Relational Contrastive Multi-view Clustering

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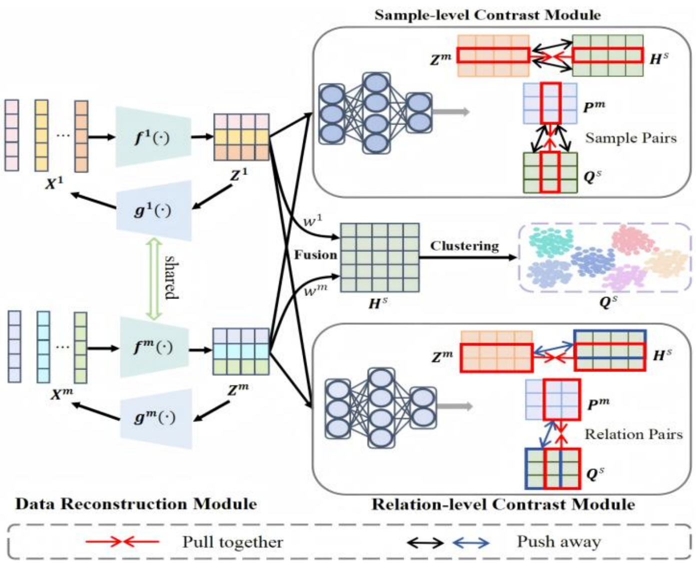
Problems & Ideas

- Problems of multi-view clustering methods:
  - Existing methods fail to consider the consistency of relational structures across different views.
  - They typically lack a guidance mechanism that leverages global feature and semantic information.
- Ideas: A novel relational contrastive multi-view clustering method, achieving dual alignment at both the sample and relation levels. Global information are incorporated to guide local view learning.



(1) The latent representation Z^v of the v-th view is obtained by the encoder. (2) The global feature information H^s and semantic information Q^s are obtained, and sample-level contrast module guides single-view learning toward more discriminative representations. (3) Relation-level contrast module aims to capture cross-view structural consistency from a global perspective.

Main Contributions

- Contributions:
  - A novel relational contrastive multi-view clustering method to achievie dual alignment at both the sample and relation levels. The former guides the representation learning for individual samples, while the latter captures relational consistency among different samples;
  - A relation-level contrastive module to explicitly align pairwise structural relationships across views;
  - Global feature information and semantic information are incorporated to guide local view learning.

Methods	Caltech-2V		Caltech-3V		Event8		Hdigit		NUS22	
	ACC	NMI	ACC	NMI	ACC	NMI	ACC	NMI	ACC	NMI
MvSCN	45.0	35.0	67.7	61.3	44.6	35.6	70.8	68.2	17.5	<u>13.0</u>
EAMC	41.9	25.6	38.9	21.4	42.2	32.6	31.8	17.3	16.2	11.9
CoMVC	46.6	42.6	54.1	50.4	51.4	<u>37.4</u>	90.3	87.1	16.7	<u>13.0</u>
MFLVC	60.6	52.8	63.1	56.6	48.5	34.9	92.7	84.3	16.9	12.8
SPDMC	64.4	50.6	70.1	63.0	47.8	31.7	<u>98.5</u>	96.2	12.9	9.0
CVCL	61.6	53.0	<u>72.3</u>	<u>63.2</u>	<u>53.3</u>	34.5	98.3	95.2	14.6	11.2
ICMVC	49.6	37.9	64.7	53.7	36.4	30.3	97.4	94.1	13.3	12.7
DIVIDE	64.1	52.9	71.6	58.5	31.4	12.4	84.5	92.7	<u>19.1</u>	12.8
PDMC-RCL	63.7	51.4	70.9	60.9	23.4	7.3	98.4	<u>96.3</u>	16.0	10.7
MSDIB	<u>67.8</u>	<u>55.2</u>	57.5	51.8	24.3	6.9	84.8	93.4	14.6	9.9
RCMVC	**69.3**	**56.4**	**77.7**	**64.1**	**59.0**	**40.7**	**99.8**	**99.4**	**21.2**	**14.2**
Ours vs Best Compared	1.5↑	1.2↑	5.4↑	0.9↑	5.7↑	3.3↑	1.3↑	3.1↑	2.1↑	1.2↑

Clustering performance on different datasets (The best results are shown in **bold**, while the second-best are <u>underlined</u>).

Experimental results show that our method outperforms state-of-the-art methods on several benchmark multi-view clustering datasets.