A Multi-turn Machine Reading Comprehension Framework with Rethink Mechanism for Emotion-Cause Pair Extraction

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https://github.com/zhoucz97/ECPE-MM-R

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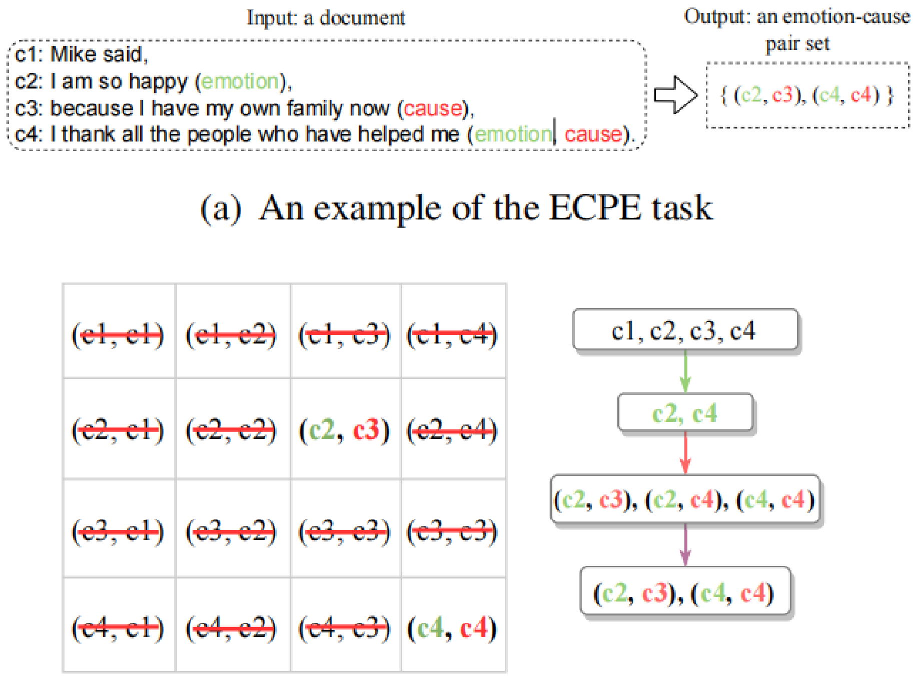
Reported by Dongdong Hu

Introduction



(b) Pairing matrix (c) Our approach

Figure 1: The green colour denotes an emotion clause, and the red colour denotes a cause clause. Figure (a) is an example of the ECPE task. Figure (b) is a pairing matrix generated by pair-level end-to-end approaches. Only (c2, c3) and (c4, c4) are valid pairs. Figure (c) shows the processing results by our MM-R in each turn.

these methods either suffer from a label sparsity problem or fail to model complicated relations between emotions and causes.

Method

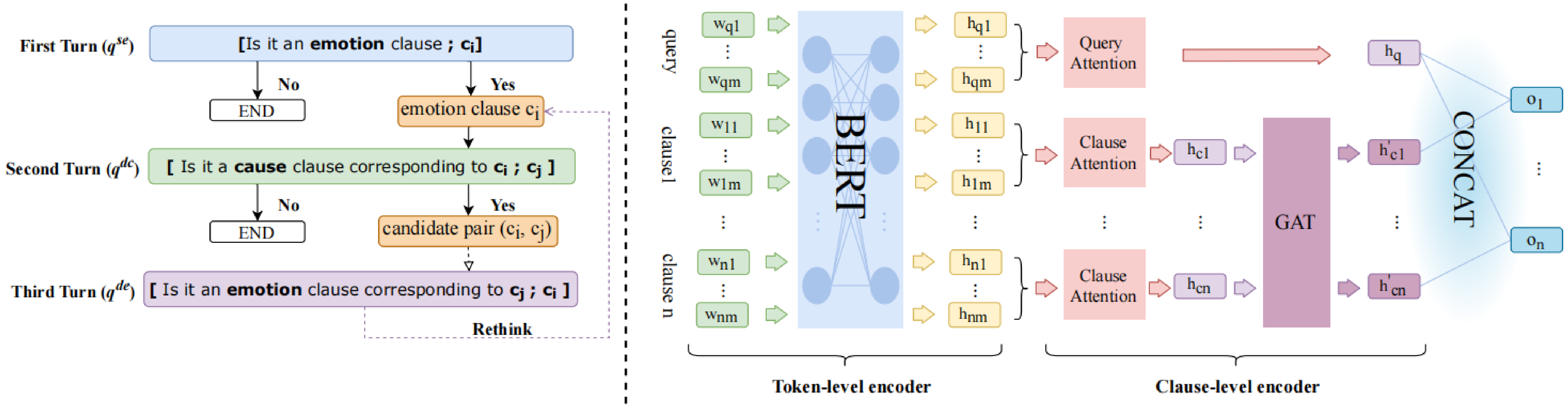
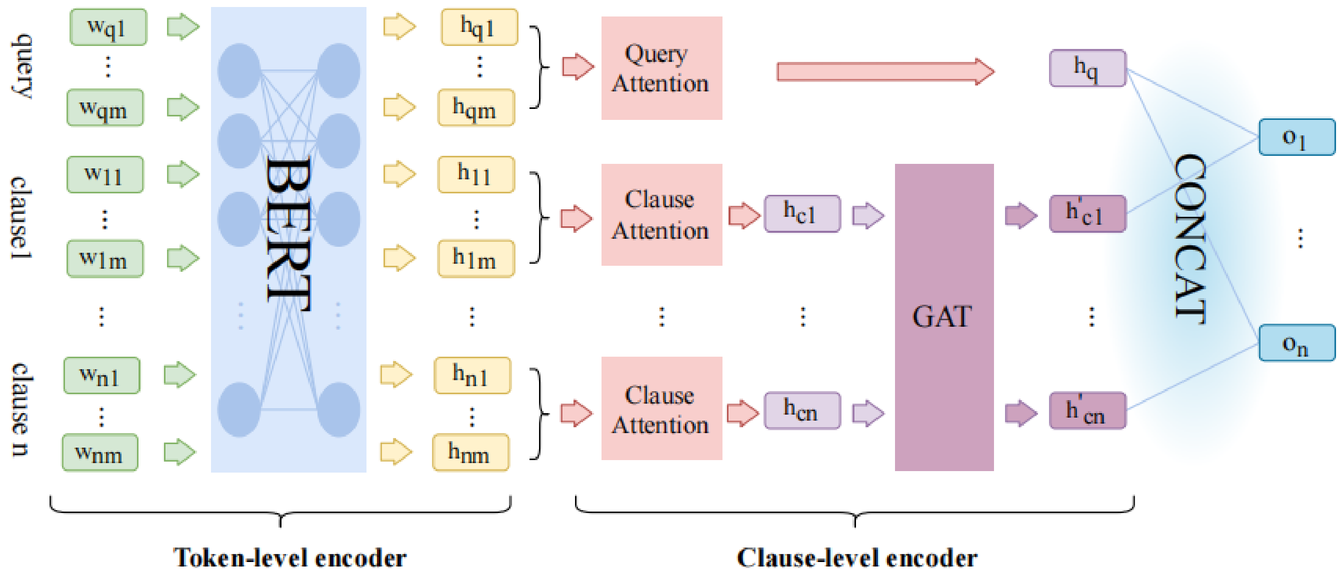


Figure 2: *Left*: The overall architecture of our MM-R framework. In each turn, the answer is yes if the probability output by the classifier is greater than 0.5, otherwise it is no. *Right*: The implementation structure of the encoding layer which includes the token-level encoder and the clause-level encoder. The token-level encoder generates the hidden representation of each token using the BERT module. The clause-level encoder provides the hidden representation of query and each clause using the attention mechanism and graph attention network. Finally, the concatenate operation (CONCAT) is executed on the hidden representations of queries and clauses.

Method

- **Static emotion query** $q^{se} \in Q^{se}$: The query "*Is it an emotion clause?*" is designed to extract all emotion clauses.
- **Static cause query** $q^{sc} \in Q^{sc}$: The query "*Is it a cause clause?*" is designed to extract all cause clauses.
- **Static pair query** $q^{sp} \in Q^{sp}$: The query "*Is it an emotion-cause pair?*" is designed to extract all emotion-cause pairs.
- **Dynamic emotion query** $q^{de} \in Q^{de}$: The query template "*Is it an emotion clause corresponding to* c_i*?*" is designed to extract emotion clauses corresponding to clause c_i.
- **Dynamic cause query** $q^{dc} \in Q^{dc}$: The query template "*Is it a cause clause corresponding to* c_i*?*" is designed to extract cause clauses corresponding to clause c_i.

Method



$$I = \{[CLS], w_{q,1}, w_{q,2}, ..., w_{q,|q|}, [SEP], w_{1,1}, w_{1,2}, ..., w_{|D|,1}, ..., w_{|D|,|c_{|D|}|}\}, \quad (2)$$

where $q = q^{se}$ in the first turn, $q = q^{dc}$ in the second turn and $q = q^{de}$ in the third turn; $w_{q,j}$ is the j-th token of query q; $w_{i,j}$ is the j-th token of the i-th clause in the document D;

$$H^I = BERT(I) = \{h_{[CLS]}, h_{q,1}, h_{q,2}, ..., h_{q,|q|}, h_{[SEP]}, h_{1,1}, h_{1,2}, ..., h_{|D|,1}, ..., h_{|D|,|c_{|D|}|}\}, \quad (3)$$

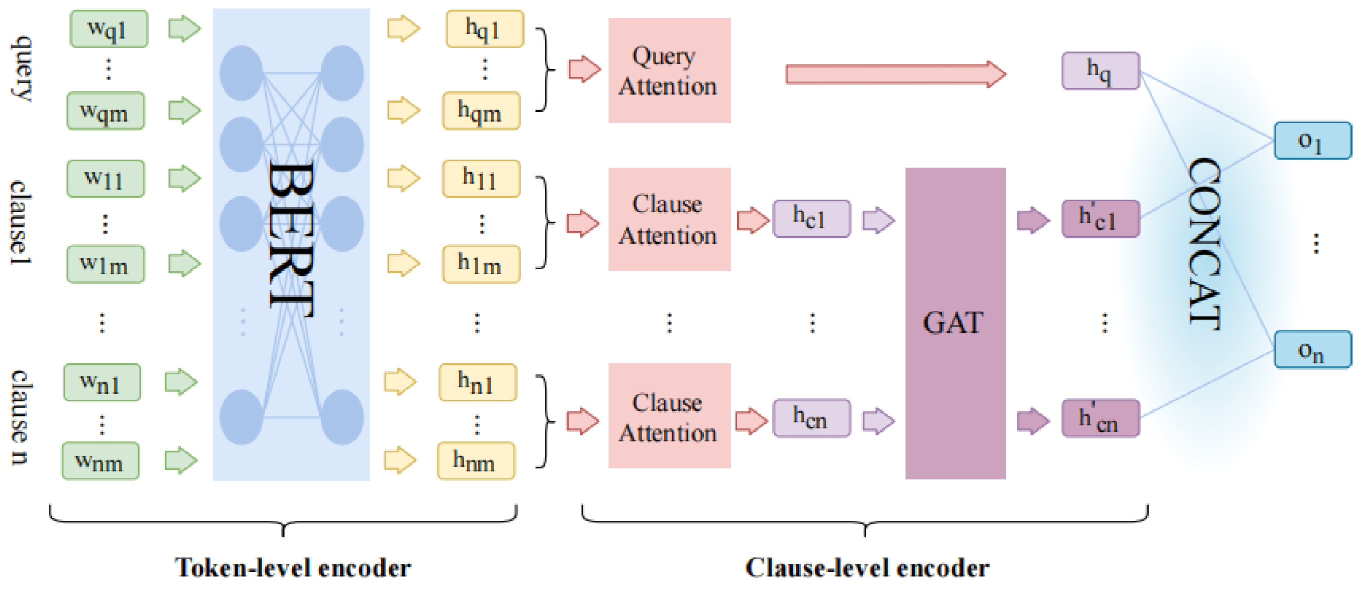
$$S_{c_i} = \{h_{i,j}\}_{j=1}^{|c_i|} \in \mathbb{R}^{|c_i| \times d}. \quad (4)$$

$$\alpha_i = softmax(w^T S_{c_i} + b) \in \mathbb{R}^{1 \times |c_i|}, \quad (5)$$

$$h_{c_i} = sum(\alpha_i S_{c_i}) \in \mathbb{R}^{1 \times d}, \quad (6)$$

$$H_C = \{h_{c_1}, h_{c_2}, ..., h_{c_{|D|}}\}. \quad (7)$$

Method



$$H_Q = \{h_q\}. \quad (8)$$

$$H'_C = GAT(H_C) = \{h'_{c_1}, h'_{c_2}, ..., h'_{c_{|D|}}\}. \quad (9)$$

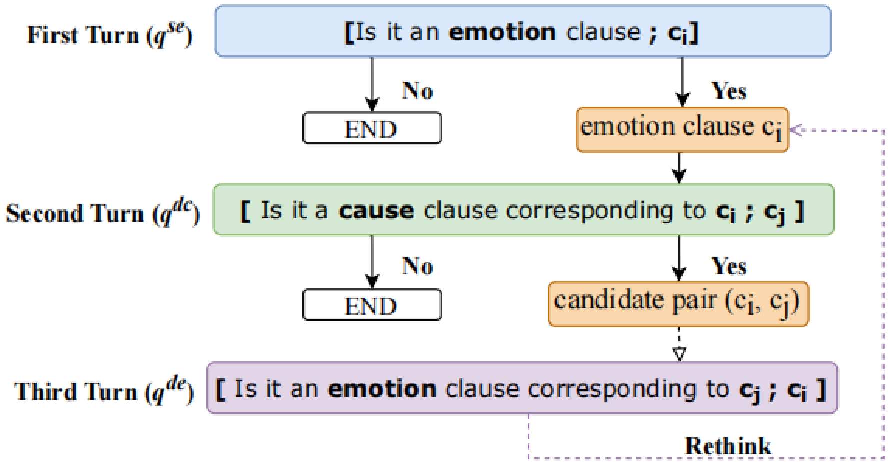
Finally, $h_q \in H_Q$ and $h'_{c_i} \in H'_C$ are concatenated to obtain $o_i = [h_q; h'_{c_i}]$,

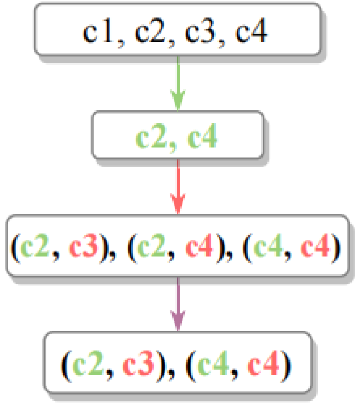
$$O_{enc} = \{o_1, o_2, ..., o_{|D|}\}. \quad (10)$$

$$\hat{y}_i = \sigma(w_S^T o_i + b_S), \quad (11)$$

If $\hat{y}_i > 0.5$, the answer is judged to be yes, meaning that clause c_i is one of the answers to query q.

Method





$$\mathcal{L}^* = -\sum_{i=1}^{N}\sum_{j=1}^{|D|}\sum_{k=1}^{|Q^*|}[p(y_{i,j,k}|c_{i,j}, q_k^*)\log \hat{p}(y_{i,j,k}|c_{i,j}, q_k^*)], \tag{12}$$

where $* \in \{se, dc, de\}$; N denotes the number of documents in the dataset; $c_{i,j}$ is the j-th clause of the i-th document; and q_k^* is the k-th query in Q^*.

$$\mathcal{L} = \mathcal{L}^{se} + \mathcal{L}^{dc} + \mathcal{L}^{de}, \tag{13}$$

$$p(c^{e_i}, c^{ca_{i,j}}) = p(c^{e_i})p(c^{ca_{i,j}}|c^{e_i})$$

$$p(c^{e_i}, c^{ca_{i,j}}) = \lambda p(c^{e_i})p(c^{ca_{i,j}}|c^{e_i}), \tag{14}$$

λ is 1 when the predicted result of the third turn is yes, otherwise λ is a unique value between 0 and 1.

$$P = \{(c^{e_i}, c^{ca_{i,j}})|(c^{e_i}, c^{ca_{i,j}}) \in P^{can}, p(c^{e_i}, c^{ca_{i,j}}) > \delta\}, \tag{15}$$

Method

Model	E-C Pair Extraction			Emotion Extraction			Cause Extraction		
	P(%)	R(%)	F1(%)	P(%)	R(%)	F1(%)	P(%)	R(%)	F1(%)
SL-NTS	72.43	63.66	67.76	81.96	73.29	77.39	74.90	66.02	70.18
TransDGC (Val)	73.74	63.07	67.99	87.16	82.44	84.74	75.62	64.71	69.74
ECPE-2D	72.92	65.44	68.89	86.27	**92.21**	89.10	73.36	69.34	71.23
PairGCN	76.92	67.91	72.02	88.57	79.58	83.75	79.07	69.28	73.75
RANKCP	71.19	76.30	73.60	91.23	89.99	90.57	74.61	77.88	76.15
ECPE-MLL	77.00	72.35	74.52	86.08	91.91	88.86	73.82	79.12	76.30
MM-R	**82.18**	**79.27**	**80.62**	**97.38**	90.38	**93.70**	**83.28**	**79.64**	**81.35**
MM-R (Val)	78.97	75.32	77.06	96.09	88.09	91.88	80.90	76.21	78.45

Table 1: Performance of our models and baselines. P, R and F1 denote precision, recall and F1-measure respectively. E-C denotes Emotion-Cause. TransDGC(Val) and MM-R(Val) use the second data split style, the rest of models use the first data split style.

Experiments

		TI(%)			TC(%)			AI(%)			AC(%)		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1
Flat EE	BERT-softmax	89.8	79.0	84.0	80.2	61.8	69.8	74.6	62.8	68.2	72.5	60.2	65.8
	BERT-CRF	**90.8**	80.8	85.5	**81.7**	63.6	71.5	75.1	64.3	69.3	72.9	61.8	66.9
	BERT-CRF-joint	89.5	79.8	84.4	80.7	63.0	70.8	**76.1**	63.5	69.2	**74.2**	61.2	67.1
Ovlp. & Nest. EE	PLMEE	83.7	85.8	84.7	75.6	74.5	75.1	74.3	67.3	70.6	72.5	65.5	68.8
	MQAEE	89.1	85.5	87.4	79.7	76.1	77.8	70.3	68.3	69.3	68.2	66.5	67.3
	CasEE	89.4	87.7	88.6	77.9	78.5	78.2	72.8	73.1	72.9	71.3	71.5	71.4
Ours	OneEE	88.7	**88.7**	**88.7**	79.1	**80.3**	**79.7**	75.4	**77.0**	**76.2**	74.0	**72.9**	**73.4**

Table 2: Results for extracting all kinds of events on FewFC, where TI, TC, AI, AC denote trigger identification, trigger classification, argument identification, and argument classification, respectively. We run our model for 5 times with different random seeds and report the median values.

Experiments

	Natural QL	Pseudo QL	Structured QL
Q^{se}	*Is it an emotion clause?*	*emotion?*	*emotion:_;cause:None*
Q^{dc}	*Is it a cause clause corresponding to* c_i*?*	c_i*;cause?*	*emotion:*c_i*;cause:_*
Q^{de}	*Is it an emotion clause corresponding to* c_i*?*	c_i*;emotion?*	*emotion:_;cause:*c_i
MM-R	80.62 (%F1)	80.51 (%F1)	79.72 (%F1)

Table 2: The performance of different query language designs (Natural, Pseudo and Structured QL) on ECPE task. "QL" denotes "Query Language". Q^{se}, Q^{dc} and Q^{de} are static emotion query, dynamic cause query and dynamic emotion query, respectively.

Experiments

Model	Extraction of. (F1 %)		
	Emotion	Cause	E-C pair
MRC-E2E	90.34	77.92	75.35
MM	93.02	77.94	78.19
MM-D	93.67	79.47	78.76
MM-R	**93.70**	**81.35**	**80.62**

Table 3: Performance of variants.

Experiments

“过年了 (c1)，债主把家里粮食都搬走了 (c2)，别家都在欢欢喜喜过年 (c3)，而俺家连割肉的钱都没有 (c4)，我和母亲抱头痛哭 (c5)”，陈怀军说 (c6)。

***Translate**: "It's the New Year (c1), and the creditor looted all food of my family (c2). Other families happily celebrate the New Year (c3), but we are too poor to buy meat (c4). This makes us very sad(c5)", said Huajun Chen (c6).*

The first turn	The second turn	Rethink	Threshold	Valid E-C pairs	Ground-truth
c3, c5	(c3, c4), $p_{(3,4)} = 0.5135$ (c5, c4), $p_{(5,4)} = 0.6313$	(c3, c4), $p_{(3,4)} = 0.3595$ (c5, c4), $p_{(5,4)} = 0.6313$	0.5	(c5, c4)	(c5, c4)

Figure 3: An example in the test set. The emotion clause set {c3, c5} was obtained in the first turn and the candidate emotion-cause pair set {(c3, c4), (c5, c4)} in the second turn. After using the rethink mechanism, the valid emotion-cause pair set was identified as {(c5, c4)}.

Experiments

Methods	Emotion Cause Extraction		
	P(%)	R(%)	F1(%)
RTHN	76.97	76.62	76.77
KAG	79.12	75.81	77.43
RHNN	81.12	77.25	79.14
2-step RANKING	80.76	78.45	79.59
MM-R	**83.59**	**83.47**	**83.48**

Table 4: Results on the Emotion Cause Extraction task.

Thanks