Decoupled Multimodal Distilling for Emotion Recognition

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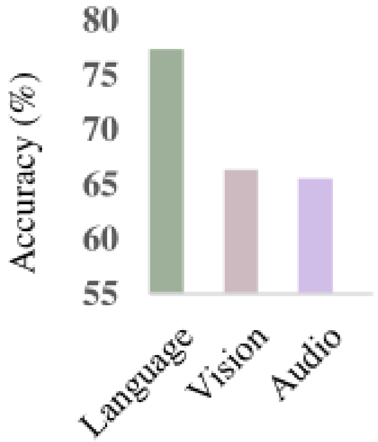
Reported by JiaWei Cheng

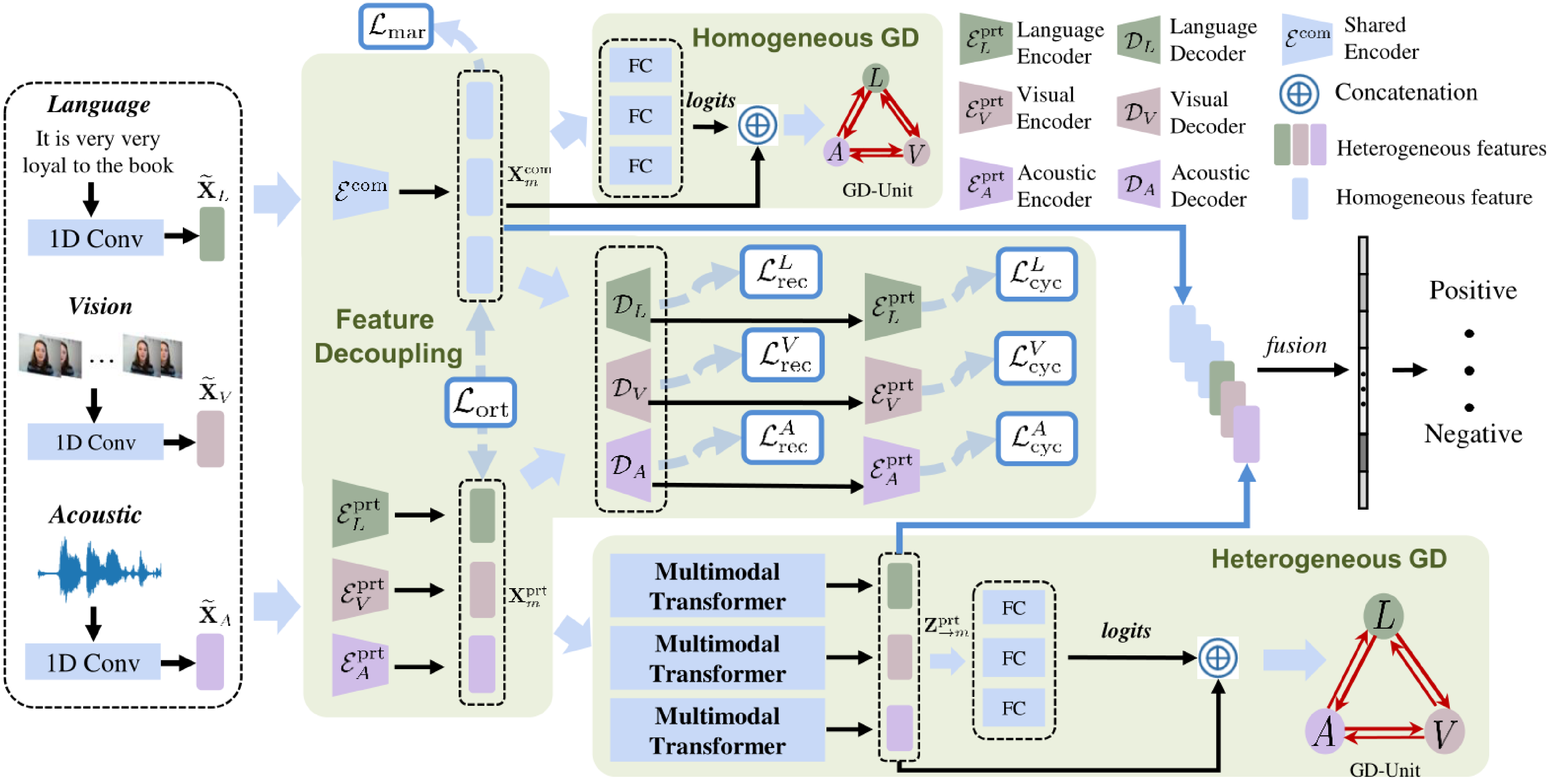
Motivation



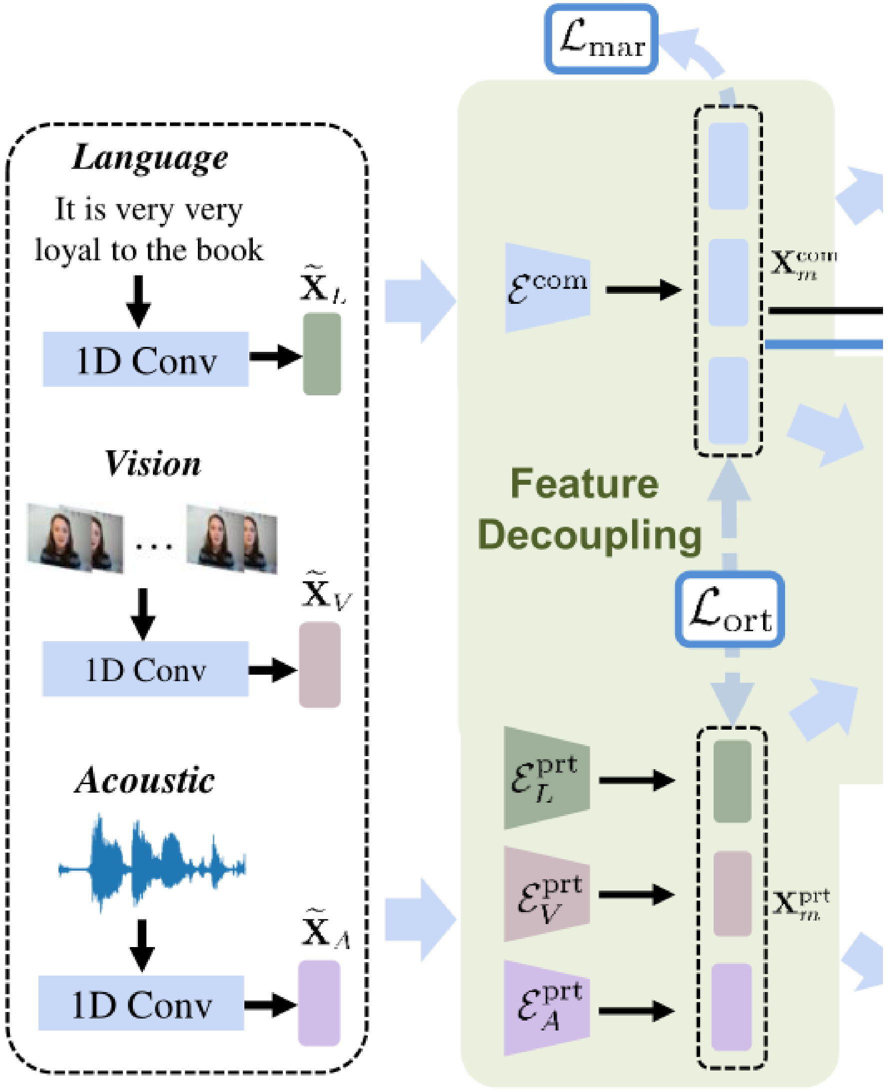
(a) Unimodal Accuracy

The intrinsic heterogeneities among different modalities still perplex us and increase the difficulty of robust multimodal representation learning

Overview


Language
It is very very loyal to the book
1D Conv
Vision
1D Conv
Acoustic
1D Conv
Feature Decoupling
Homogeneous GD
FC
FC
FC
logits
GD-Unit
Heterogeneous GD
Multimodal Transformer
Multimodal Transformer
Multimodal Transformer
FC
FC
FC
logits
GD-Unit
fusion
Positive
Negative
Language Encoder
Visual Encoder
Acoustic Encoder
Language Decoder
Visual Decoder
Acoustic Decoder
Shared Encoder
Concatenation
Heterogeneous features
Homogeneous feature

Method



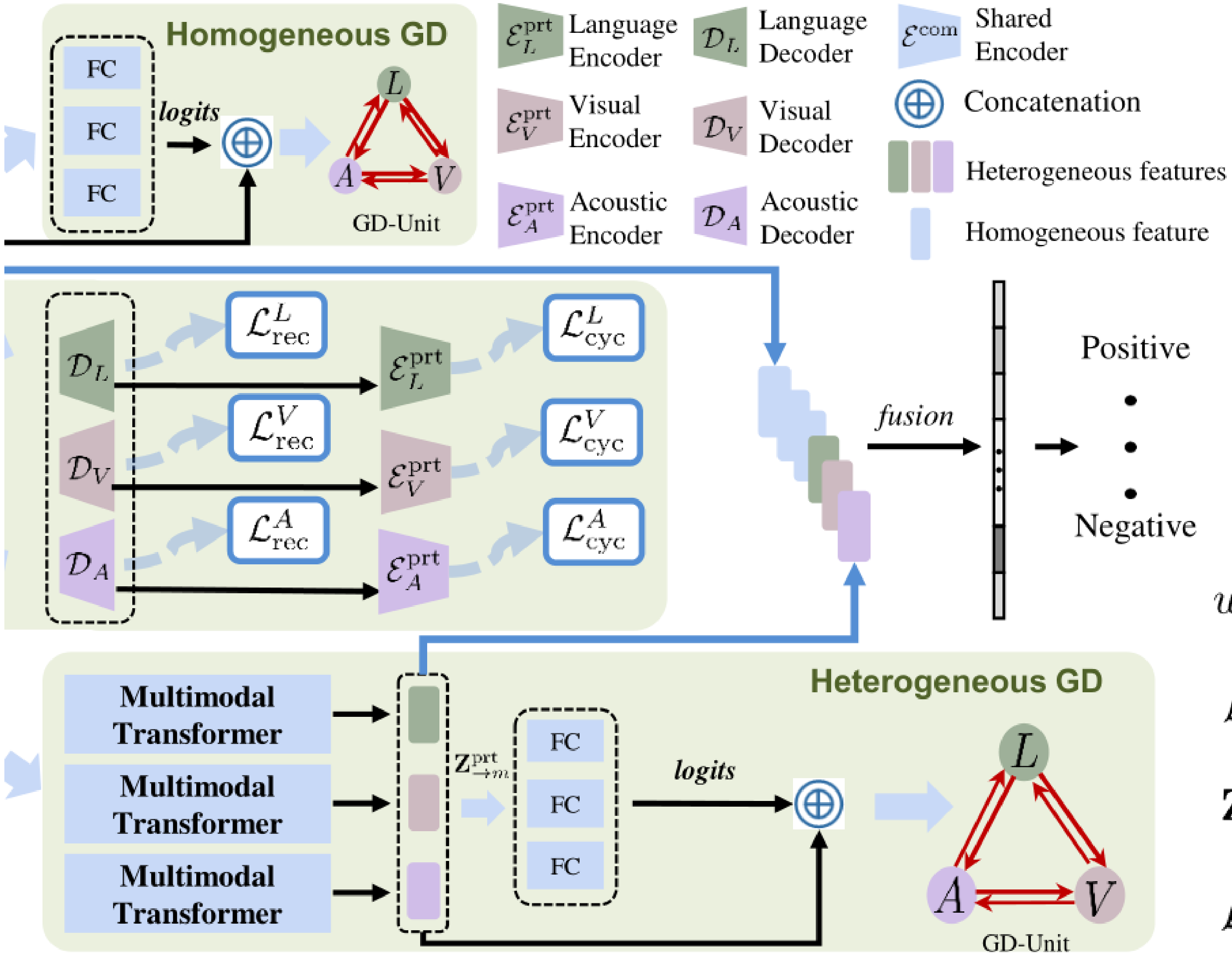
$$\mathbf{X}_m^{\text{com}} = \mathcal{E}^{\text{com}}(\widetilde{\mathbf{X}}_m), \mathbf{X}_m^{\text{prt}} = \mathcal{E}_m^{\text{prt}}(\widetilde{\mathbf{X}}_m). \tag{1}$$

$$\widetilde{\mathbf{X}}_m \in \mathbb{R}^{T_m \times d_m}, \text{ where } m \in \{L, V, A\}$$

$$\mathcal{L}_{\text{mar}} = \frac{1}{|S|} \sum_{(i,j,k)\in S} \max(0, \alpha - \cos(\mathbf{X}_{m[i]}^{\text{com}}, \mathbf{X}_{m[j]}^{\text{com}}) + \cos(\mathbf{X}_{m[i]}^{\text{com}}, \mathbf{X}_{m[k]}^{\text{com}})), \tag{4}$$

$$\mathcal{L}_{\text{ort}} = \sum_{m\in\{L,V,A\}} \cos(\mathbf{X}_m^{\text{com}}, \mathbf{X}_m^{\text{prt}}). \tag{5}$$

Method



$$\mathcal{L}_{\text{rec}} = \|\widetilde{\mathbf{X}}_m - \mathcal{D}_m([\mathbf{X}_m^{\text{com}}, \mathbf{X}_m^{\text{prt}}])\|_F^2. \quad (2)$$

$$\mathcal{L}_{\text{cyc}} = \|\mathbf{X}_m^{\text{prt}} - \mathcal{E}_m^{\text{prt}}(\mathcal{D}_m([\mathbf{X}_m^{\text{com}}, \mathbf{X}_m^{\text{prt}}]))\|_F^2. \quad (3)$$

$$\mathcal{L}_{\text{dec}} = \mathcal{L}_{\text{rec}} + \mathcal{L}_{\text{cyc}} + \gamma(\mathcal{L}_{\text{mar}} + \mathcal{L}_{\text{ort}}), \quad (6)$$

$$\zeta_{:j} = \sum_{v_i \in \mathcal{N}(v_j)} w_{i\to j} \times \epsilon_{i\to j}, \quad (7)$$

$$w_{i\to j} = g([[f(\mathbf{X}_i, \theta_1), \mathbf{X}_i], [f(\mathbf{X}_j, \theta_1), \mathbf{X}_j]], \theta_2), \quad (8)$$

$$\mathcal{L}_{\text{dtl}} = \|\mathbf{W} \odot \mathbf{E}\|_1, \quad (9)$$

$$\mathbf{Z}_{L\to V}^{\text{prt}} = \text{softmax}\left(\frac{\mathbf{Q}_V \mathbf{K}_L^\top}{\sqrt{d}}\right)\mathbf{V}_L, \quad (10)$$

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{task}} + \lambda_1 \mathcal{L}_{\text{dec}} + \lambda_2 \mathcal{L}_{\text{dtl}}, \quad (11)$$

Experiments

Table 1. Comparison on CMU-MOSI dataset. **Bold** is the best.

Methods	Setting	ACC_7 (%)	ACC_2 (%)	F1 (%)
EF-LSTM	Aligned	33.7	75.3	75.2
LF-LSTM		35.3	76.8	76.7
TFN [33]		32.1	73.9	73.4
LMF [14]		32.8	76.4	75.7
MFM [29]		36.2	78.1	78.1
RAVEN [30]		33.2	78.0	76.6
MCTN [26]		35.6	79.3	79.1
MulT [28]		40.0	83.0	82.8
PMR [17]		40.6	83.6	83.4
DMD (**Ours**)		**41.4**	**84.5**	**84.4**
MISA [7]*	Aligned	42.3	83.4	83.6
FDMER [32]*		44.1	84.6	84.7
DMD (**Ours**)*		**45.6**	**86.0**	**86.0**
EF-LSTM	Unaligned	31.0	73.6	74.5
LF-LSTM		33.7	77.6	77.8
RAVEN [30]		31.7	72.7	73.1
MCTN [26]		32.7	75.9	76.4
MulT [28]		39.1	81.1	81.0
PMR [17]		40.6	82.4	82.1
MICA [13]		40.8	82.6	82.7
DMD (**Ours**)		**41.9**	**83.5**	**83.5**

* means the input language features are BERT-based.

Experiments

Table 2. Comparison on CMU-MOSEI dataset. **Bold** is the best.

Methods	Setting	ACC_7 (%)	ACC_2 (%)	F1 (%)
EF-LSTM	Aligned	47.4	78.2	77.9
LF-LSTM		48.8	80.6	80.6
Graph-MFN [36]		45.0	76.9	77.0
RAVEN [30]		50.0	79.1	79.5
MCTN [26]		49.6	79.8	80.6
MulT [28]		51.8	82.5	82.3
PMR [17]		52.5	83.3	82.6
DMD (**Ours**)		**53.7**	**85.0**	**84.9**
MISA [7]*	Aligned	52.2	85.5	85.3
FDMER [32]*		54.1	86.1	85.8
DMD (**Ours**)*		**54.5**	**86.6**	**86.6**
EF-LSTM	Unaligned	46.3	76.1	75.9
LF-LSTM		48.8	77.5	78.2
RAVEN [30]		45.5	75.4	75.7
MCTN [26]		48.2	79.3	79.7
MulT [28]		50.7	81.6	81.6
PMR [17]		51.8	83.1	82.8
MICA [13]		52.4	83.7	83.3
DMD (**Ours**)		**54.6**	**84.8**	**84.7**

* means the input language features are BERT-based.

Experiments

Table 3. Ablation study of the key components in DMD.

Dataset	FD	HomoGD	CA	HeteroGD	ACC_7	F1
MOSI	✓	✓	✓	✓	**41.9**	**83.5**
	✓	✓	✓	×	38.8	81.1
	✓	✓	×	✓	37.5	80.6
	✓	✓	×	×	37.2	80.8
	✓	×	×	×	34.7	79.3
	×	×	×	×	32.4	79.0
MOSEI	✓	✓	✓	✓	**54.6**	**84.7**
	✓	✓	✓	×	53.2	84.1
	✓	✓	×	✓	52.4	83.8
	✓	✓	×	×	52.4	84.3
	✓	×	×	×	51.6	82.8
	×	×	×	×	50.0	81.9

Experiments

Table 4. Unimodal accuracy comparison on MOSEI dataset.

Methods	w/o FD	w/ FD
	Acc_2 (%) / F1 (%)	Acc_2 (%) / F1 (%)
L only	81.2 / 81.4	**82.7 / 82.5**
V only	58.2 / 52.2	**62.8 / 60.0**
A only	53.4 / 54.0	**64.9 / 62.5**
Mean	64.3 / 62.5	**70.1 / 68.3**
STD	12.1 / 13.4	**8.9 / 10.1**

Experiments

Table 5. Ablation study of graph distillation (GD) on MulT.

Methods	CMU-MOSI			CMU-MOSEI		
	ACC_7	ACC_2	F1	ACC_7	ACC_2	F1
MulT	39.1	81.1	81.0	50.7	81.6	81.6
MulT (*w/ GD*)	39.4	82.2	82.2	51.0	82.3	82.5
DMD (**Ours**)	**41.9**	**83.5**	**83.5**	**54.6**	**84.8**	**84.7**

Experiments

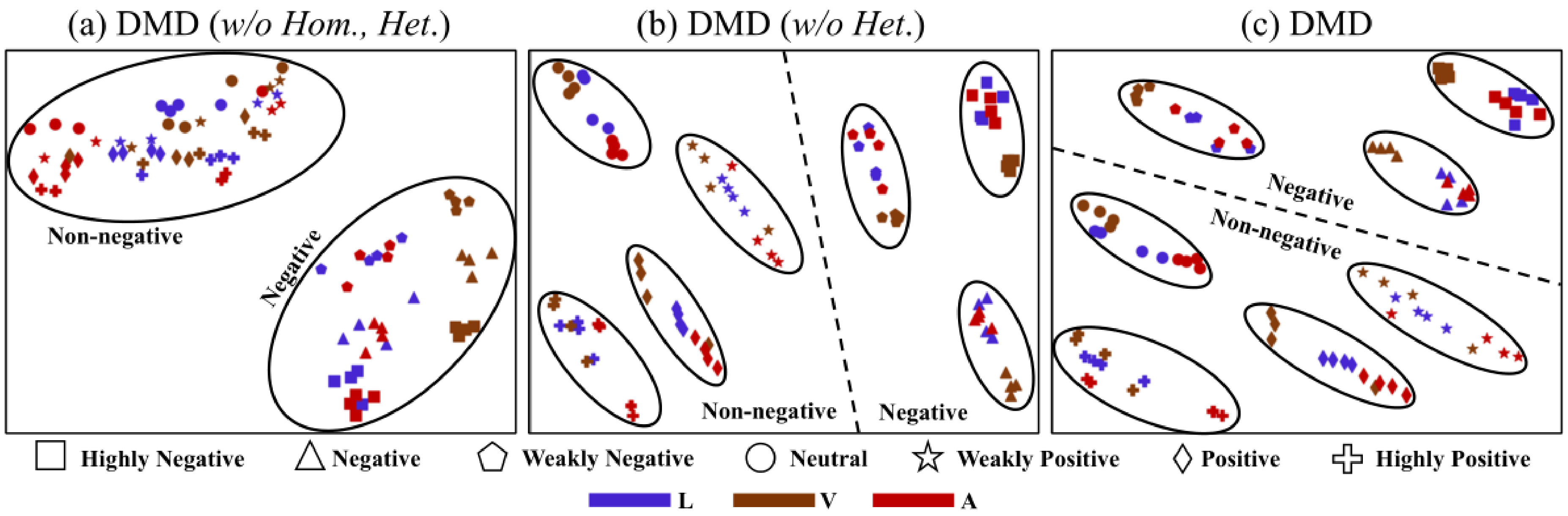


Figure 3. t-SNE visualization of decoupled homogeneous space on MOSEI. DMD shows the promising emotion category (binary or 7-class) separability in (c).

Experiments

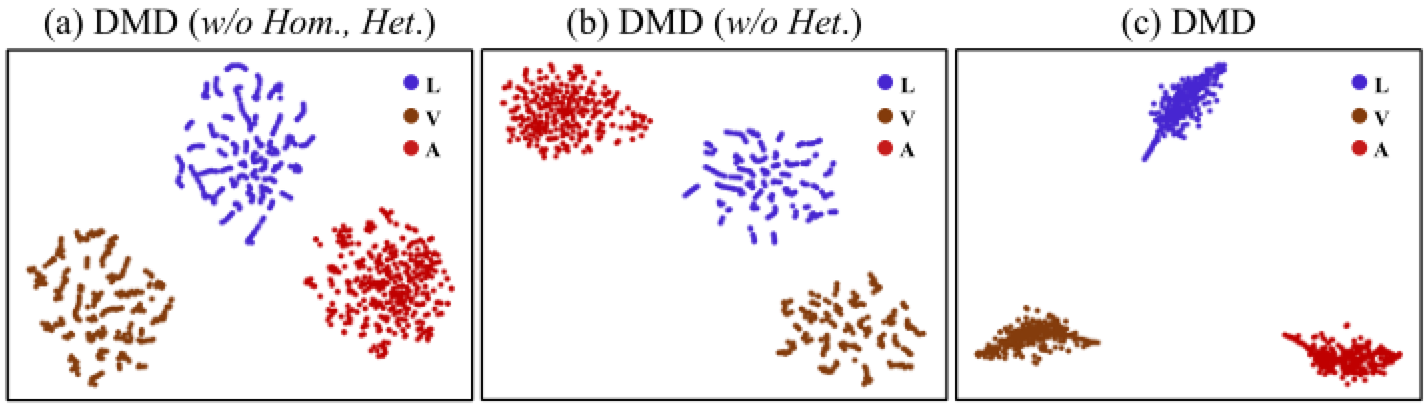
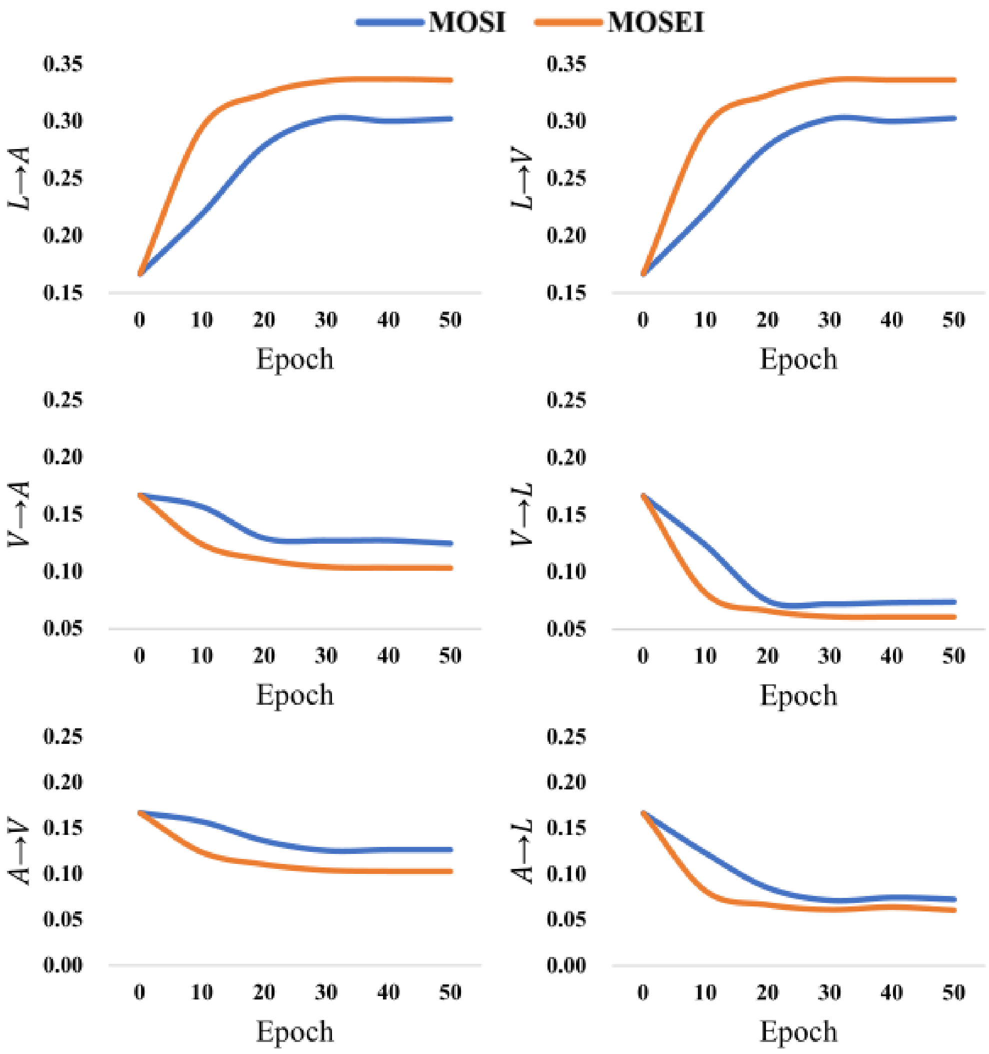
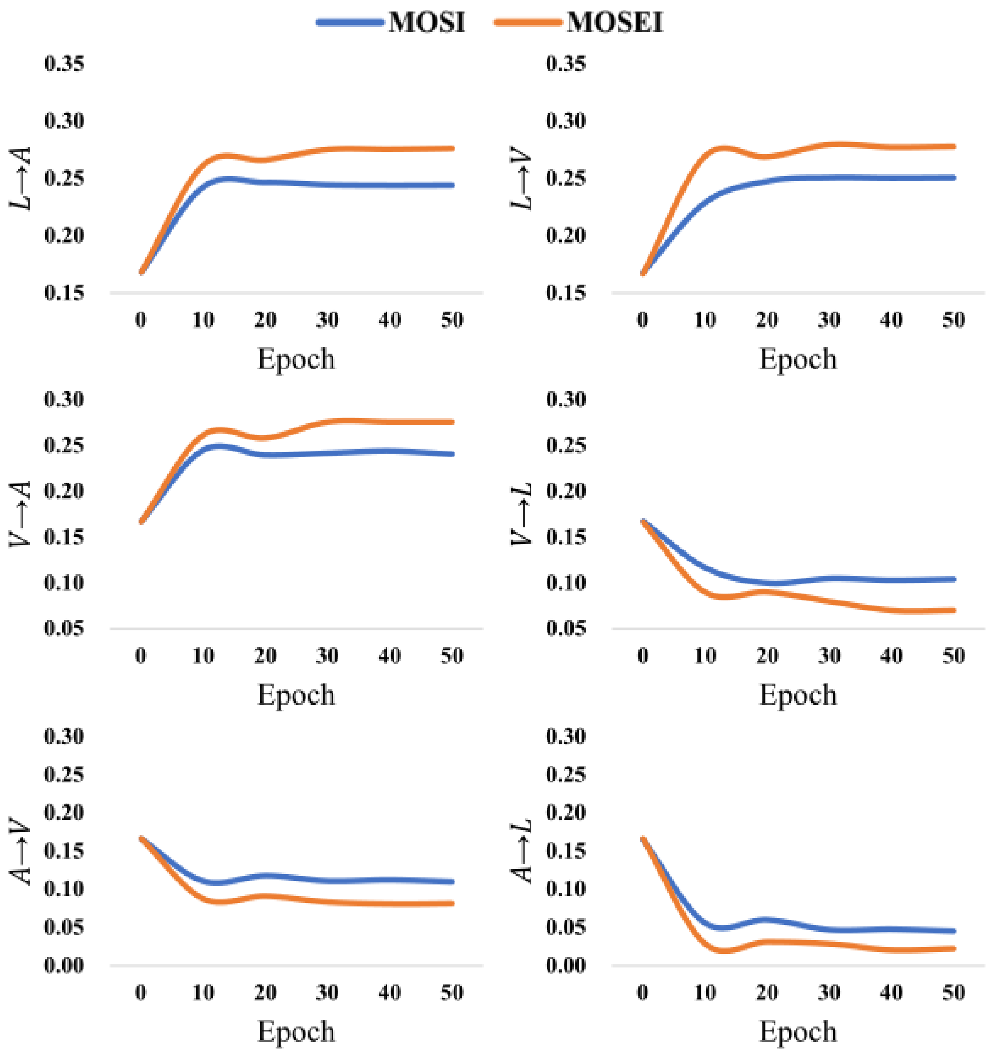


Figure 4. Visualization of the decoupled heterogeneous features on MOSEI. DMD shows the best modality separability in (c).

Experiments



(a) Graph edges in HomoGD



(b) Graph edges in HeteroGD

Thanks!