Incomplete Multi-view Deep Clustering with Data Imputation and Alignment

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Introduction

Multi-view Data. It refers to the data observations of an object or event from multiple different aspects, such as multi-modal data, multi-angle data and multi-feature data.

Fig. 1 Example of multi-modal, multi-angle and multi-feature data.

Multi-view Deep Clustering. It is an unsupervised machine learning technique to group multi-view data into categories with utilizing deep neural networks to extract higher-quality latent representations.

Incomplete Multi-view Deep Clustering. The collected multi-view data are often incomplete where one or more views are missing. It makes the most of available data observations rather than discarding the data samples with missing views.

2-st Problem and Solution

Problem. Most incomplete multi-view deep clustering methods fail to utilize the pair-wise similarities of missing data observations in latent representation learning sufficiently, leading to unsatisfactory clustering performance.

Solution. A linear alignment measurement of linear complexity is defined to compute the pair-wise similarities of all data observations, especially including those of the missing.

Definition 1 (Linear Alignment). *Given two arbitrary matrices* $\mathbf{X}_1$ *and* $\mathbf{X}_2$ *of size* $n \times d_1$ *and* $n \times d_2$ *,respectively, the linear alignment is computed as*

$$LA = \frac{L_F^2(\mathbf{X}_1^\top \mathbf{X}_2)}{L_F(\mathbf{X}_1^\top \mathbf{X}_1) \cdot L_F(\mathbf{X}_2^\top \mathbf{X}_2)},$$

in which $L_F(\cdot)$ *denotes the Frobenius norm of matrix. Corresponding computation complexity is linear to* n.

1-st Problem and Solution

Problem. Most of existing multi-view deep clustering encode data observations into multiple view-specific latent representations and subsequently integrate them for the next clustering task. This ignores the fact that the latent representations are unique to a fixed set of data samples in all views.

Solution. Assuming that each data sample corresponds to a same latent representation among all views, we project the latent representations into feature spaces with multiple independent neural networks.

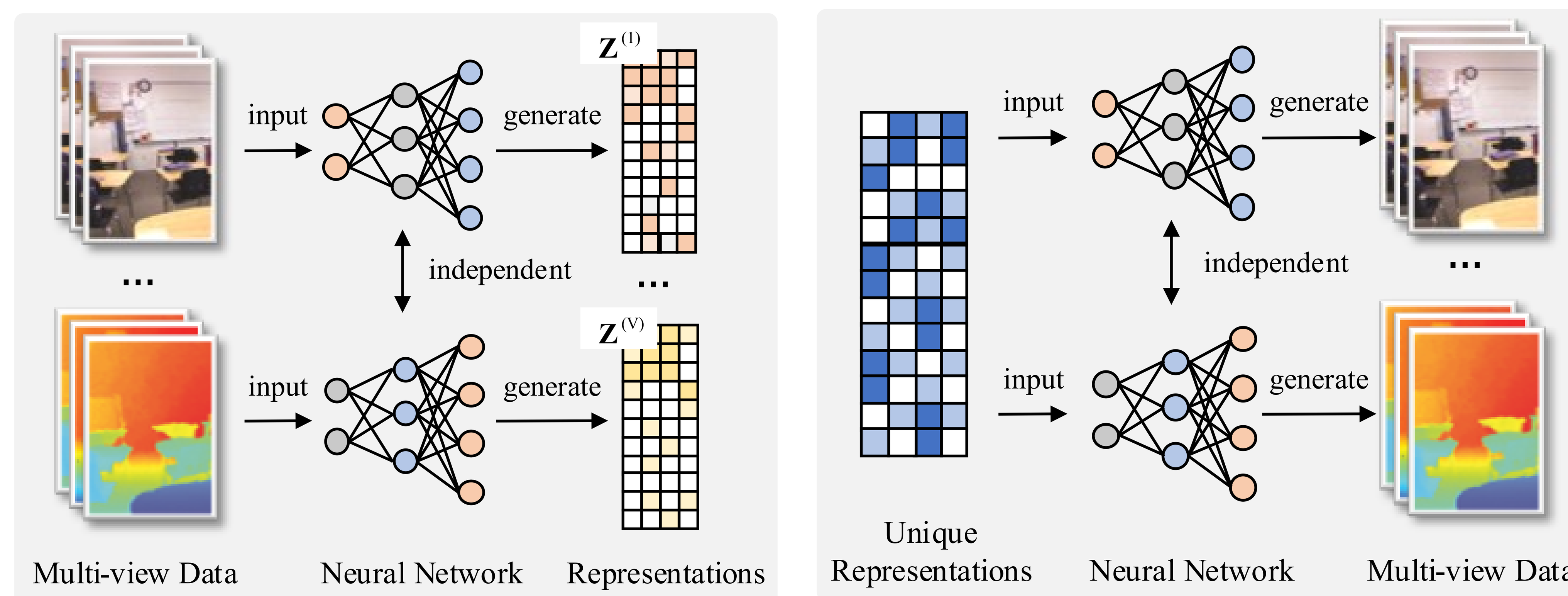

Fig. 2 (left) Paradigm of most existing methods; (right) Paradigm of the proposed IMDC-DIA method.

The proposed IMDC-DIA method

It aims to learn the high-quality latent representations which are subsequently fed to off-the-shelf clustering algorithms so as to group the data accurately.

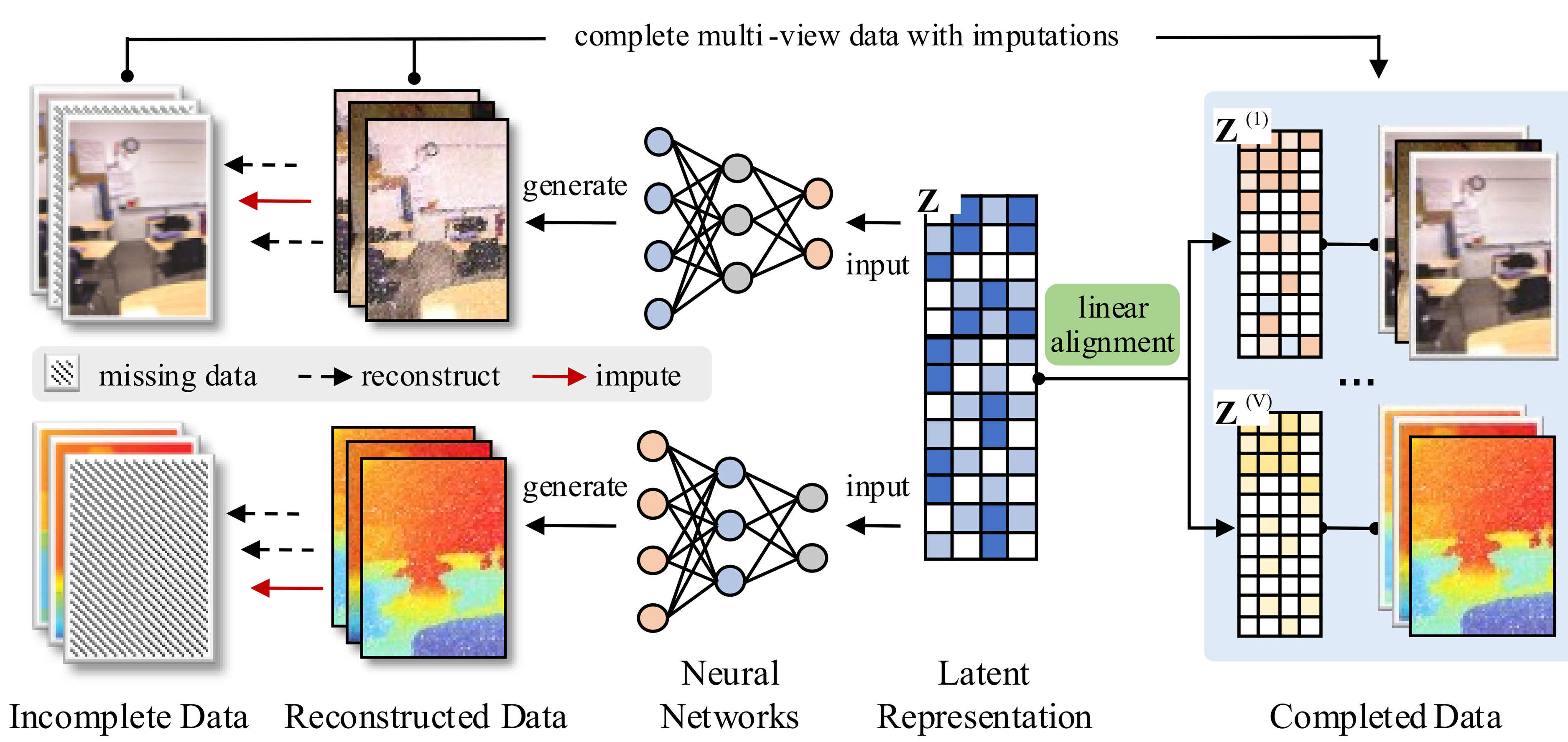

Fig. 3 Framework of the proposed IMDC-DIA method. Note that, arbitrary number of views and any types of neural networks are compatible.

Experimental Results

Tab. 1 Performance comparison between the proposed IMDC-DIA and recent approaches. The *avg.* column refers to performance averages of all missing ratios.

Metric		ACC					
Missing ratio		0.1	0.3	0.5	0.7	0.9	avg.
HandWritten	DITA-IMVC	75.48	78.92	81.37	81.02	55.00	74.36
	DSIMVC	79.55	80.73	78.83	77.48	50.87	73.49
	DCP	81.95	75.73	77.23	71.77	13.07	63.95
	DVIMC	86.42	83.05	45.48	25.20	18.92	51.81
	CPSPAN	90.42	91.25	91.08	90.27	86.73	89.95
	IMDC-DIA	**96.37**	**93.68**	**91.80**	**90.65**	**87.93**	**92.09**
Caltech5V	DITA-IMVC	79.10	75.76	68.02	58.90	40.29	64.41
	DSIMVC	76.64	73.14	66.36	57.38	44.95	63.69
	DCP	44.50	46.95	46.45	44.67	16.98	39.91
	DVIMC	**88.64**	81.36	**84.93**	80.86	68.81	80.92
	CPSPAN	83.29	81.10	77.21	76.79	79.02	79.48
	IMDC-DIA	86.05	**85.05**	83.33	**85.02**	**81.29**	**84.15**
Flower17	DITA-IMVC	18.75	17.52	13.77	13.16	12.84	15.21
	DSIMVC	18.63	16.86	13.50	13.36	13.36	15.14
	DCP	26.15	25.49	22.21	15.05	10.78	19.94
	DVIMC	36.69	31.23	26.84	23.41	21.69	27.97
	CPSPAN	36.27	39.34	31.15	37.35	36.00	36.02
	IMDC-DIA	**52.03**	**46.47**	**44.22**	**41.54**	**39.14**	**44.68**
MSRCV1	DITA-IMVC	76.03	74.60	70.95	66.83	55.87	68.86
	DSIMVC	78.57	76.98	70.48	71.59	64.76	72.48
	DCP	17.94	20.00	22.06	22.22	22.70	20.98
	DVIMC	74.60	61.43	56.67	43.17	38.25	54.82
	CPSPAN	85.08	86.51	85.40	84.29	77.62	83.78
	IMDC-DIA	**91.27**	**92.22**	**86.03**	**85.08**	**83.02**	**87.52**

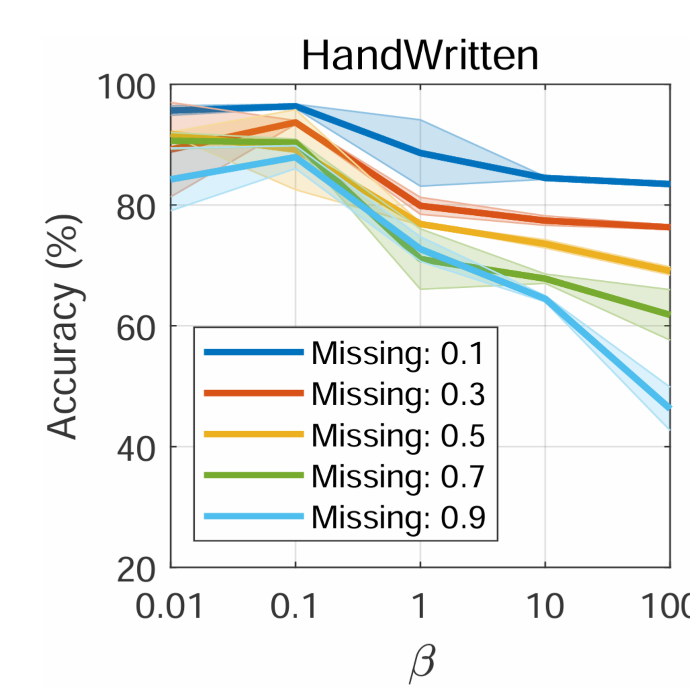

Fig. 4 Accuracy variation to parameter β in different missing ratios.

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