Robust Contrastive Multi-view Clustering against Dual Noisy Correspondence

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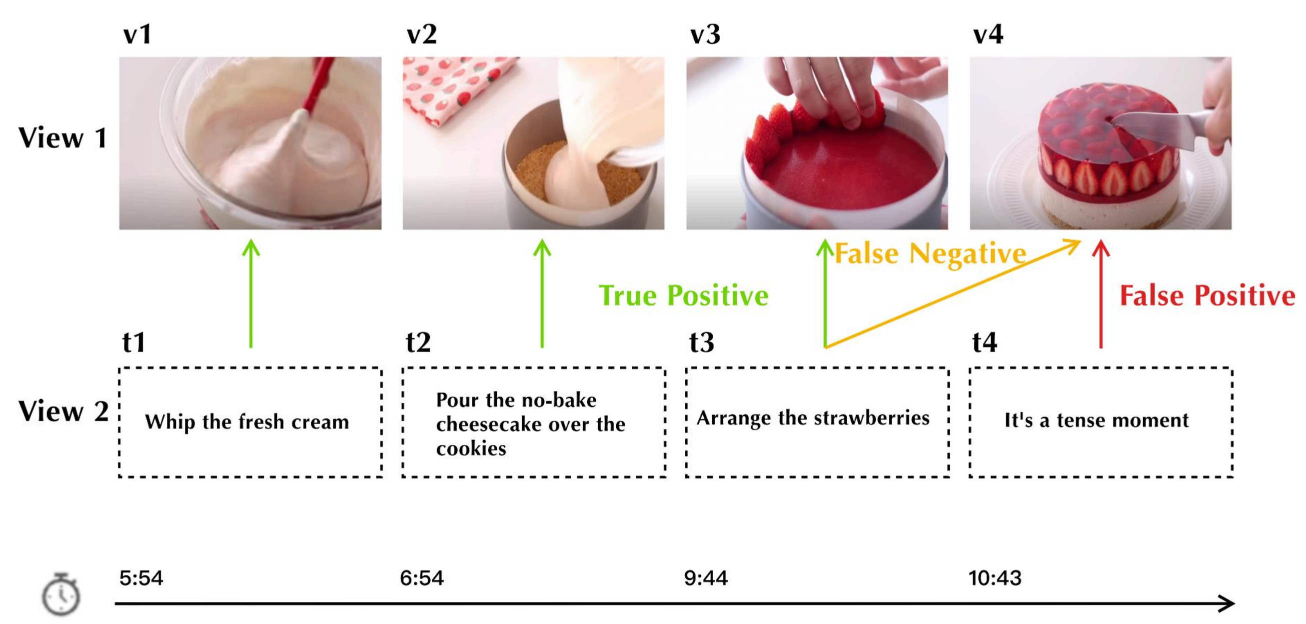
Observations & Motivations

Dual Noisy Correspondence Problem: Vanilla contrastive learning uses off-the-shelf pairs as positive, and randomly chooses samples across views as negative.

- However, on the one hand, some of the positive pairs are not correctly associated, leading to the **false positive problem**.
- On the other hand, some within-class samples are wrongly treated as negative, causing the **false negative problem.**



Demonstration of the Dual Noisy Correspondence. Taken from YouCook2 Dataset.

Our key idea is alleviating **dual noisy correspondence problem** by **increasing similarities of false negatives and decreasing similarities of false positives**. Our method uses the semantic-based method to identify and rectify false negative correlations, and uses the spectral-based method to denoise false positive correlations

Highlights & Contributions

- We introduce a new challenge in contrastive multi-view clustering called **dual noisy correspondence** (DNC), which deals with noise in both positive and negative cross-view pairs.
- We propose Contextually-spectral based correspondence refinery (CANDY), a robust method to counter DNC in contrastive multiview clustering, 1) treating affinity as context to identify false negatives, and 2) denoising on high-order affinity graphs to alleviate false positives.

* Equal Contribution
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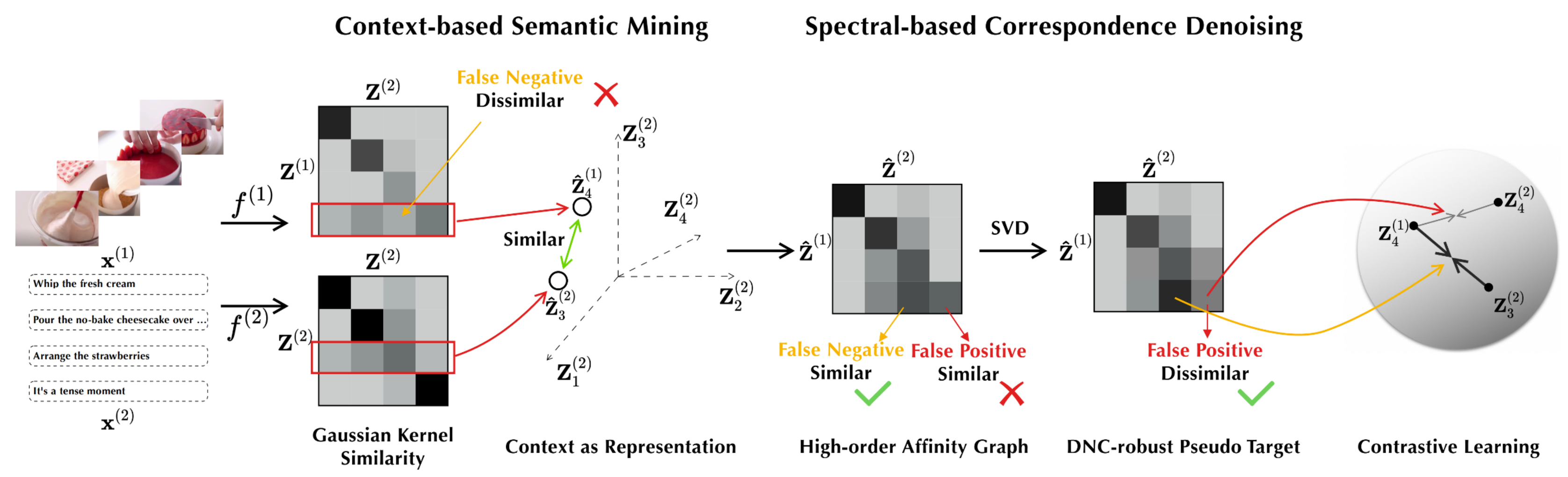
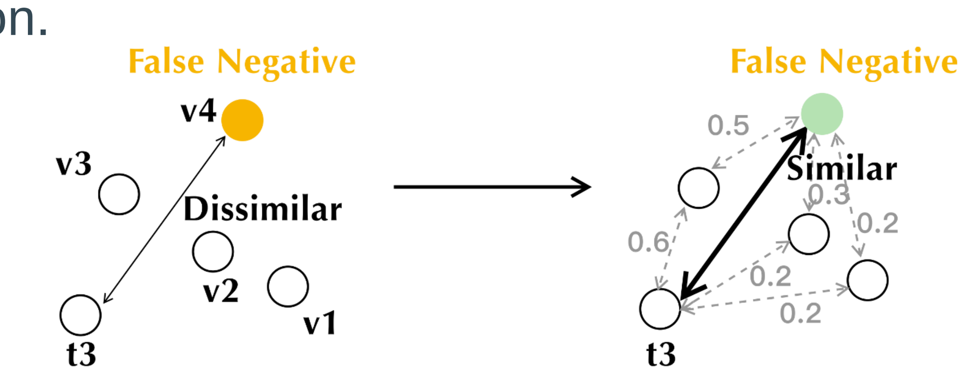
Method



Our method is composed of two modules: the **context-based semantic mining** (CSM) and **spectral-based correspondence denoising** (SCD). With these two modules, we can construct robust pseudo targets for contrastive learning.

The CSM module formulates the context representation of each sample by considering cross-modal high-order neighborhood information.



Context-based Semantic Mining

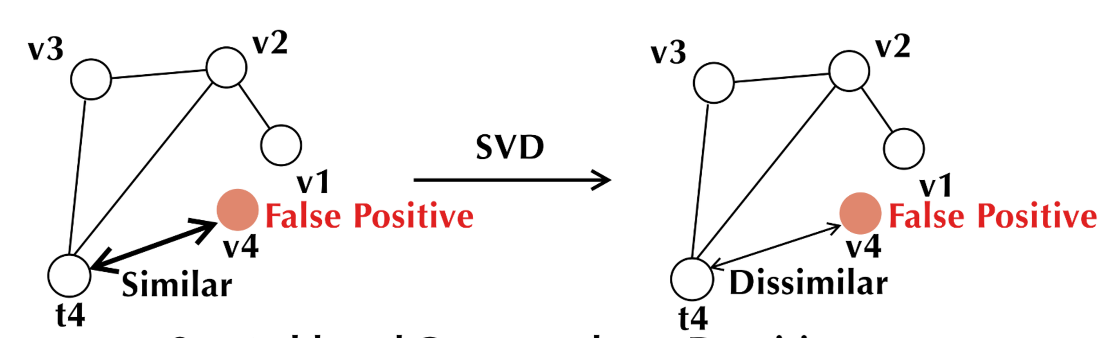
Mathematically, we obtain the similarity graph of the features by

$$\mathbf{A}_{ij}^{(v_1\to v_2)} = \exp\left(-\left\|\left[\mathbf{Z}^{(v_1)}\right]_i - \left[\mathbf{Z}^{(v_2)}\right]_j\right\|^2 / \sigma\right),$$

And compose the similarity graph as

$$\mathbf{G}^{(v_1\to v_2)} = \mathbf{A}^{(v_1\to v_2)}\mathbf{A}^{(v_2\to v_2)^\top}$$

The SCD module leverages singular value decomposition to alleviate the false positives in the sample.



Spectral-based Correspondence Denoising

We use singular value decomposition to obtain the eigenvalues and eigenvectors.

$$\mathbf{G}^{(v_1\to v_2)} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\top, \quad \mathbf{\Sigma} = \mathrm{diag}(\lambda_1, \lambda_2, \ldots, \lambda_n)$$

and remove eigenvectors whose eigenvalue is below a certain threshold.

$$\tilde{\mathbf{\Sigma}} = \mathrm{diag}(\lambda_1, \ldots, \lambda_L, 0, \ldots, 0) \quad \tilde{\mathbf{G}}^{(v_1\to v_2)} = \mathbf{U}\tilde{\mathbf{\Sigma}}\mathbf{V}^\top,$$

Experiments

➢ Comparison on five datasets under various noise rates

FP Ratio	Methods	Scene15			Caltech-101			LandUse21			Reuters			NUS-WIDE			Average		
		ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI	ACC	NMI	ARI
0%	DCCAE (ICML'15)	34.6	39.0	19.7	45.8	68.6	37.7	15.6	24.4	4.4	42.0	20.3	8.5	47.5	17.1	37.6	37.1	33.9	21.6
	BMVC (TPAMI'18)	40.5	41.2	24.1	50.1	72.4	33.9	25.3	28.6	11.4	42.4	21.9	15.1	36.0	21.0	16.5	38.9	37.0	20.2
	PVC (NeurIPS'20)	38.0	39.8	21.1	20.5	51.4	15.7	16.8	25.2	5.6	44.1	27.1	27.1	19.3	7.7	3.8	27.7	30.2	14.7
	MVCLN (CVPR'21)	37.9	42.3	25.6	39.6	65.3	32.8	26.1	30.7	12.5	38.8	**42.1**	25.2	54.1	38.3	35.7	39.3	43.7	26.4
	SURE (TPAMI'23)	41.0	43.2	25.0	43.8	70.1	29.5	25.1	28.3	10.9	49.1	29.9	23.6	57.4	44.8	38.3	43.3	43.3	25.5
	GCFAgg (CVPR'23)	42.2	42.5	24.4	56.6	80.7	37.9	27.5	31.3	14.0	34.4	23.8	10.5	41.1	32.1	18.6	40.4	42.1	21.1
	CGCN (TCSVT'24)	42.9	43.4	25.0	49.1	75.2	33.8	28.8	36.0	15.0	45.8	27.0	22.3	61.2	48.1	**41.2**	45.6	45.9	27.5
	DIVIDE (AAAI'24)	**49.1**	**48.7**	**31.6**	62.2	83.0	50.5	**32.3**	**39.7**	**18.1**	**59.3**	39.5	29.0	45.1	30.9	19.4	49.6	**48.4**	29.7
	CANDY (Ours)	42.0	41.6	24.7	**67.3**	**83.8**	**60.0**	30.6	36.5	16.2	57.7	30.8	**37.1**	**62.1**	**49.0**	37.0	**51.9**	48.3	**35.0**
20%	DCCAE (ICML'15)	32.9	17.1	**29.6**	36.9	39.2	**60.1**	15.0	3.8	**17.4**	41.6	13.1	19.3	41.6	11.6	26.9	33.6	17.0	30.7
	BMVC (TPAMI'18)	20.0	10.2	4.7	42.7	58.2	24.6	16.1	13.0	4.3	36.4	11.9	8.1	27.7	10.7	7.7	28.6	20.8	9.9
	PVC (NeurIPS'20)	31.2	25.5	13.6	8.3	30.2	3.8	22.8	28.0	8.4	32.4	15.4	15.3	34.3	22.2	13.6	25.8	24.3	10.9
	MVCLN (CVPR'21)	39.3	36.7	21.7	43.3	64.0	52.8	24.4	26.1	10.8	37.9	35.9	20.3	42.5	29.3	21.3	37.5	38.4	25.4
	SURE (TPAMI'23)	40.0	37.3	21.5	26.9	49.9	18.0	25.2	27.4	11.6	40.7	20.9	15.8	57.0	45.0	**38.6**	38.0	36.1	21.1
	GCFAgg (CVPR'23)	40.9	38.6	22.7	50.1	70.6	30.1	25.7	27.8	11.9	35.2	19.0	10.8	38.6	23.3	15.6	38.1	35.9	18.2
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	DIVIDE (AAAI'24)	**42.4**	39.9	24.5	48.3	69.1	38.0	**30.9**	35.1	16.2	**55.3**	**36.9**	31.0	44.9	28.3	18.2	44.4	41.9	25.6
	CANDY (Ours)	40.4	**40.3**	23.7	**65.9**	**82.3**	**60.1**	30.5	**35.3**	15.7	54.2	27.9	**33.8**	**60.3**	**47.1**	36.9	**50.3**	**46.6**	**34.0**
50%	DCCAE (ICML'15)	26.8	10.2	19.8	27.0	26.8	49.8	13.3	2.8	13.2	37.7	9.2	12.5	32.3	7.1	13.5	27.4	11.2	21.8
	BMVC (TPAMI'18)	13.6	3.9	1.4	26.5	34.2	8.9	13.5	7.5	1.9	26.6	3.3	2.3	18.4	3.1	1.9	19.7	10.4	3.3
	PVC (NeurIPS'20)	20.3	10.2	13.6	7.4	21.8	5.0	20.6	28.5	8.7	42.9	23.5	23.4	24.1	10.1	9.9	23.1	18.8	12.1
	MVCLN (CVPR'21)	**41.3**	19.7	15.1	21.4	39.1	11.7	21.4	21.8	7.8	34.8	**35.5**	19.7	31.7	16.6	10.7	30.1	26.5	13.0
	SURE (TPAMI'23)	37.1	35.7	20.3	19.9	41.7	13.2	23.1	22.8	8.9	38.0	18.5	14.3	35.0	17.4	12.0	30.6	27.2	13.7
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	CANDY (Ours)	**41.3**	**39.4**	**24.0**	**60.7**	**79.0**	**56.6**	**29.9**	**33.1**	**15.2**	**47.4**	21.7	**27.3**	**58.1**	**43.2**	**34.5**	**47.5**	**43.3**	**31.5**
80%	DCCAE (ICML'15)	20.9	6.7	14.4	18.4	15.8	41.8	14.5	3.2	13.4	35.3	7.6	10.0	36.2	14.9	21.9	25.1	9.6	20.3
	BMVC (TPAMI'18)	10.5	1.5	0.3	11.9	18.3	1.5	10.1	4.2	0.4	21.3	0.5	0.1	13.1	0.6	0.2	13.4	5.0	0.5
	PVC (NeurIPS'20)	20.3	10.2	4.6	7.5	20.8	4.2	22.5	29.3	9.3	35.7	13.2	13.1	19.3	7.7	3.8	21.1	16.2	7.0
	MVCLN (CVPR'21)	35.7	16.2	13.9	13.9	34.2	10.9	17.0	15.7	4.4	24.3	**28.1**	12.4	24.3	10.0	5.7	23.0	20.8	9.5
	SURE (TPAMI'23)	27.4	30.7	14.2	16.2	38.3	9.0	18.0	17.6	5.5	34.6	15.5	13.0	23.7	9.4	5.4	24.0	22.3	9.4
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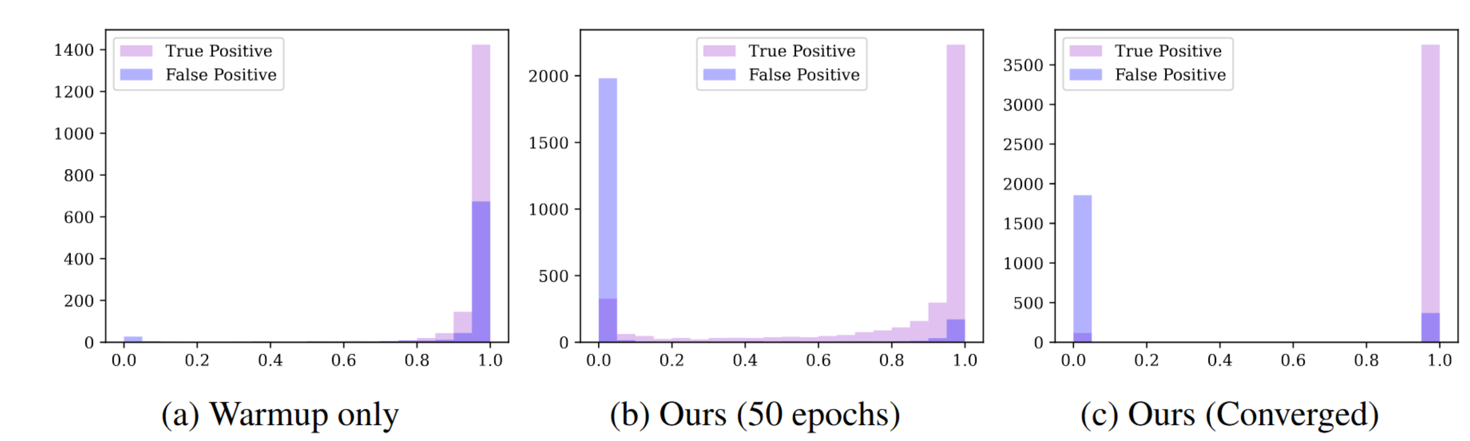
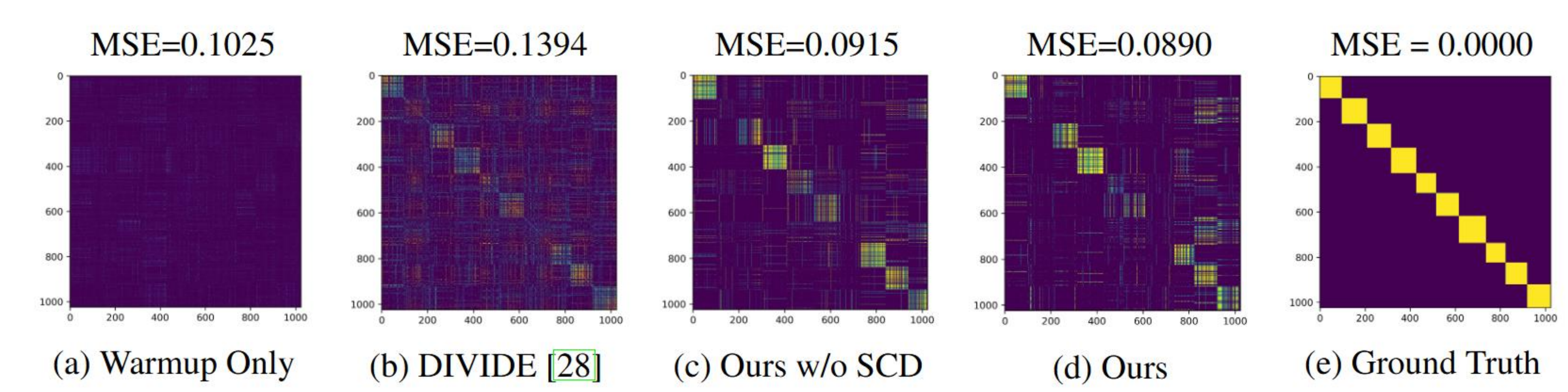
	CANDY (Ours)	**38.8**	**36.6**	**20.7**	**52.6**	**76.8**	**52.9**	**28.1**	**31.3**	**13.5**	37.0	12.4	15.6	**55.6**	**39.1**	**32.6**	**42.4**	**39.2**	**27.1**

➢ Visualization on the Robustness



Confidence for the True Positive and False Positive using our method.

➢ Visualization of the pseudo target



Contact

Code is available at:
`https://github.com/XLearning-SCU/2024-NeurIPS-CANDY`

E-mail: `guoruiming.gm@gmail.com`

GitHub Repo

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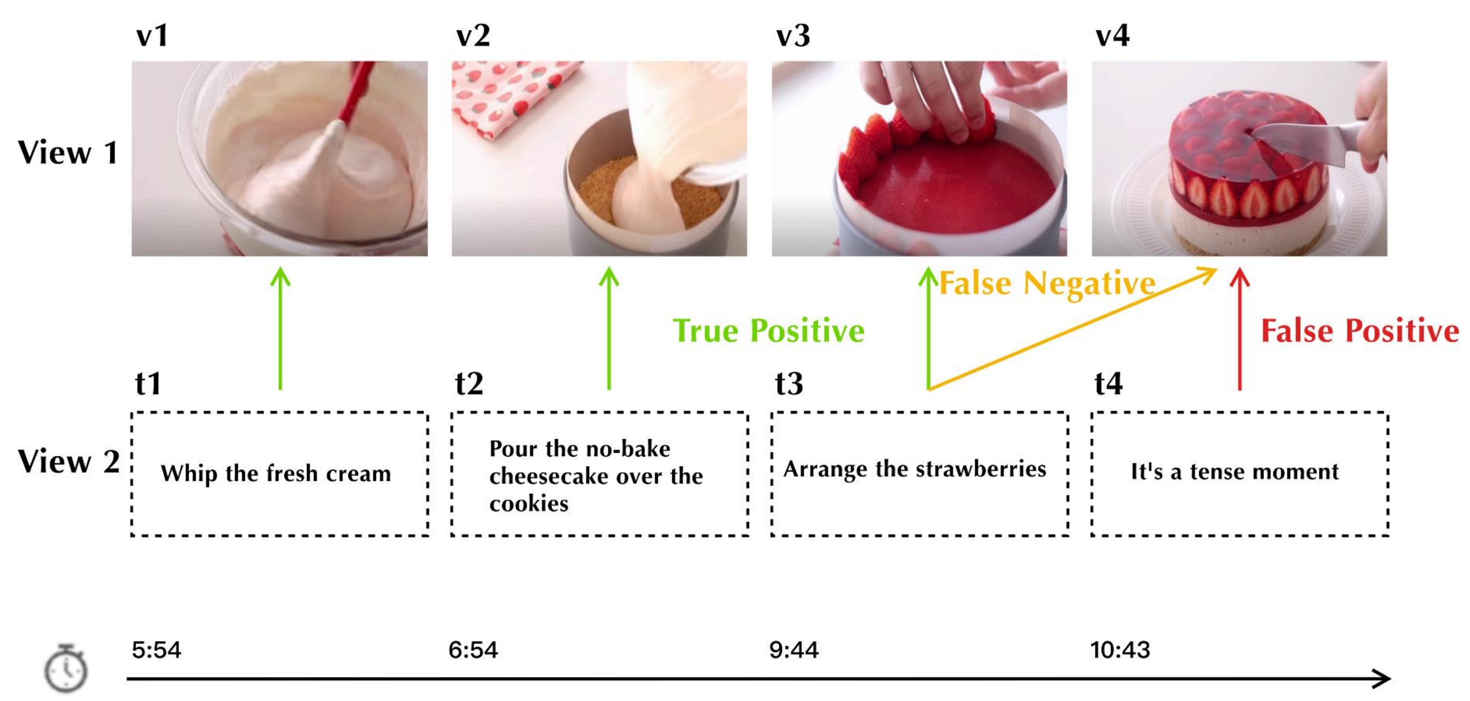
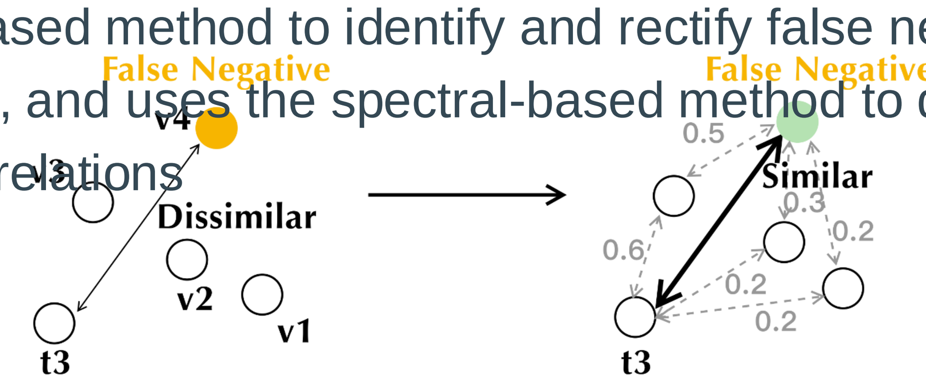
Observations & Motivations

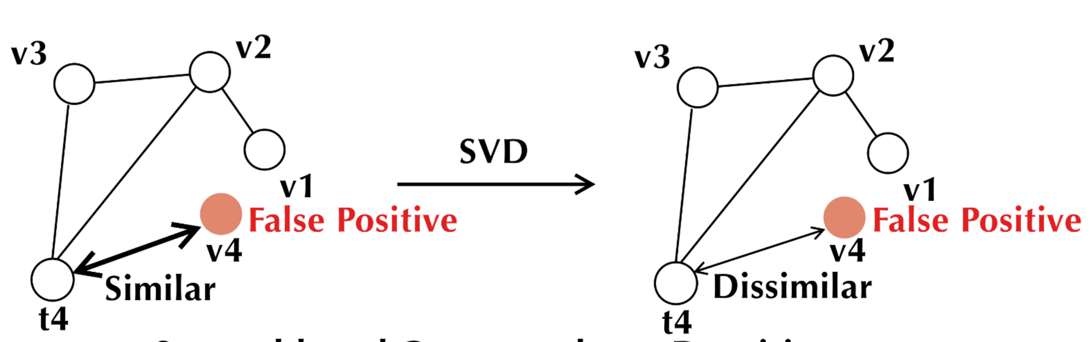
Dual Noisy Correspondence Problem: Vanilla contrastive learning uses off-the-shelf pairs as positive, and randomly chooses samples across views as negative. However, on the one hand, some of the positive pairs are not correctly associated, leading to the **false positive problem**. On the other hand, some within-class samples are wrongly treated as negative, causing the **false negative problem.**



Our key idea is alleviating **dual noisy correspondence problem** by **increasing similarities of false negatives and decreasing similarities of the false positives**. Our method uses the semantic based method to identify and rectify false negative correlations, and uses the spectral-based method to denoise false positive correlations.



Context-based Semantic Mining

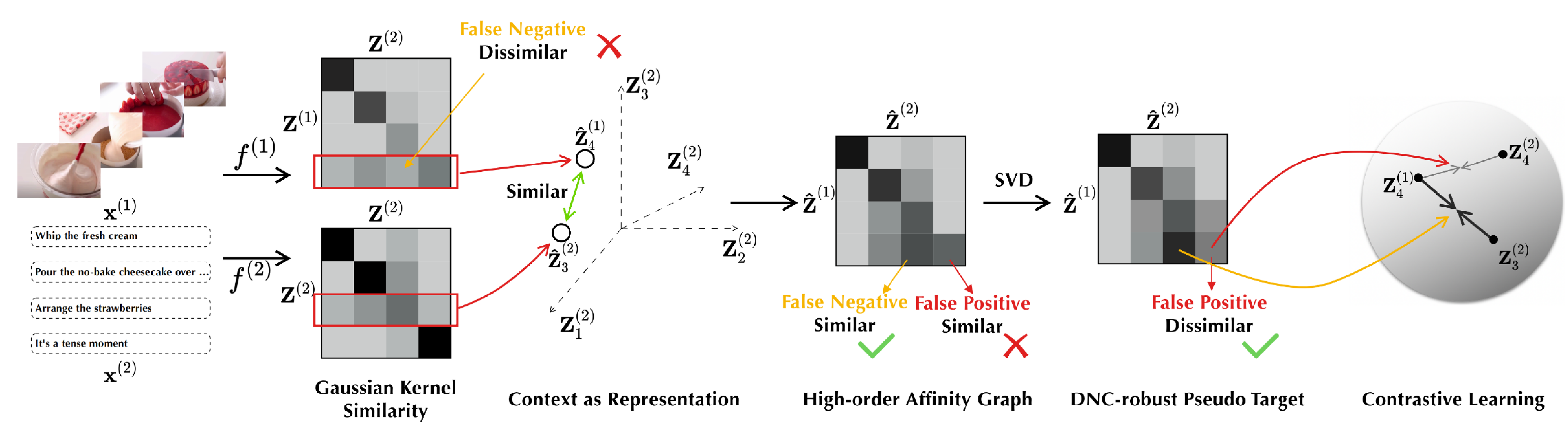


Spectral-based Correspondence Denoising

* Equal Contribution

Corresponding Author

Method



Experiments

➤ **Comparison on five datasets under various noise rates**

FP Ratio	Methods	Scene15 ACC	Scene15 NMI	Scene15 ARI	Caltech-101 ACC	Caltech-101 NMI	Caltech-101 ARI	LandUse21 ACC	LandUse21 NMI	LandUse21 ARI	Reuters ACC	Reuters NMI	Reuters ARI	NUS-WIDE ACC	NUS-WIDE NMI	NUS-WIDE ARI	Average ACC	Average NMI	Average ARI
0%	DCCAE (ICML'15)	34.6	39.0	19.7	45.8	68.6	37.7	15.6	24.4	4.4	42.0	20.3	8.5	47.5	17.1	37.6	37.1	33.9	21.6
	BMVC (TPAMI'18)	40.5	41.2	24.1	50.1	72.4	33.9	25.3	28.6	11.4	42.4	21.9	15.1	36.0	21.0	16.5	38.9	37.0	20.2
	PVC (NeurIPS'20)	38.0	39.8	21.1	20.5	51.4	15.7	16.8	25.2	5.6	44.1	27.1	27.1	19.3	7.7	3.8	27.7	30.2	14.7
	MVCLN (CVPR'21)	37.9	42.3	25.6	39.6	65.3	32.8	26.1	30.7	12.5	38.8	42.1	25.2	54.1	38.3	35.7	39.3	43.7	26.4
	SURE (TPAMI'23)	41.0	43.2	25.0	43.8	70.1	29.5	25.1	28.3	10.9	49.1	29.9	23.6	57.4	44.8	38.3	43.3	43.3	25.5
	GCFAgg (CVPR'23)	42.2	42.5	24.4	56.6	80.7	37.9	27.5	31.3	14.0	34.4	23.8	10.5	41.1	32.1	18.6	40.4	42.1	21.1
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	DIVIDE (AAAI'24)	49.1	48.7	31.6	62.2	83.0	50.5	32.3	39.7	18.1	59.3	39.5	29.0	45.1	30.9	19.4	49.6	48.4	29.7
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20%	DCCAE (ICML'15)	32.9	17.1	29.6	36.9	39.2	60.1	15.0	3.8	17.4	41.6	13.1	19.3	41.6	11.6	26.9	33.6	17.0	30.7
	BMVC (TPAMI'18)	20.0	10.2	4.7	42.7	58.2	24.6	16.1	13.0	4.3	36.4	11.9	8.1	27.7	10.7	7.7	28.6	20.8	9.9
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	MVCLN (CVPR'21)	39.3	36.7	21.7	43.3	64.0	52.8	24.4	26.1	10.8	37.9	35.9	20.3	42.5	29.3	21.3	37.5	38.4	25.4
	SURE (TPAMI'23)	40.0	37.3	21.5	26.9	49.9	18.0	25.2	27.4	11.6	40.7	20.9	15.8	57.0	45.0	38.6	38.0	36.1	21.1
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50%	DCCAE (ICML'15)	26.8	10.2	19.8	27.0	26.8	49.8	13.3	2.8	13.2	37.7	9.2	12.5	32.3	7.1	13.5	27.4	11.2	21.8
	BMVC (TPAMI'18)	13.6	3.9	1.4	26.5	34.2	8.9	13.5	7.5	1.9	26.6	3.3	2.3	18.4	3.1	1.9	19.7	10.4	3.3
	PVC (NeurIPS'20)	20.3	10.2	13.6	7.4	21.8	5.0	20.6	28.5	8.7	42.9	23.5	23.4	24.1	10.1	9.9	23.1	18.8	12.1
	MVCLN (CVPR'21)	41.3	19.7	15.1	21.4	39.1	11.7	21.4	21.8	7.8	34.8	35.5	19.7	31.7	16.6	10.7	30.1	26.5	13.0
	SURE (TPAMI'23)	37.1	35.7	20.3	19.9	41.7	13.2	23.1	22.8	8.9	38.0	18.5	14.3	35.0	17.4	12.0	30.6	27.2	13.7
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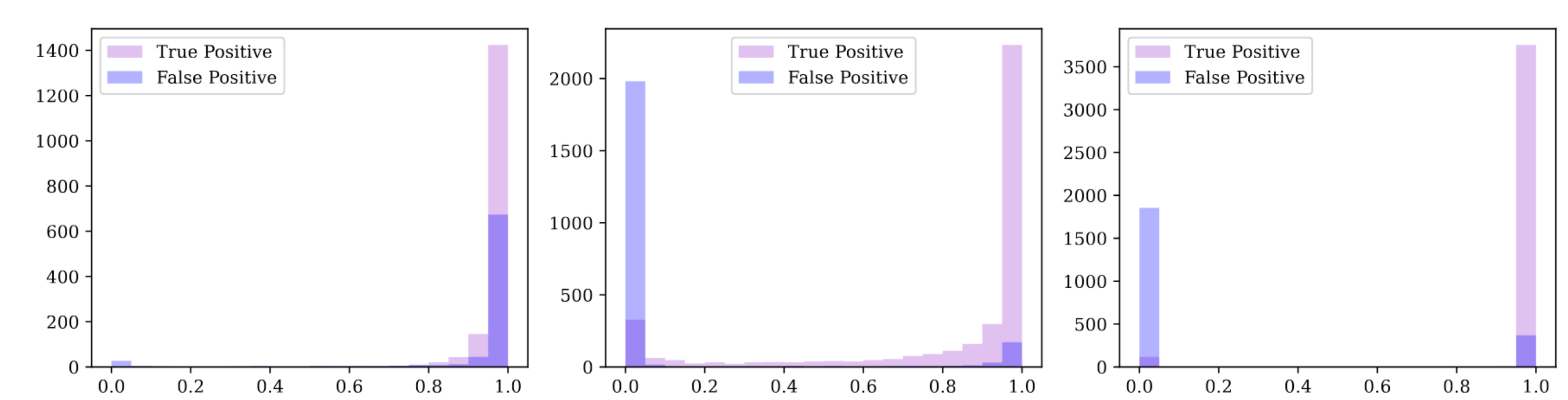
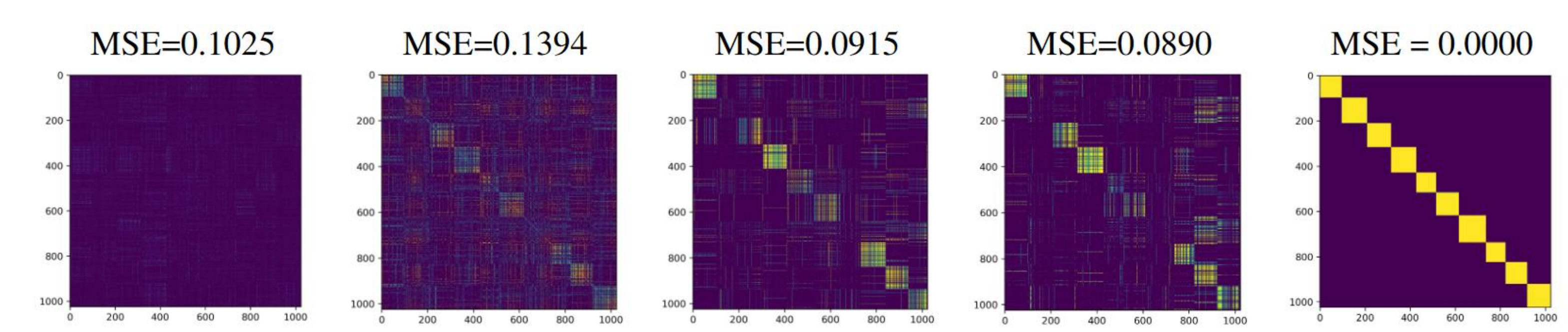
	CANDY (Ours)	41.3	39.4	24.0	60.7	79.0	56.6	29.9	33.1	15.2	47.4	21.7	27.3	58.1	43.2	34.5	47.5	43.3	31.5
80%	DCCAE (ICML'15)	20.9	6.7	14.4	18.4	15.8	41.8	14.5	3.2	13.4	35.3	7.6	10.0	36.2	14.9	21.9	25.1	9.6	20.3
	BMVC (TPAMI'18)	10.5	1.5	0.3	11.9	18.3	1.5	10.1	4.2	0.4	21.3	0.5	0.1	13.1	0.6	0.2	13.4	5.0	0.5
	PVC (NeurIPS'20)	20.3	10.2	4.6	7.5	20.8	4.2	22.5	29.3	9.3	35.7	13.2	13.1	19.3	7.7	3.8	21.1	16.2	7.0
	MVCLN (CVPR'21)	35.7	16.2	13.9	13.9	34.2	10.9	17.0	15.7	4.4	24.3	28.1	12.4	24.3	10.0	5.7	23.0	20.8	9.5
	SURE (TPAMI'23)	27.4	30.7	14.2	16.2	38.3	9.0	18.0	17.6	5.5	34.6	15.5	13.0	23.7	9.4	5.4	24.0	22.3	9.4
	GCFAgg (CVPR'23)	26.5	24.8	11.4	26.7	45.5	12.6	22.4	23.0	8.7	25.6	4.6	2.7	17.0	3.0	1.5	23.6	20.2	7.4
	CGCN (TCSVT'24)	28.7	24.0	12.5	21.3	46.6	13.2	25.2	27.7	11.4	29.0	7.9	6.5	50.1	34.6	28.0	30.9	28.2	14.3
	DIVIDE (AAAI'24)	34.4	30.4	18.3	27.8	50.8	21.1	27.1	28.1	12.8	41.1	24.7	19.5	45.8	28.3	19.1	35.2	32.5	18.2
	CANDY (Ours)	38.8	36.6	20.7	52.6	76.8	52.9	28.1	31.3	13.5	37.0	12.4	15.6	55.6	39.1	32.6	42.4	39.2	27.1

➤ **Visualization on the Robustness**



(a) Warmup only (b) Ours (50 epochs) (c) Ours (Converged)

➤ **Visualization of the pseudo target**



(a) Warmup Only (b) DIVIDE [28] (c) Ours w/o SCD (d) Ours (e) Ground Truth

Contact

Code is available at:

`https://github.com/XLearning-SCU/2024-NeurIPS-CANDY`

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GitHub Repo