Supplementary: Diffusion-based Missing-view Generation With the Application on Incomplete Multi-view Clustering

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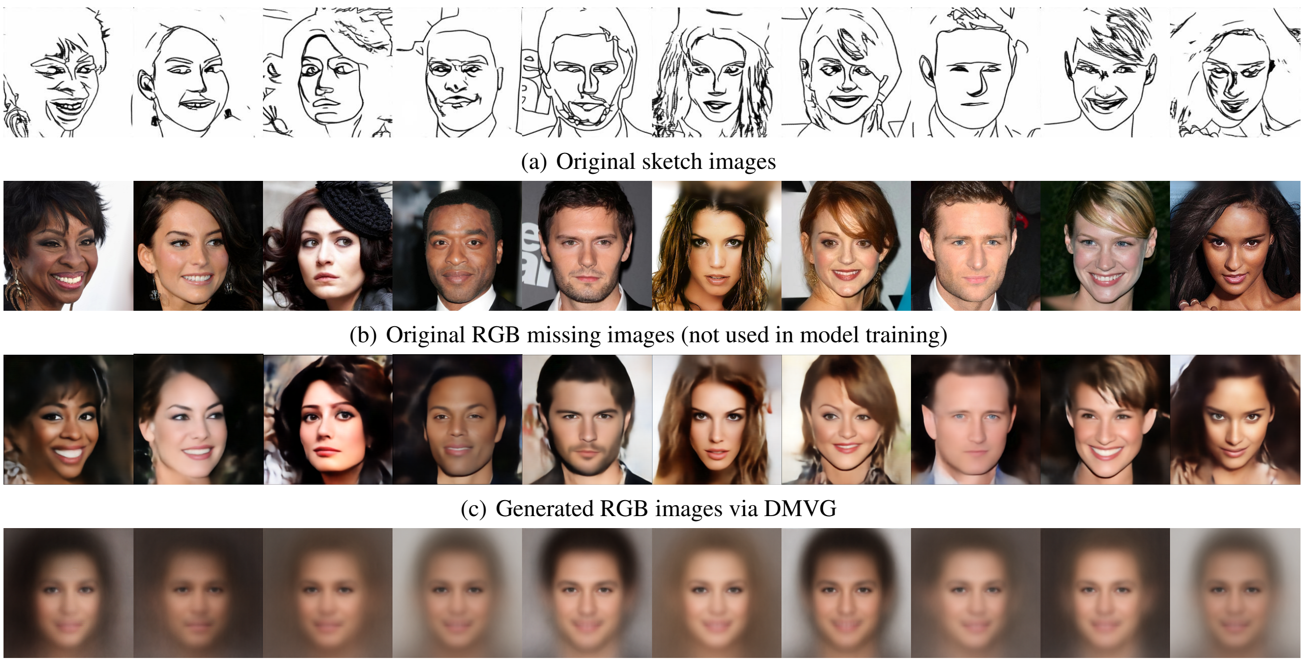
1. More Experiments on Missing-view Generation

Firstly, we show more generated examples on Multi-Modal CelebA-HQ in Figures 1 and 2.



(a) Original sketch images

(b) Original RGB missing images (not used in model training)

(c) Generated RGB images via DMVG

(d) Generated RGB images via VIGAN

Figure 1. Generating RGB missing images according to their sketch images on Multi-Modal CelebA-HQ.

Secondly, we compare our proposed method with VIGAN and CRA on several datasets usually used in IMVC, *i.e.*, BBCSports (Greene & Cunningham, 2006), Handwritten (Newman, 2007), Caltech7 (Li et al., 2015), and Animal (Zhang et al., 2019). Because BBCSports, Handwritten, and Caltech7 have more than two views, we compare DA-DMVG with CRA on these datasets with 0.1, 0.3, and 0.5 missing views. The quantitative results in terms of RMSE, NMSE, and PSNR are shown in Tables 1, 2, and 3, respectively. It is obvious that DA-DMVG is always better than CRA. Furthermore, Figure 3 shows many visualization results on Handwritten with 0.1 missing views. DA-DMVG nearly recovered the missing view 1 perfectly.

Because Animal is a dual-view dataset, we cannot augment more data via the proposed data augmentation strategy. So we

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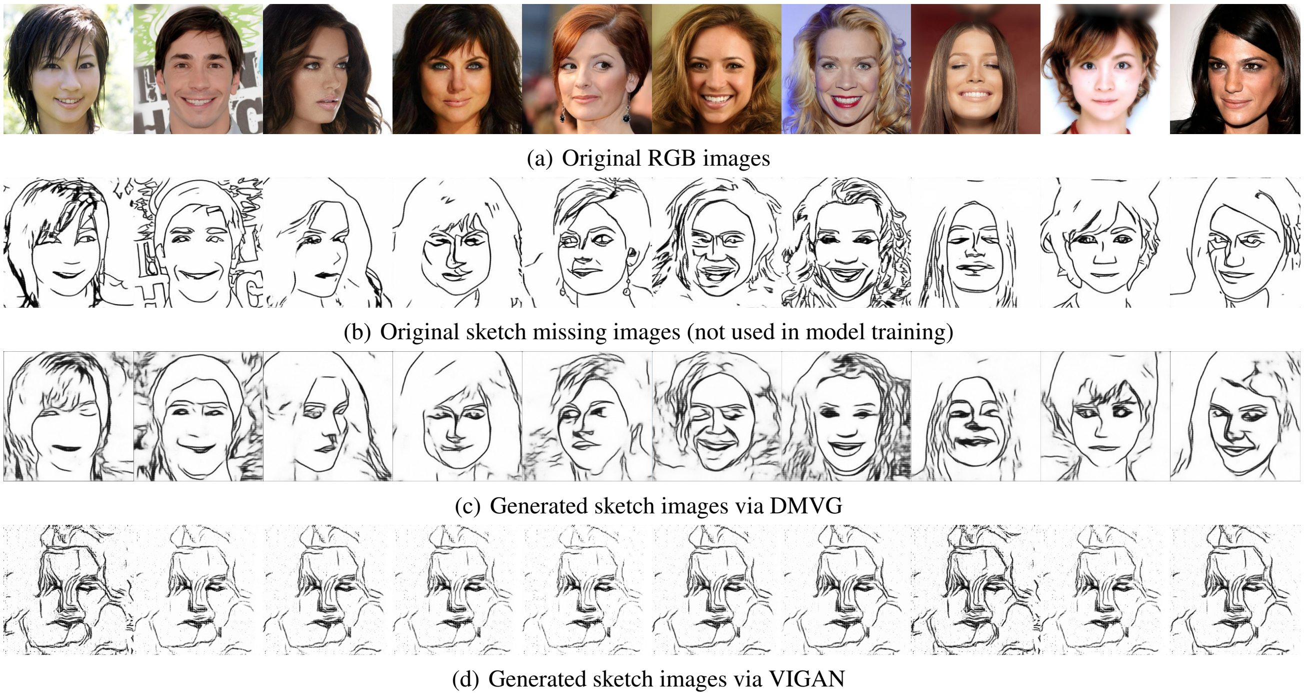


(a) Original RGB images

(b) Original sketch missing images (not used in model training)

(c) Generated sketch images via DMVG

(d) Generated sketch images via VIGAN

Figure 2. Generating sketch missing images according to their RGB images on Multi-Modal CelebA-HQ.

Table 1. RMSE, NMSE, and PSNR of CRA and DA-DMVG on BBCSport with 10%, 30%, and 50% missing views.

		RMSE↓			NMSE↓			PSNR↑		
VIEW	METHOD	0.1	0.3	0.5	0.1	0.3	0.5	0.1	0.3	0.5
2*1	CRA	0.06	0.06	0.06	2.33	3.89	4.87	24.90	25.03	24.91
	DA-DMVG	**0.05**	**0.03**	**0.03**	**1.60**	**1.42**	**1.53**	**26.54**	**29.41**	**29.94**
2*2	CRA	0.06	0.06	0.05	4.21	4.74	3.88	24.79	24.93	25.96
	DA-DMVG	**0.03**	**0.03**	**0.04**	**1.16**	**1.26**	**1.99**	**30.39**	**30.70**	**28.85**
2*3	CRA	0.05	0.06	0.05	3.52	6.71	5.04	26.11	24.75	26.16
	DA-DMVG	**0.03**	**0.04**	**0.03**	**1.46**	**2.49**	**1.65**	**29.92**	**29.05**	**31.01**
2*4	CRA	0.06	0.05	0.06	2.17	10.16	11.74	24.59	25.59	24.89
	DA-DMVG	**0.04**	**0.02**	**0.02**	**1.10**	**2.30**	**1.85**	**27.51**	**32.05**	**32.91**

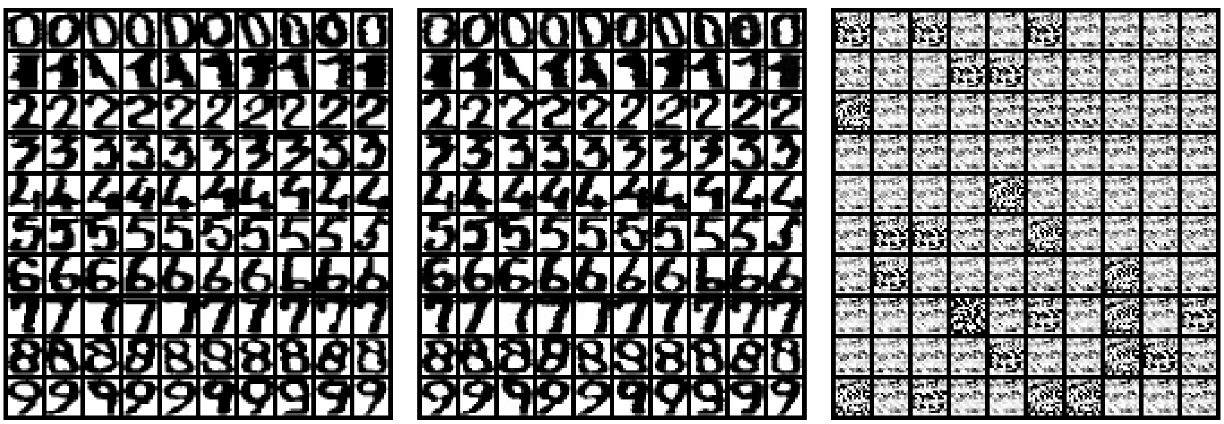
Table 2. RMSE, NMSE, and PSNR of CRA and DA-DMVG on Handwritten with 10%, 30%, and 50% missing views.

		RMSE↓			NMSE↓			PSNR↑		
VIEW	METHOD	0.1	0.3	0.5	0.1	0.3	0.5	0.1	0.3	0.5
2*1	CRA	0.45	0.46	0.50	1.00	1.02	1.22	6.86	6.78	5.99
	DA-DMVG	**0.25**	**0.22**	**0.29**	**0.31**	**0.22**	**0.41**	**11.91**	**13.25**	**10.72**
2*2	CRA	0.35	0.30	0.38	6.43	5.31	9.21	9.17	10.41	8.30
	DA-DMVG	**0.08**	**0.08**	**0.09**	**0.37**	**0.40**	**0.52**	**21.56**	**21.64**	**20.74**
2*3	CRA	0.06	0.06	0.06	0.05	0.05	0.05	24.22	24.90	24.91
	DA-DMVG	**0.02**	**0.02**	**0.05**	**0.00**	**0.01**	**0.03**	**35.27**	**32.36**	**26.62**
2*4	CRA	0.10	0.10	0.09	0.39	0.41	0.39	19.86	19.82	20.55
	DA-DMVG	**0.02**	**0.03**	**0.04**	**0.02**	**0.04**	**0.09**	**33.07**	**30.47**	**27.14**
2*5	CRA	0.11	0.15	0.17	2.07	3.61	4.25	18.80	16.48	15.56
	DA-DMVG	**0.03**	**0.04**	**0.06**	**0.13**	**0.26**	**0.54**	**30.67**	**27.85**	**24.53**

compare DMVG with VIGAN on this dataset with 0.3, 0.5, and 0.7 paired views. The quantitative results in terms of RMSE, NMSE, and PSNR are shown in Table 4, which demonstrate that DMVG outperforms VIGAN all the time.

Table 3. RMSE, NMSE, and PSNR of CRA and DA-DMVG on Caltech7 with 10%, 30%, and 50% missing views.

		RMSE↓			NMSE↓			PSNR↑		
VIEW	METHOD	0.1	0.3	0.5	0.1	0.3	0.5	0.1	0.3	0.5
2*1	CRA	0.20	0.22	0.14	9.90	10.82	6.00	13.80	13.15	17.22
	DA-DMVG	**0.05**	**0.06**	**0.03**	**0.62**	**0.89**	**0.34**	**25.39**	**23.99**	**29.67**
2*2	CRA	0.19	0.20	0.23	0.46	0.49	0.67	14.33	13.94	12.70
	DA-DMVG	**0.14**	**0.13**	**0.11**	**0.24**	**0.20**	**0.16**	**17.07**	**17.93**	**18.83**
2*3	CRA	0.10	0.13	0.14	5.05	9.59	10.78	20.02	17.80	17.36
	DA-DMVG	**0.03**	**0.03**	**0.02**	**0.45**	**0.21**	**0.16**	**30.56**	**34.46**	**35.74**
2*4	CRA	0.28	0.31	0.31	1.01	1.18	1.17	10.93	10.24	10.28
	DA-DMVG	**0.20**	**0.21**	**0.21**	**0.50**	**0.55**	**0.58**	**13.93**	**13.51**	**13.35**
2*5	CRA	0.25	0.34	0.34	5.38	12.40	11.92	12.16	9.26	9.48
	DA-DMVG	**0.08**	**0.06**	**0.07**	**0.54**	**0.42**	**0.52**	**22.15**	**23.93**	**23.07**
2*6	CRA	0.35	0.43	0.28	15.99	25.80	10.84	9.04	7.28	11.01
	DA-DMVG	**0.04**	**0.08**	**0.06**	**0.24**	**0.79**	**0.49**	**27.20**	**22.40**	**24.44**



(a) Original missing view 1 (b) Recovered view 1 via DA-DMVG (c) Recovered view 1 via CRA

Figure 3. Generating missing view 1 according to other available views on Handwritten dataset with 10% missing views.

Table 4. RMSE, NMSE, and PSNR of VIGAN and DMVG on Animal with 30%, 50%, and 70% paired views.

		RMSE↓			NMSE↓			PSNR↑		
VIEW	METHOD	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7
2*1	VIGAN	0.08	**0.07**	0.07	1.55	1.24	1.28	21.99	22.83	23.49
	DMVG	**0.07**	**0.07**	**0.06**	**1.15**	**1.18**	**1.15**	**23.28**	**23.08**	**23.93**
2*2	VIGAN	0.08	**0.08**	0.09	1.20	1.22	1.20	21.88	21.70	21.31
	DMVG	**0.07**	**0.08**	**0.08**	**0.88**	**1.16**	**1.01**	**23.22**	**21.92**	**22.06**

2. More Experiments on IMVC after Missing-view Generation

Here are more experiments on IMVC after missing-view generation. Specifically, we filled BBCSport and Handwritten via DA-DMVG, and Animal via DMVG (since Animal is a dual-view dataset and cannot undergo data augmentation). Specifically,"D"/"DAD+" denotes the processes of filling missing views via DMVG/DA-DMVG first and then clustering via the corresponding clustering methods. The clustering results of the popular IMVC methods with/without our proposed DMVG/DA-DMVG methods on BBCSports, Handwritten, and Animal are shown in Tables 5, 6, and 7, respectively. Combined with the results on Caltech7 shown in Table **??**, we obtain the following conclusions:

(1) DMVG and DA-DMVG generally enhance clustering performance while are less effective for datasets with fewer samples. In all experiments, DMVG or DA-DMVG improved incomplete multi-view clustering performance in about 76% cases, indicating the great potential of missing-view generation for IMVC. Specifically, clustering performance improved by about 46% on BBCSport, 70% on Handwritten, 96% on Caltech7, and 88% on Animal, respectively. However, experiments

Table 5. ACC(%) and NMI(%) of different methods on BBCSport with 10%, 30%, 50%, and 70% missing views.

	ACC				NMI			
METHOD	0.1	0.3	0.5	0.7	0.1	0.3	0.5	0.7
BSV	58.62	51.31	44.03	36.43	43.73	31.03	21.40	12.05
DAD+BSV	**62.41**	**62.59**	**53.97**	**39.31**	42.22	**40.24**	**29.94**	**12.67**
CONCAT	70.62	58.72	33.21	35.95	61.69	38.92	18.61	8.58
DAD+CONCAT	62.41	**63.97**	**49.83**	33.28	49.99	**48.88**	**29.42**	8.29
MULTINMF	48.58	42.75	40.34	35.69	23.48	18.25	14.79	7.84
DAD+MULTINMF	45.86	**46.67**	**42.24**	**36.03**	21.09	**20.50**	**15.92**	**8.67**
CCR-MVSC	72.76	70.06	61.38	35.86	62.79	57.69	39.55	14.11
DAD+CCR-MVSC	72.41	65.69	60.00	**36.55**	**63.54**	52.71	37.40	13.34
DAIMC	68.62	63.45	56.89	39.59	56.62	50.17	37.89	17.16
DAD+DAIMC	**71.03**	**66.55**	52.93	35.00	**57.49**	**51.49**	32.34	12.55
OPIMC	54.14	52.93	45.69	44.34	35.66	31.56	21.75	14.65
DAD+OPIMC	35.17	43.10	36.55	33.10	11.15	20.68	13.18	4.51
EEIMVC	76.03	73.45	62.76	47.41	65.34	61.25	46.91	25.95
DAD+EEIMVC	**76.90**	67.24	56.90	34.48	**67.26**	53.92	33.36	9.56
PIC	75.52	74.48	69.48	31.89	70.94	64.18	53.91	9.99
DAD+PIC	75.34	72.59	68.62	**39.31**	68.89	**65.61**	53.73	**16.28**
IMSR	78.45	72.41	63.45	41.21	69.39	61.56	43.35	20.00
DAD+IMSR	**84.31**	**84.31**	**84.14**	**84.43**	**72.02**	**72.02**	**72.79**	**72.85**
SRLC	69.83	57.24	43.28	34.83	50.76	35.96	21.37	9.12
DAD+SRLC	66.03	**61.21**	**59.66**	**37.93**	**52.54**	**42.19**	**35.36**	**11.88**
OSLF-IMVC	75.86	75.34	61.21	45.52	67.17	67.30	44.73	21.47
DAD+OSLF-IMVC	**77.59**	73.45	**63.10**	37.24	**68.36**	60.71	40.98	12.41
PIMVC	79.66	75.17	73.97	52.07	71.12	64.22	60.81	29.32
DAD+PIMVC	79.66	71.55	67.07	39.14	70.86	58.71	49.07	15.64

Table 6. ACC(%) and NMI(%) of different methods on Handwritten with 10%, 30%, 50%, and 70% missing views.

	ACC				NMI			
METHOD	0.1	0.3	0.5	0.7	0.1	0.3	0.5	0.7
BSV	68.27	51.49	38.24	27.15	62.82	47.01	32.21	19.48
DAD+BSV	**79.89**	**82.08**	**76.15**	**66.09**	**75.18**	**74.83**	**67.05**	**51.72**
CONCAT	75.06	55.48	42.19	28.31	73.08	51.66	38.24	23.50
DAD+CONCAT	**88.73**	**89.56**	**85.62**	**67.38**	**81.97**	**81.34**	**75.61**	**53.10**
MULTINMF	82.35	71.74	52.03	31.85	72.05	60.11	41.99	20.88
DAD+MULTINMF	**82.46**	**80.40**	**81.12**	**69.00**	**72.93**	**71.32**	**69.55**	**56.45**
CCR-MVSC	74.61	73.17	70.15	64.62	70.90	68.23	62.86	53.14
DAD+CCR-MVSC	**75.92**	**76.15**	**74.46**	**73.09**	**71.51**	**71.18**	**67.70**	**60.44**
DAIMC	88.86	86.73	81.92	60.44	79.78	76.65	68.77	47.10
DAD+DAIMC	85.81	82.36	80.57	**70.69**	76.82	74.26	70.22	**54.17**
OPIMC	80.20	76.45	69.50	56.66	77.26	73.74	66.57	51.86
DAD+OPIMC	75.63	72.92	**72.62**	**63.06**	73.53	70.54	**67.41**	51.39
EEIMVC	88.60	85.23	76.70	51.74	78.64	73.30	62.26	40.21
DAD+EEIMVC	86.12	83.22	**84.19**	**77.71**	76.82	**74.19**	**72.90**	**62.90**
PIC	84.20	83.90	83.24	80.97	85.41	84.79	82.25	77.56
DAD+PIC	83.69	83.25	80.76	75.17	**86.16**	84.77	82.04	70.26
IMSR	90.36	89.74	83.68	62.10	83.26	81.57	72.81	53.92
DAD+IMSR	87.03	86.98	**86.99**	**87.05**	79.79	79.77	**79.75**	**79.81**
SRLC	95.09	88.62	81.04	69.46	90.15	84.27	75.33	62.70
DAD+SRLC	**96.06**	**94.84**	**87.62**	**81.10**	**91.66**	**89.27**	**81.14**	**69.00**
OSLF-IMVC	75.04	70.21	55.17	35.79	67.16	60.98	44.70	27.07
DAD+OSLF-IMVC	**79.60**	**81.46**	**80.66**	**69.33**	**74.68**	**73.58**	**69.92**	**57.99**
PIMVC	94.88	93.79	91.23	88.61	89.74	87.71	83.88	79.56
DAD+PIMVC	**94.97**	**93.99**	**91.27**	79.51	89.25	**87.92**	83.25	67.96

on BBCSport suggest that missing-view generation does not always yield benefits, because we just use a small number of

Table 7. ACC(%), NMI(%), and PUR(%) of different methods on Animal with 30%, 50%, and 70% paired views.

		ACC			NMI			PUR	
METHOD	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7
BSV	42.05	48.63	56.22	48.16	55.91	63.99	45.20	52.26	60.31
D+BSV	**55.75**	**60.49**	**64.95**	**63.23**	**67.16**	**71.73**	**61.20**	**65.42**	**70.14**
CONCAT	42.79	49.34	53.99	55.46	59.31	63.88	48.12	53.24	59.26
D+CONCAT	**52.91**	**58.02**	**59.63**	**60.06**	**64.75**	**68.25**	**58.11**	**62.78**	**65.46**
CCR-MVSC	52.03	54.72	56.73	55.31	58.31	61.71	56.28	59.36	61.98
D+CCR-MVSC	**54.17**	**57.83**	**58.29**	**57.48**	**60.87**	**63.43**	**58.25**	**61.94**	**63.33**
DAIMC	50.18	53.87	56.42	55.03	59.36	62.76	54.82	59.51	62.12
D+DAIMC	**53.75**	**58.27**	**59.25**	**59.60**	**64.16**	**67.14**	**58.75**	**63.41**	**65.62**
OPIMC	46.33	53.14	53.88	52.34	58.51	62.04	49.49	56.23	57.91
D+OPIMC	**53.58**	**57.70**	**58.52**	**60.32**	**64.40**	**67.77**	**58.43**	**62.15**	**64.42**
EEIMVC	45.90	53.34	57.15	53.72	57.92	62.02	51.30	57.40	61.74
D+EEIMVC	**56.07**	**59.41**	**61.15**	**59.94**	**63.40**	**66.37**	**60.57**	**63.21**	**65.61**
PIC	55.94	56.84	57.67	62.35	64.37	65.82	63.07	64.75	65.42
D+PIC	**56.01**	51.48	55.36	**62.71**	60.75	65.51	**63.64**	60.81	65.30
IMSR	47.02	53.15	58.38	55.87	60.00	65.43	52.61	57.80	63.78
D+IMSR	**59.60**	**60.03**	**59.72**	**68.02**	**68.10**	**67.44**	**65.63**	**65.75**	**65.47**
SRLC	51.14	53.93	55.76	56.77	60.43	63.54	58.08	61.24	63.90
D+SRLC	**51.42**	**54.17**	**57.87**	**57.14**	**61.16**	**65.12**	**58.26**	**62.18**	**65.48**
OSLF-IMVC	40.53	48.24	55.07	50.53	54.23	58.51	45.31	51.68	56.93
D+OSLF-IMVC	**54.64**	**58.19**	**57.99**	**57.23**	**61.00**	**62.91**	**56.82**	**59.98**	**60.36**
PIMVC	55.56	57.47	59.24	61.54	63.92	65.84	60.45	63.04	64.75
D+PIMVC	54.09	**57.54**	**59.28**	60.23	62.61	**65.88**	59.31	61.83	64.44

samples on BBCSport, which may hinder DA-DMVG from effectively learning the intrinsic correlations from conditional views to the target view.

(2) Empirical filling methods like zero-filling and mean-filling negatively impact clustering. Except experiments on BBCSport, all experiments combining the missing-view generation with MVC algorithms show improved clustering performance, because these MVC algorithms have to rely on zero-filling or mean-filling for IMVC without DMVG or DA-DMVG integration. Zero-filling and mean-filling tend to cluster samples with missing-views together, significantly affecting clustering results. In contrast, DMVG and DA-DMVG accurately predict missing views, often significantly improving performance when combined with methods like BSV, where ACC improves by exceeding 10% across different datasets and missing rates.

(3) Existing IMVC methods often fail to fully exploit the information contained in available views. Except BBCSport, about 75% experiments combining missing-view generation with IMVC methods show improved clustering performance. Although IMVC methods can independently perform IMVC, DMVG or DA-DMVG often further improve their clustering performance. This indicates that existing IMVC methods do not fully exploit information from available views, that is, focusing on consistent information across views while neglecting complementary information. On the contrary, DMVG and DA-DMVG utilize all information from available views to predict missing views as accurately as possible.

(4) Missing-view generation significantly reduces sensitivity to missing view rates in existing methods. After combining DMVG or DA-DMVG with existing clustering methods, models showed much lower sensitivity to missing view rates.

(5) Noise introduced by missing view generation can negatively impact clustering. We also observed that in some experiments (except experiments on BBCSport), DMVG and DA-DMVG not only failed to enhance clustering performance, but even degraded clustering performance, such as the experimental results of DAIMC and PIC on Handwritten. It is speculated that the impact of missing-view generation for IMVC is two-sided. On one hand, missing-view generation essentially learns correlations between different views, aiding clustering models in easily learning consistent representations shared across views. On the other hand, noise introduced by DMVG or DA-DMVG can reduce clustering performance. When the disadvantages of noise outweigh the benefits of missing-view generation, clustering performance may decline.

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