Artificial

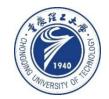
MuCDN: Mutual Conversational Detachment Network for Emotion Recognition in Multi-Party Conversations

Weixiang Zhao, Yanyan Zhao*, Bing Qin
Research Center for Social Computing and Information Retrieval
Harbin Institute of Technology, China
{wxzhao, yyzhao, qinb}@ir.hit.edu.cn

Code: https://github.com/circle-hit/MuCDN

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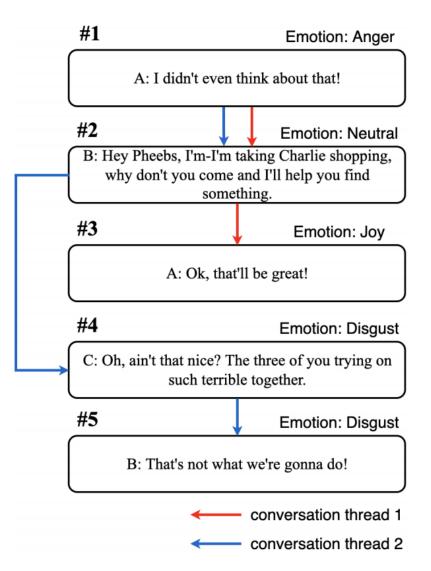




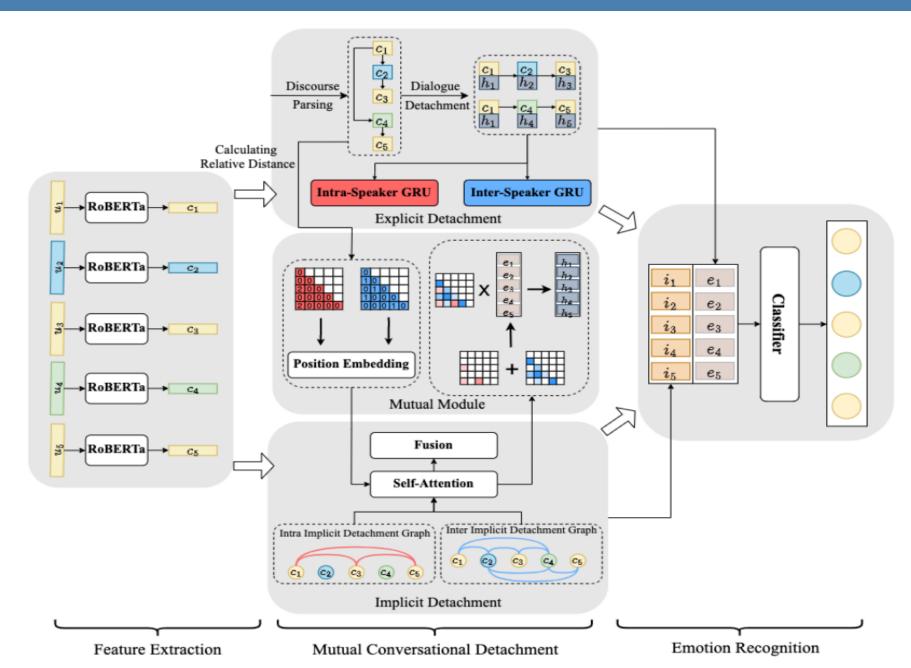


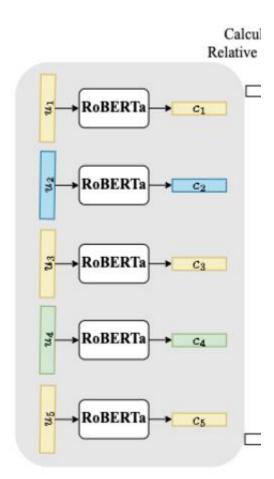


Introduction

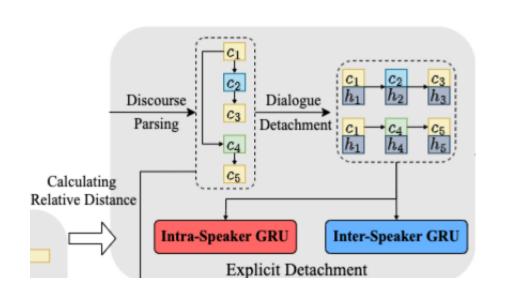


Intelligenc





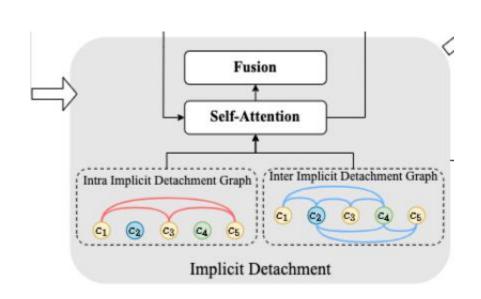
$$c_i = \text{RoBERTa}([CLS], w_1, w_2, \cdots, w_L)$$
 (1)



$$\{(i, j, e_{ij}), \dots\} = \text{Parser}(\{u_1, u_2, \dots, u_N\})$$
(2)

$$D_{i,j} = \begin{cases} 1, & \text{if } e_{ij} \text{ exists in discourse tree} \\ 0, & \text{otherwise} \end{cases}$$
(3)

$$e_{i} = \begin{cases} GRU^{intra}(c_{i}, e_{p}), & \text{if } \phi(u_{i}) = \phi(u_{p}) \\ GRU^{inter}(c_{i}, e_{p}), & \text{otherwise} \end{cases}$$
(4)



$$IDG_{i,j}^{intra} = \begin{cases} 0, \text{ if } j <= i \text{ and } \phi(u_i) = \phi(u_j) \\ -\infty, \text{ otherwise} \end{cases}$$

$$IDG_{i,j}^{inter} = \begin{cases} 0, \text{ if } j < i \text{ and } \phi(u_i) \neq \phi(u_j) \\ -\infty, \text{ otherwise} \end{cases}$$

$$G = \text{MHSA}(C, IDG^t),$$

$$Att(Q, K, V, IDG^t) = \text{Softmax}(\frac{QK^T}{\sqrt{d_k}} + IDG^t)V$$

$$(7)$$

$$F^t = \text{ReLU}(\text{FC}([C, G^t, C - G^t, C \odot G^t])),$$

$$g = \text{Sigmoid}(\text{FC}[F^{intra}, F^{inter}]),$$

$$I = g \odot F^{intra} + (1 - g) \odot F^{inter}$$

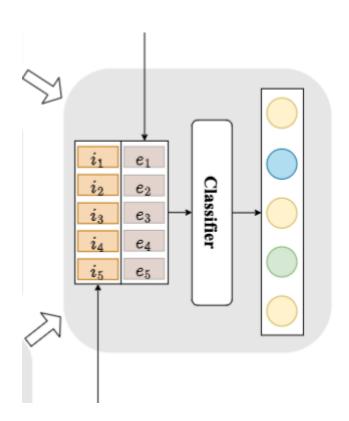
$$(8)$$

Parsing Detachment ance Intra-Speaker GRU Inter-Speaker GRU **Explicit Detachment** Position Embedding Mutual Module Fusion Self-Attention Intra Implicit Detachment Graph Implicit Detachment

$$h_{i} = A_{i, < i}^{joint} \times E_{< i}$$
 (9)
$$e_{i} = \begin{cases} GRU^{intra}([c_{i}, h_{i}], e_{p}), & \text{if } \phi(u_{i}) = \phi(u_{p}) \\ GRU^{inter}([c_{i}, h_{i}], e_{p}), & \text{otherwise} \end{cases}$$
 (10)
$$Pos^{t} = \text{Embedding}(P^{t}),$$

$$G = \text{MHSA}(C, IDG^{t}, Pos^{t}),$$

$$\text{Att}(Q, K, V, IDG^{t}, Pos^{t}) = \text{Softmax}(\frac{QK^{T}}{\sqrt{d_{k}}} + IDG^{t} + Pos^{t})V$$
 (11)



$$\hat{y} = \text{Softmax}(W_e[C, E, I] + b_e) \tag{12}$$

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{Emo} \hat{y}_i^j \cdot log(y_i^j)$$
 (13)

Dataset	Dialogues			Utterances		
	Train	Val	Test	Train	Val	Test
EmoryNLP MELD	713 1,039	99 114	85 280	9,934 9,989	1,344 1,109	1,328 2,610

Table 1: Dataset statistics

Model	EmoryNLP	MELD			
ERMC Methods					
ConGCN	-	57.40			
DialogXL	34.73	62.41			
ERMC-DisGCN	36.38	64.22			
ERC Methods with CSK					
KET	34.39	58.18			
KAITML	35.59	58.97			
KI-Net	-	63.24			
SKAIG	38.88	65.18			
COSMIC	38.11	65.21			
COSMIC w/o CSK	37.10	64.28			
ERC Methods without CSK					
DialogueRNN	31.7	57.03			
DialogueGCN	-	58.1			
IEIN	-	60.72			
RGAT	34.42	60.91			
DialogueCRN	-	58.39			
DAG-ERC	39.02	63.65			
MuCDN (Ours)	40.09	65.37			

Model	EmoryNLP	MELD
MuCDN	40.09	65.37
w/o explicit detachment	38.45	64.45
w/o implicit detachment	38.84	64.47
w/o E2I interaction	39.28	64.61
w/o I2E interaction	39.54	64.56

Model	EmoryNLP	MELD
MuCDN	40.09	65.37
sequence	39.05	64.51
randomness	38.72	64.71

Model	EmoryNLP	MELD
MuCDN	40.09	65.37
w/o intra and inter GRU	39.42	64.49
w/o intra and inter graph	38.91	64.46



Thanks!