## Pair-Based Joint Encoding with Relational Graph Convolutional Networks for Emotion-Cause Pair Extraction

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Code: https://github.com/tutuDoki/PBJE-ECPE

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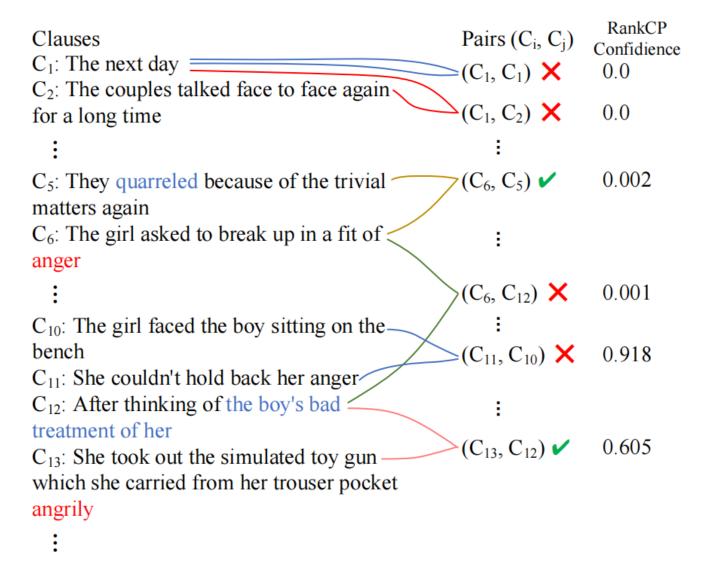






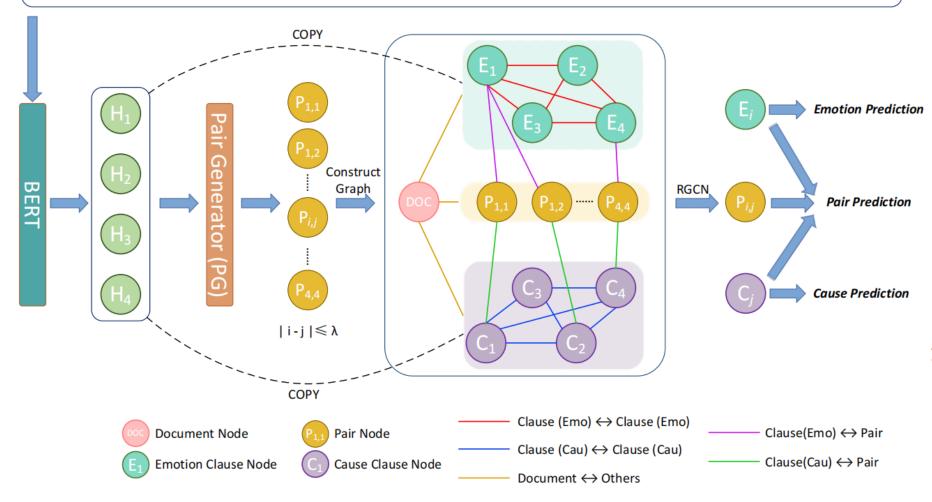


## Introduction



#### **Overview**

C<sub>1</sub>: [CLS] The ... day [SEP] C<sub>2</sub>: [CLS] The ... time [SEP] C<sub>3</sub>: [CLS] The ... eased [SEP] C<sub>4</sub>: [CLS] That afternoon [SEP] ...



$$D = (c_1, c_2, \dots, c_N)$$

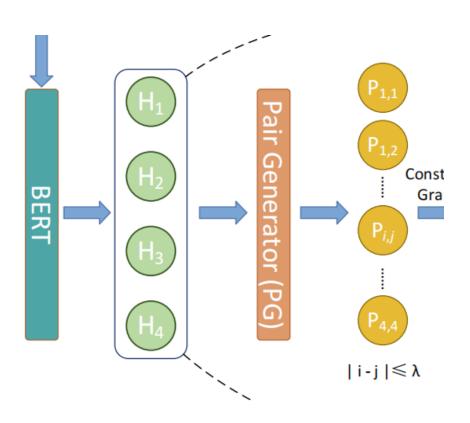
$$c_i = (w_1^i, w_2^i, \dots, w_M^i)$$

$$P = \{\dots, (c_i, c_j), \dots\} \quad (1 \le i, j \le N) \quad (1)$$

$$y_i^{emo} = \begin{cases} 1, & if \quad \exists c_j \in D, (c_i, c_j) \in P \\ 0, & otherwise \end{cases}$$
 (2)

where  $y_i^{emo} = 1$  means  $c_i$  is an emotion clause. The extraction of cause clauses is the same as emotion clauses.

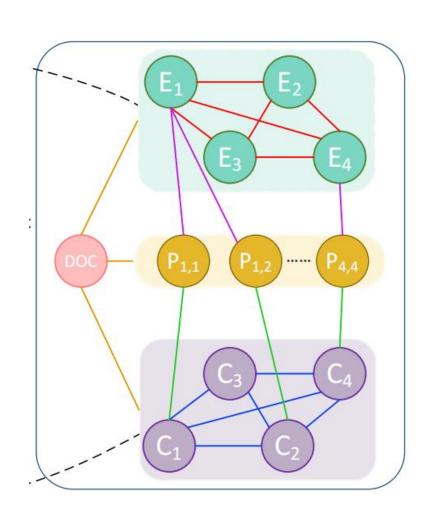
#### Method



$$H = \{h_1, h_2, \dots, h_N\}$$
 (3)

$$p_{ij} = W_p[h_i, h_j] + b_p + r_{i-j}$$
 (4)

## Method



$$H_E^{(0)} = H, H_C^{(0)} = H$$
 (5)

$$H_P^{(0)} = \{p_{11}, p_{12}, \dots, p_{NN}\}$$
 (6)

$$H_D^{(0)} = Avgpool(H) \in \mathbb{R}^d \tag{7}$$

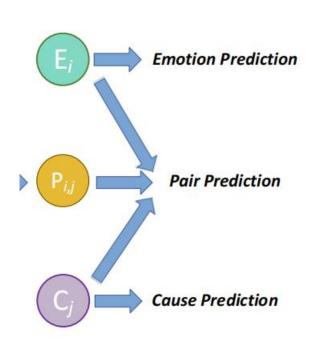
$$s_u^{(l)} = W_s^{(l)} h_u^{(l)} + b_s^{(l)}$$
 (8)

$$t_u^{(l+1)} = s_u^{(l)} + \sum_{r \in \mathcal{R}} \sum_{v \in \mathcal{N}_r(u)} \frac{1}{|\mathcal{N}_r(u)|} W_r^{(l)} h_v^{(l)} + b_r^{(l)}$$

(9)

$$h_u^{(l+1)} = ReLU\left(t_u^{(l+1)}\right) \tag{10}$$

#### Method



$$\hat{y}_{ij}^p = \sigma\left(MLP\left([P_{ij}, E_i, C_j]\right)\right) \tag{12}$$

$$\mathcal{L}_p = -\sum_{i}^{N} \sum_{j}^{N} y_{ij}^p \log(\hat{y}_{ij}^p)$$
 (13)

$$\hat{y}_i^e = \sigma \left( W_e E_i + b_e \right) \tag{14}$$

$$\hat{y}_i^c = \sigma \left( W_c C_j + b_c \right) \tag{15}$$

$$\mathcal{L}_e = -\sum_{i}^{N} y_i^e \log(\hat{y}_i^e) \tag{16}$$

$$\mathcal{L}_c = -\sum_{j}^{N} y_j^c \log(\hat{y}_j^c) \tag{17}$$

$$E = H_E^{(\theta)}, C = H_C^{(\theta)}, P = H_P^{(\theta)}$$
 (11)

(11) 
$$\mathcal{L} = \alpha \mathcal{L}_p + \beta \mathcal{L}_e + \gamma \mathcal{L}_c$$
 (18)

Item	Quantity	Percentage(%)
# of documents	1,945	100
- w/ 1 pair	1,746	89.77
- w/ 2 pairs	177	9.10
- w/ $\geq 3$ pairs	22	1.13
# of pairs	2167	100
- w/ 0 relative position	511	23.58
- w/ 1 relative position	1342	61.93
- w/ 2 relative position	224	10.34
- w/ $\geq 3$ relative position	90	4.15
Avg. # of clauses per document	14.77	
Max. # of clauses per document	73	

Table 1: The detail of the Chinese corpus.

Approach Emotion-Cause Pair Extraction		<b>Emotion Clause Extraction</b>			<b>Cause Clause Extraction</b>				
Approach	P	R	F1	P	R	F1	P	R	F1
ECPE-2D	72.92	65.44	68.89	86.27	92.21	89.10	73.36	69.34	71.23
TransECPE	<u>77.08</u>	65.32	70.72	88.79	83.15	85.88	78.74	66.89	72.33
PairGCN	76.92	67.91	72.02	88.57	79.58	83.75	79.07	68.28	73.75
UTOS	73.89	70.62	72.03	88.15	83.21	85.56	76.71	73.20	74.71
MTST-ECPE◊	75.78	70.51	72.91	85.83	80.94	83.21	77.64	72.36	74.77
RankCP	71.19	<b>76.30</b>	73.60	91.23	89.99	90.57	74.61	77.88	76.15
ECPE-MLL†	77.00	72.35	<u>74.52</u>	86.08	<u>91.91</u>	88.86	73.82	79.12	76.30
PBJE	79.22	73.84	76.37*	90.77	86.91	88.76	81.79	76.09	78.78

Table 2: The results comparison with baselines on the ECPE corpus for Emotion-Cause Pair Extraction and the two sub-tasks: Emotion clause Extraction and Cause clause Extraction. We introduce these baselines in Appendix A. The best performance is in **bold** and the second best performance is <u>underlined</u>. Approach with  $\dagger$  is previous state-of-the-art method. Approach with  $\diamond$  is based on our implementation. \* denotes p < 0.0005 for a two-tailed t-test against the RankCP.

Approach	<b>Emotion-Cause Pair Extraction</b>		<b>Emotion Clause Extraction</b>			Cause Clause Extraction			
	P	R	F1	P	R	F1	P	R	F1
PBJE	79.22	73.84	76.37	90.77	86.91	88.76	81.79	76.09	78.78
- w/o Clause-Clause Edge	77.81	<u>73.36</u>	<u>75.45</u>	90.76	<u>87.64</u>	89.14	80.07	75.3	<u>77.54</u>
<ul> <li>w/o Clause-Pair Edge</li> </ul>	<u>78.14</u>	72.62	75.21	90.76	86.74	88.66	80.15	74.51	77.16
- w/o Pair Node	76.92	72.37	74.54	89.83	86.62	88.18	79.50	74.81	77.05
- w/o PG	78.02	72.13	74.93	91.22	86.73	88.89	80.07	74.00	76.89
- w/o Pair Node & PG	74.49	73.24	73.76	89.93	87.83	88.82	78.94	<u>75.63</u>	77.18

Table 3: The results of ablation study on the benchmark corpus for emotion-cause pair extraction and the two sub-tasks. The best performance is in **bold** and the second best performance is <u>underlined</u>.

#Pairs	Approach	P	R	F1
1 par dos	PBJE	78.44	80.00	79.21
1 per doc.	RankCP	72.03	81.23	76.33
2 or more	PBJE	83.98	45.29	58.84
per doc.	RankCP	67.72	51.46	58.02

Table 4: The results of ECPE for documents with different numbers of pairs.

Relative Position	Approach	P	R	F
≤ 1	PBJE	80.69	81.26	80.97
	RankCP	77.45	83.38	80.30
	PBJE	58.55	28.43	38.28
$\geq 2$	RankCP	31.60	32.91	32.24

Table 5: The results of ECPE for pairs of different relative positions.

...It's time for Chinese New Year. $(c_4)$  The creditor removed all his family's grain. $(c_5)$  Other families are celebrating the New Year happily. $(c_6)$  But his family even did not have money for meat. $(c_7)$  His daughter and wife sorrowed. $(c_8)$ ...

PBJE	$[c_8, c_7]$	RankCP	$[c_6,c_5],[c_6,c_7],[c_8,c_7]$
Ground Truth	$[c_8, c_7]$		

Table 6: An example predicted by PBJE and RankCP. The words in red are the emotion keywords, and the words in blue are the cause keywords. The pairs in green are the correct prediction, and the pairs in red are incorrect. We translate it from Chinese into English for ease of reading.

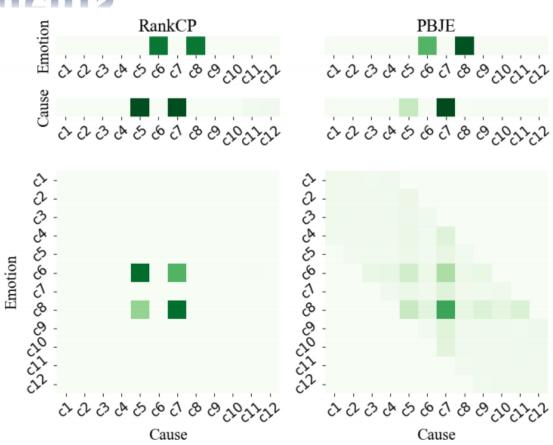


Figure 3: Visualization of the confidence of each prediction in RankCP and PBJE. The deeper color means the higher confidence.

# Thanks!