Artificial

CauAIN: Causal Aware Interaction Network for Emotion Recognition in Conversations

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

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Reported by Renhui Luo





- 1.Introduction
- 2.Overview
- 3.Methods
- 4. Experiments











Introduction

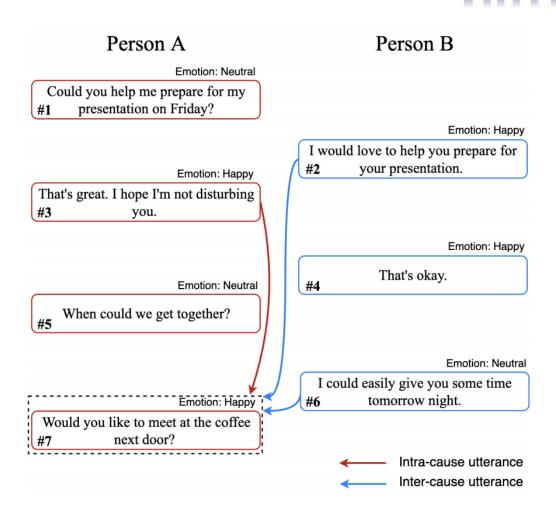


Figure 1: An example for intra- and inter-cause utterances triggerir the emotion of the target utterance.

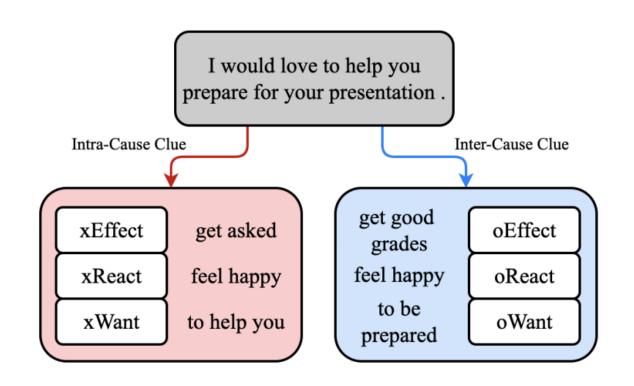


Figure 2: An example of six types of intra- and inter-cause clues.

Overview

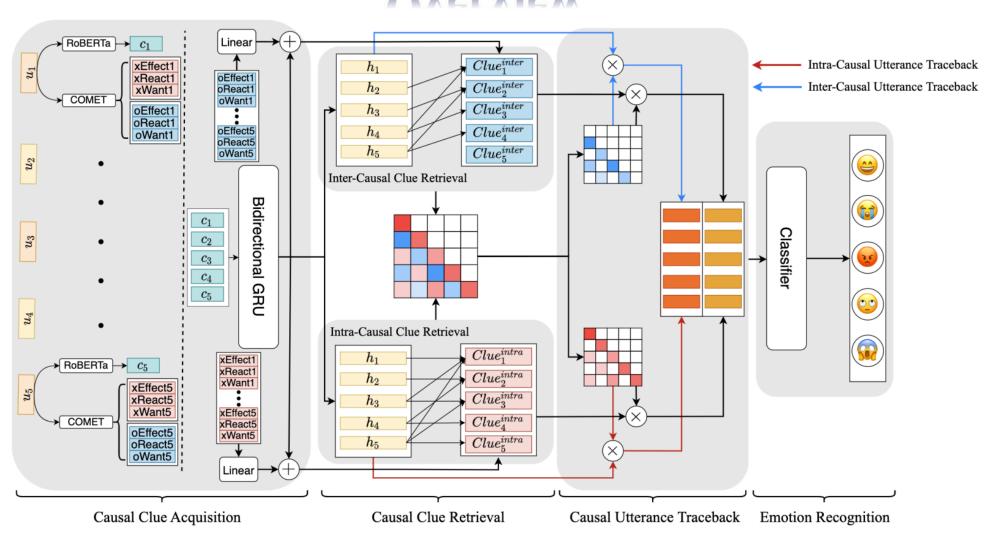
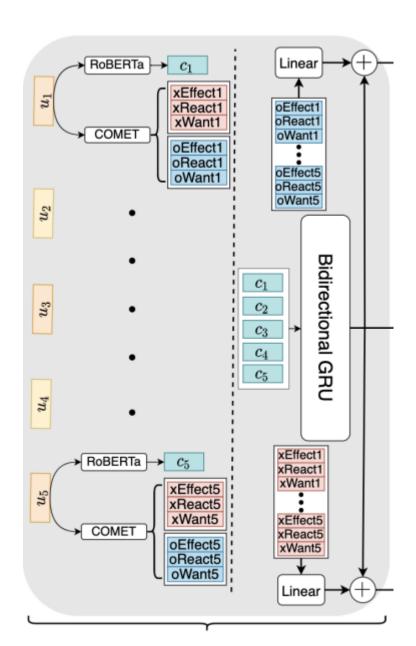
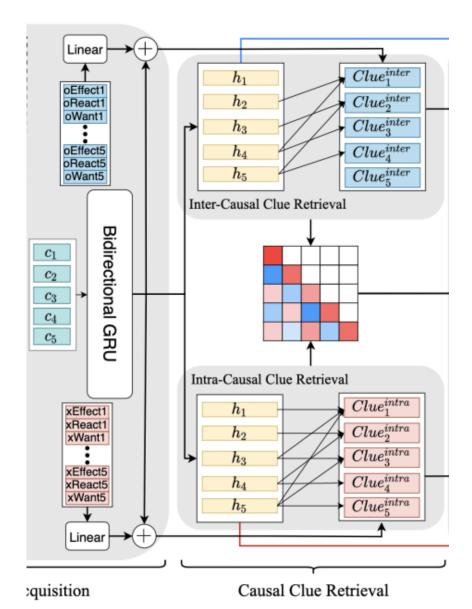


Figure 3: The overall architecture of our proposed model.



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

$$h_i = \overrightarrow{GRU}(c_i, h_{i-1}) \tag{2}$$



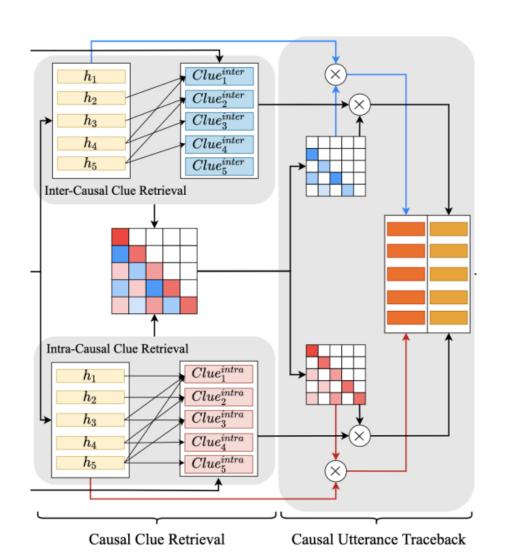
$$scores_{i,j}^{intra} = \frac{[f_q(h_i)(f_k(h_j) + f_e(Clue_j^{intra}))]mask_{i,j}^{intra}}{\sqrt{d_h}}$$
(3)

$$mask_{i,j}^{intra} = \begin{cases} 1, & if \ j <= i \ and \ \phi(h_i) = \phi(h_j) \\ 0, & otherwise \end{cases}$$
 (4)

$$scores_{i,j}^{inter} = \frac{[f_q(h_i)(f_k(h_j) + f_e(Clue_j^{inter}))]mask_{i,j}^{inter}}{\sqrt{d_h}}$$
(5)

$$mask_{i,j}^{inter} = \begin{cases} 1, & if \ j < i \ and \ \phi(h_i) \neq \phi(h_j) \\ 0, & otherwise \end{cases}$$
 (6)

$$\alpha_{i,j}^{joint} = softmax(scores_{i,j}^{intra} + scores_{i,j}^{inter})$$
 (7)



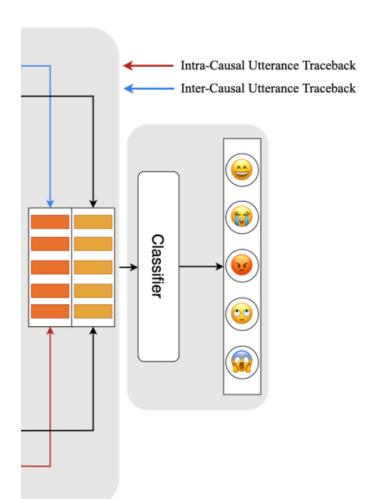
$$\tilde{h}_i = \sum_{j \in S(i)} \alpha_{i,j}^{intra} f_q(h_j) + \sum_{j \in O(i)} \alpha_{i,j}^{inter} f_q(h_j)$$
 (8)

$$\tilde{c_i} = \sum_{j \in S(i)} \alpha_{i,j}^{intra} C_j^{intra} + \sum_{j \in O(i)} \alpha_{i,j}^{inter} C_j^{inter}$$
(9)

$$C_j^{intra} = f_k(h_j) + f_e(Clue_j^{intra})$$
 (10)

$$C_j^{inter} = f_k(h_j) + f_e(Clue_j^{inter})$$
 (11)

$$h_i^f = \tilde{h_i} \oplus \tilde{c_i} \tag{12}$$



Emotion Recognition

nce Traceback

$$\hat{y} = softmax(W_e h^f + b_e) \tag{13}$$

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{E} \hat{y_i}^j \cdot log(y_i^j)$$
 (14)

where E is the number of emotion class and y_i^j stands for the ground-truth emotion label of the utterance i.

Experiments

Dataset	Dialogues			Utterances		
	Train	Val	Test	Train	Val	Test
IEMOCAP	120		31	5,810		1,623
DailyDialog	11,118	1,000	1,000	87,170	8,069	7,740
MELD	1,039	114	280	9,989	1,109	2,610

Table 1: Dataset statistics

Experiments

Model	IEMOCAP	DailyDialog		MELD	
	weighted-F1	micro-F1	macro-F1	weighted-F1	
ICON	58.54	-	-	-	
DialogueRNN	62.57	55.95	41.8	57.03	
DialogueGCN	64.18	-	-	58.1	
IEIN	64.37	-	-	60.72	
DialogueCRN	66.2	-	-	58.39	
RGAT	65.22	54.31	-	60.91	
COSMIC	65.28	58.48	51.05	65.21	
DialogXL	65.94	54.93	-	62.41	
KI-Net	66.98	57.3	-	63.24	
SKAIG	66.96	59.75	51.95	65.18	
CauAIN (Ours)	67.61	58.21	53.85	65.46	
w/o Inter Cause	64.61	54.23	49.53	62.83	
w/o Intra Cause	64.66	55.24	48.7	59.52	
w/o Causal Clue	63.77	57.2	51.73	65.2	

Table 2: Comparison of our model against state-of-the-art baselines. Intra Cause and Inter Cause are the process of intra- and inter cause detection, respectively and Causal Clue refers to causal clue generated from COMET.

Experiments

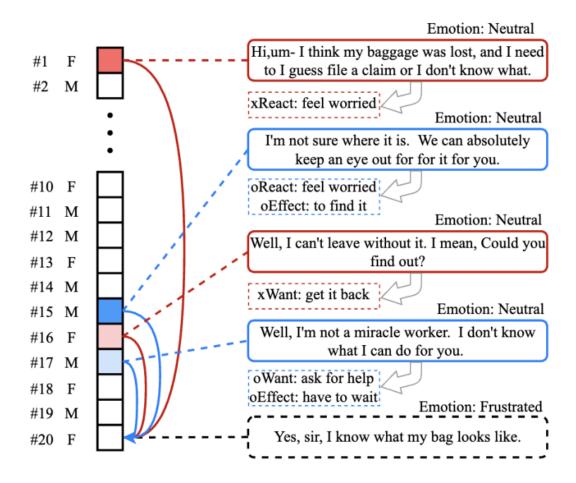


Figure 4: A case that our model gives the correct prediction. The most two relevant intra- and inter-cause utterances are illustrated through the process of Causal Utterance Traceback.



Thanks!