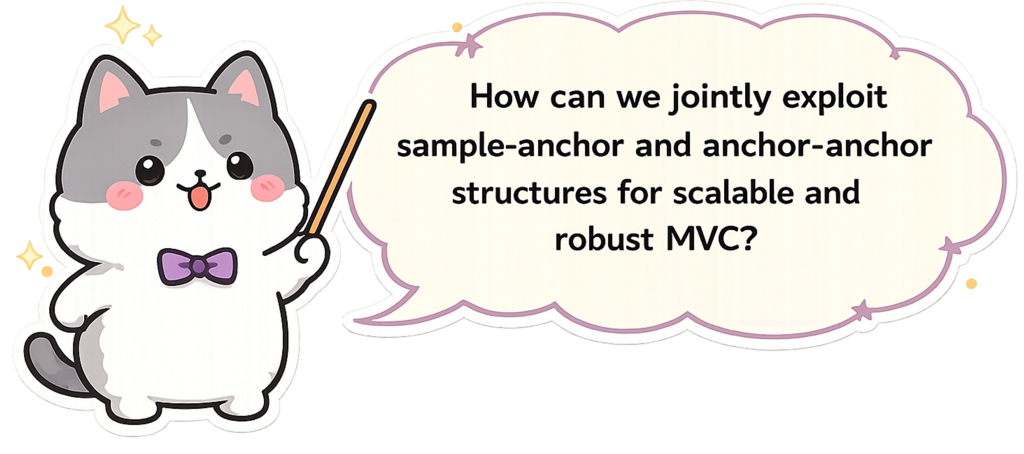
- Existing anchor-based MVC methods mainly focus on sample-anchor relationships while ignoring the intrinsic topology among anchors. Meanwhile, rigid anchor constraints may distort data distributions and limit the ability to capture global structures.
- We propose DOTA, a dual-topology learning framework with adaptive anchors, to jointly model sample-anchor and anchor-anchor relationships. An adaptive view weighting strategy is further developed to exploit complementary information across views.

DOTA Method



1. Adaptive Bipartite Graph Construction:

$$\min_{\mathbf{Z}^v,\mathbf{S}\mathbf{1}_n=\mathbf{1}_m,\mathbf{S}\geq 0} \|\mathbf{X}^v - \mathbf{Z}^v\mathbf{S}\|_F^2 + \beta\|\mathbf{S}-\hat{\mathbf{S}}\|_F^2$$



2. Prior-Driven Anchor Similarity Learning:

$$\min_{\mathbf{Z}^v,\mathbf{S},\mathbf{P},\alpha} \sum_{v=1}^{V} \alpha_v^2 (\underbrace{\|\mathbf{X}^v - \mathbf{Z}^v\mathbf{S}\|_F^2}_{\text{Reconstruction}} + \lambda \boxed{\underbrace{\textstyle\sum_{i,j=1}^{m} \|\mathbf{z}_i^v - \mathbf{z}_j^v\|_2^2 p_{ij}}_{\text{Manifold Regularizer}}})$$
$$+ \beta(\underbrace{\|\mathbf{P} - \hat{\mathbf{S}}\hat{\mathbf{S}}^T\|_F^2 + \|\mathbf{S}-\hat{\mathbf{S}}\|_F^2}_{\text{Prior Consistency}})$$
$$\text{s.t. } \mathbf{S}\mathbf{1}_n = \mathbf{1}_m, \mathbf{P}\mathbf{1}_m = \mathbf{1}_m, \mathrm{diag}(\mathbf{P}) = 0, \boldsymbol{\alpha}^T\mathbf{1}_V = 1,$$

We add anchor consistency regularization to reuse the historical anchor knowledge, and also refine it based on the new data.

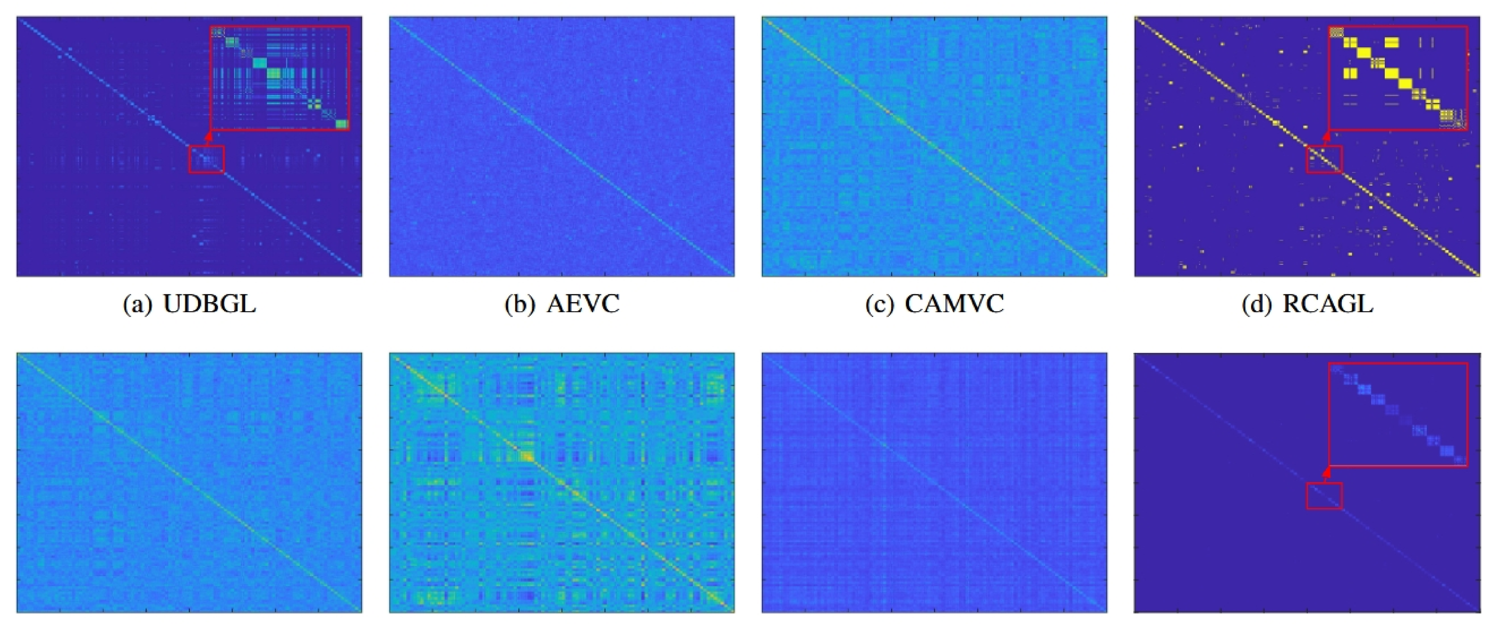
Main Results

Clustering Performance Comparison

Dataset	UDBGL	AEVC	CAMVC	RCAGL	ALPC	AGLDR	HRAL	DOTA
				ACC (%)				
Leaves	65.31±0.00	79.28±1.51	81.38±1.84	69.81±0.00	80.08±1.93	69.22±0.92	76.56±2.05	**89.86**±1.21
COIL100	56.47±0.00	58.59±1.16	57.39±1.35	52.65±0.00	60.22±1.56	63.21±1.88	49.45±1.14	**79.42**±1.13
Hdigit	84.19±0.00	85.04±0.01	87.24±5.68	78.44±0.00	78.82±7.89	87.28±0.02	72.21±5.62	**97.25**±0.00
MNIST	36.57±0.00	46.35±0.28	43.30±1.82	44.02±0.00	38.46±2.49	48.13±0.16	44.40±4.41	**52.37**±2.18
KSA	23.70±0.00	29.66±0.01	44.32±0.18	21.12±0.00	30.70±0.47	23.49±0.00	34.20±0.35	**45.09**±3.22
CIFAR100	84.55±0.00	92.96±1.20	91.04±1.56	**99.97**±0.00	92.22±1.92	95.04±0.03	89.57±1.94	99.92±0.00
Ave. Score	0.5847	0.6531	0.6745	0.6100	0.6342	0.6440	0.6107	**0.7732**
Ave. Rank	6.83	4.00	4.00	5.67	4.67	3.83	5.83	**1.17**
				NMI (%)				
Leaves	82.98±0.00	92.06±0.53	94.04±0.58	87.81±0.00	92.90±0.53	86.29±0.18	91.49±0.61	**96.01**±0.30
COIL100	79.37±0.00	81.90±0.42	82.04±0.37	78.19±0.00	83.21±0.49	84.34±0.55	74.90±0.57	**91.55**±0.28
Hdigit	76.38±0.00	72.25±0.02	82.20±3.18	73.32±0.00	78.87±4.27	75.21±0.02	66.20±2.62	**93.05**±0.00
MNIST	22.36±0.00	30.95±0.10	33.46±1.15	36.86±0.00	28.70±0.67	35.65±0.16	32.25±2.73	**49.40**±0.53
KSA	2.84±0.00	10.53±0.02	**26.32**±0.60	1.24±0.00	10.36±0.24	1.80±0.00	18.36±0.01	24.17±1.17
CIFAR100	96.75±0.00	98.82±0.21	98.52±0.25	**99.95**±0.00	98.73±0.30	99.04±0.02	98.26±0.32	99.88±0.00
Ave. Score	0.6011	0.6442	0.6943	0.6290	0.6546	0.6372	0.6358	**0.7568**
Ave. Rank	6.67	5.00	3.17	5.00	4.33	4.50	6.00	**1.33**
				PUR (%)				
Leaves	69.94±0.00	82.33±1.16	84.65±1.58	82.94±0.00	83.13±1.69	72.60±0.71	80.03±1.63	**91.03**±1.01
COIL100	60.24±0.00	62.42±1.02	61.47±0.82	67.03±0.00	63.87±1.37	66.94±1.39	54.16±1.59	**81.50**±0.85
Hdigit	84.19±0.00	85.04±0.01	87.97±4.63	86.97±0.00	81.69±6.25	87.28±0.02	73.48±4.05	**97.25**±0.00
MNIST	39.57±0.00	49.31±0.34	47.32±1.85	**57.57**±0.00	42.54±1.36	51.55±0.20	47.63±3.87	57.12±1.22
KSA	23.70±0.00	29.67±0.01	44.32±0.18	25.05±0.00	31.82±0.01	23.50±0.00	34.37±0.05	**45.99**±1.98
CIFAR100	87.76±0.00	94.93±0.86	93.58±1.11	**99.97**±0.00	94.43±1.36	95.15±0.07	92.38±1.59	99.92±0.00
Ave. Score	0.6090	0.6728	0.6989	0.6992	0.6625	0.6617	0.6368	**0.7880**
Ave. Rank	7.33	4.67	4.00	3.00	5.00	4.50	6.17	**1.33**

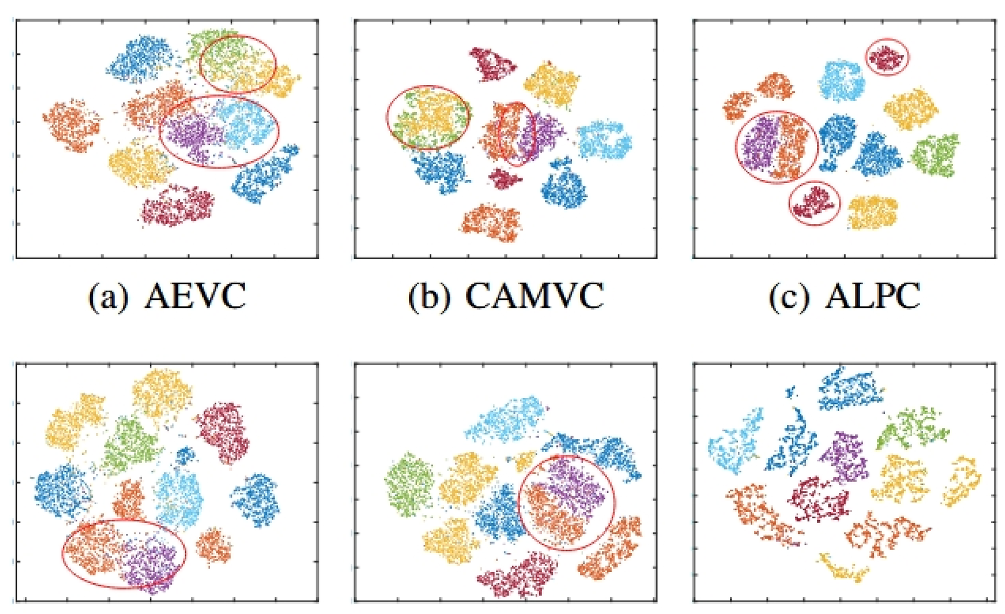
- UDBGL and AEVC are two-stages methods, RCAGL,ALPC and AGLDR are orthogonality methods, CAMVC and HRAL are constrained methods
- DOTA achieves competitive or superior results across datasets.

Similarity Matrices Visual Comparison



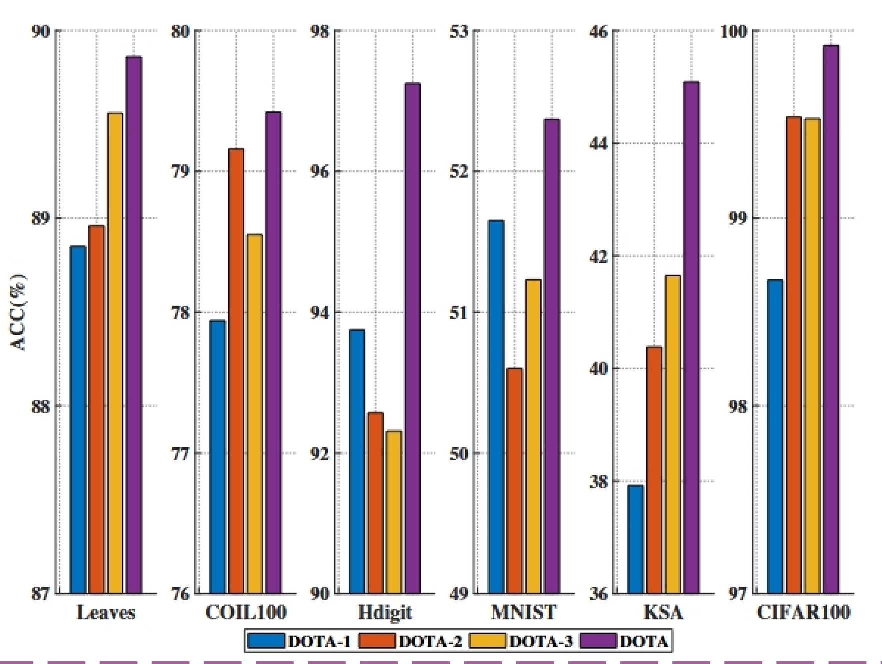
(a) UDBGL (b) AEVC (c) CAMVC (d) RCAGL (e) ALPC (f) AGLDR (g) HRAL (h) DOTA

T-SNE Results

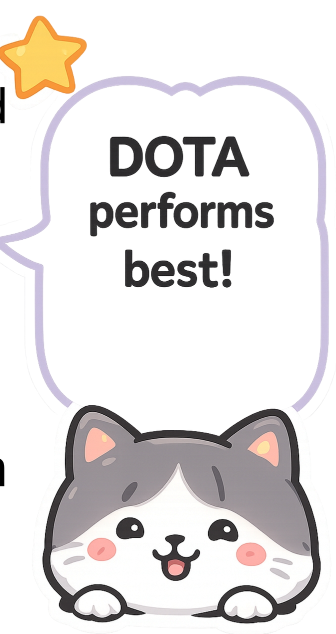


(a) AEVC (b) CAMVC (c) ALPC (d) AGLDR (e) HRAL (f) DOTA

Ablation Study



(1) DOTA-1 omits the anchor-based manifold regularizer term.
(2) DOTA-2 discards the prior consistency term.
(3) DOTA-3 removes the adaptive view-weighting mechanism by assigning equal importance to all views.



Conclusion

- We propose a novel **dual-topology learning method with adaptive anchors** for multi-view clustering. The proposed method jointly models sample-anchor and anchor-anchor relationships to preserve intrinsic structures. Experimental results demonstrate its effectiveness and superiority
- Our method adaptively learns anchor structures and view contributions, avoiding rigid constraints and improving the robustness of multi-view clustering.