



# Multi-Granularity Semantic Aware Graph Model for Reducing Position Bias in Emotion-Cause Pair Extraction

## Multi-Granularity Semantic Aware Graph Model for Reducing Position Bias in Emotion-Cause Pair Extraction

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2022. 04. 17 • ChongQing

2022\_ACL



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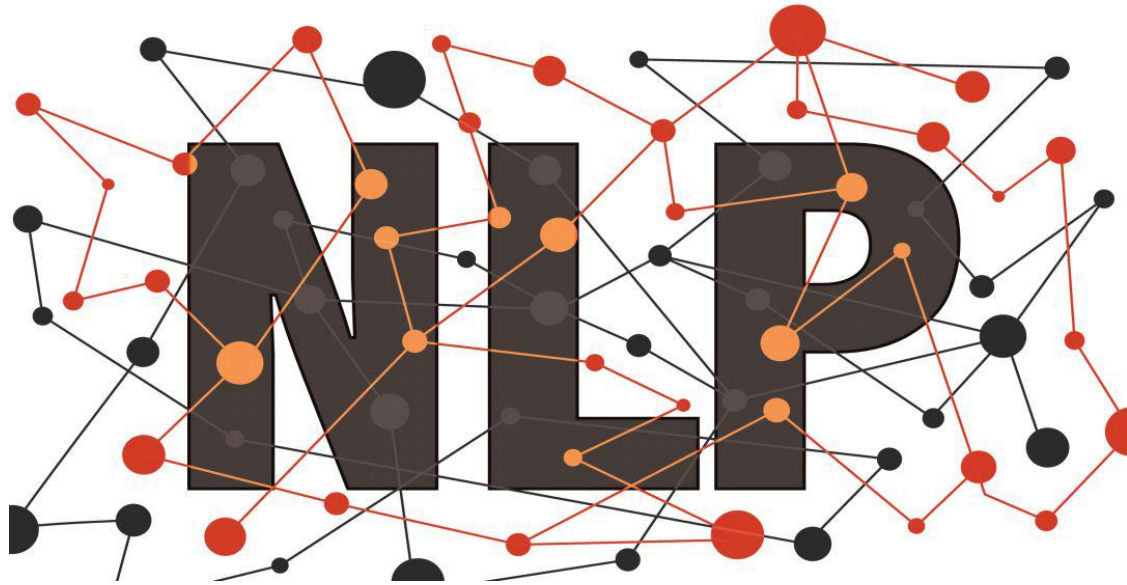


Reported by Yidan Liu

Code:None



## NATURAL LANGUAGE PROCESSING



- 1. Introduction**
- 2. Method**
- 3. Experiments**



# Introduction

**Example.** *When the driver was about to start the bus to leave the station ( $c_1$ ), an old lady ran to the front of the bus with a fast speed and sat down on the ground ( $c_2$ ). Passengers standing in the front of the bus can see this scene clearly ( $c_3$ ). Seeing this scene ( $c_4$ ), the passengers in the car immediately became restless ( $c_5$ ), and had a heated debate ( $c_6$ ). Some of the passengers were **angry** ( $c_7$ ), and told the driver he shouldn't be meddlesome ( $c_8$ ).*

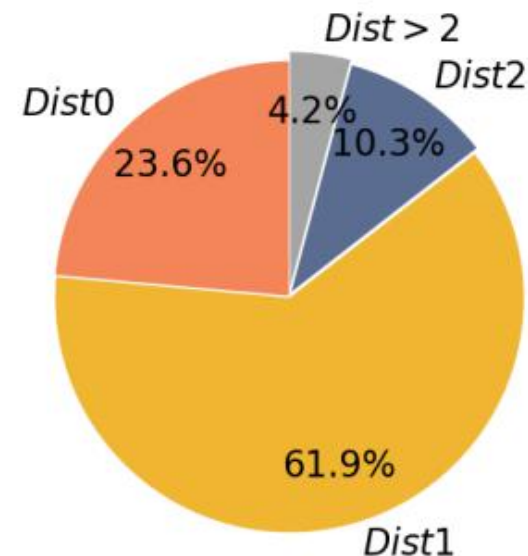


Figure 1: The distribution of the relative distance of an emotion clause and a cause clause that comprise a pair in the ECPE dataset (Xia and Ding, 2019).  $Dist0$ ,  $Dist1$ , and  $Dist2$  mean the relative distances between the two clauses are 0, 1, and 2 respectively.  $Dist > 2$  means the relative distances are larger than 2.

# Method

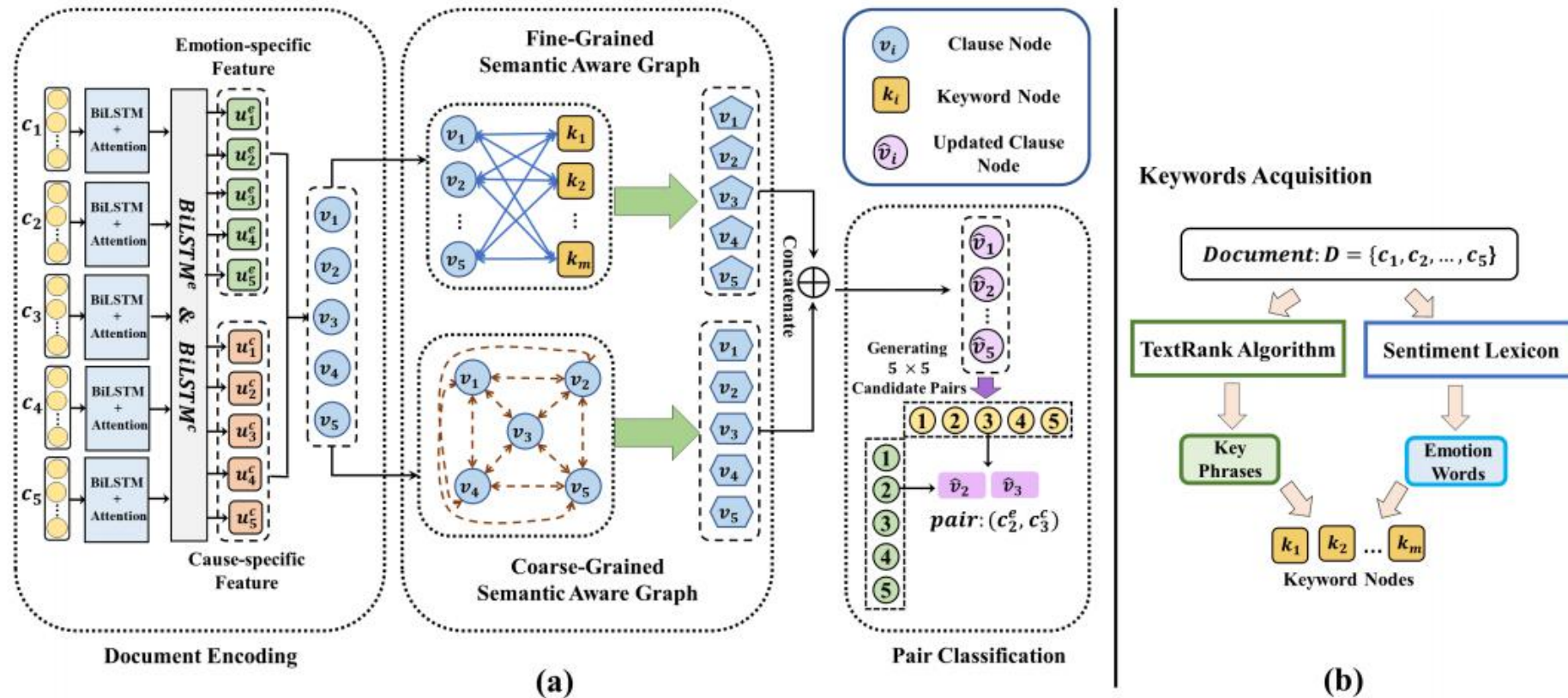
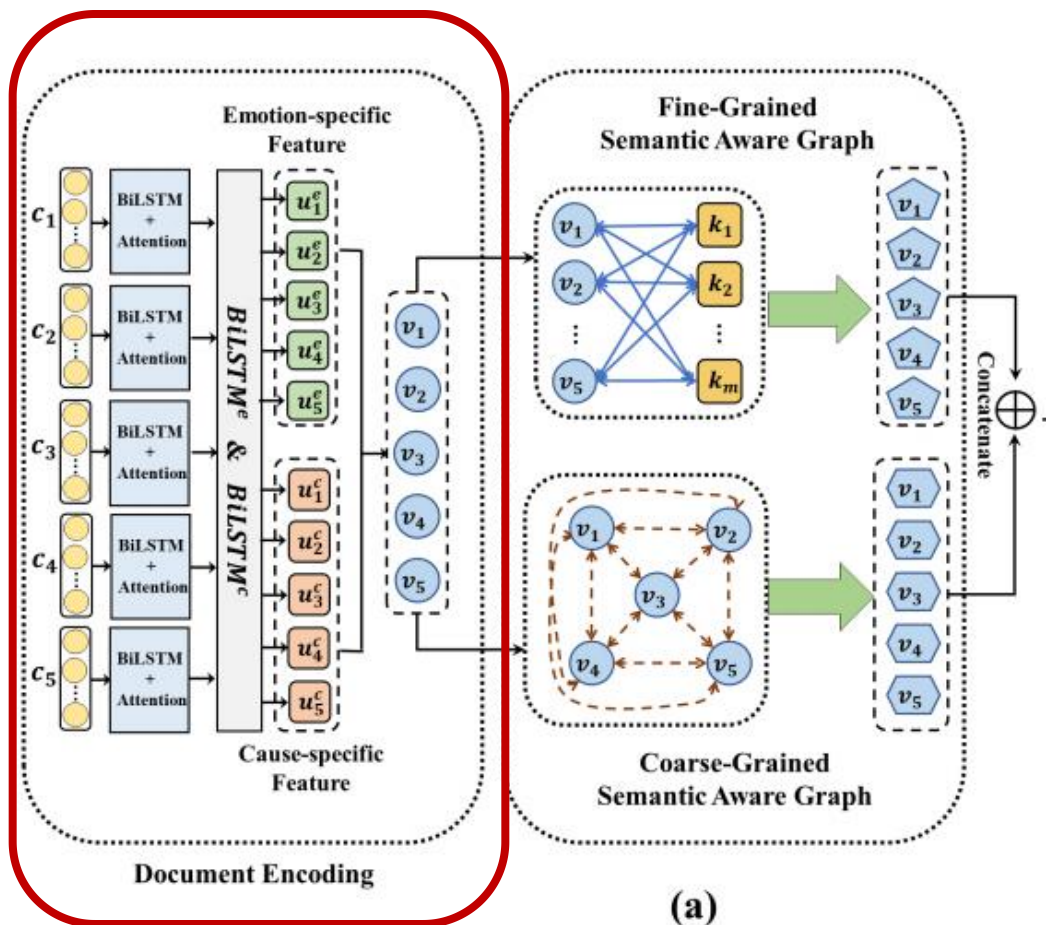


Figure 2: (a) shows an overview of MGSAG. (b) shows the process of keywords acquisition.

# Method



## Word-Level Encoder

For each clause  $c_i = \{w_1^i, w_2^i, \dots, w_{|c_i|}^i\}$ ,

$(h_1^i, h_2^i, \dots, h_{|c_i|}^i)$ .

$$\mathbf{h}_i = \sum_{j=1}^{|c_i|} \alpha_j h_j^i \quad \alpha_j = \text{softmax}(\mathbf{W}_a h_j^i)$$

## Clause-Level Encoder

$$\mathbf{u}_i^e = \text{BiLSTM}^e(\mathbf{h}_i), \quad (1)$$

$$\mathbf{u}_i^c = \text{BiLSTM}^c(\mathbf{h}_i),$$

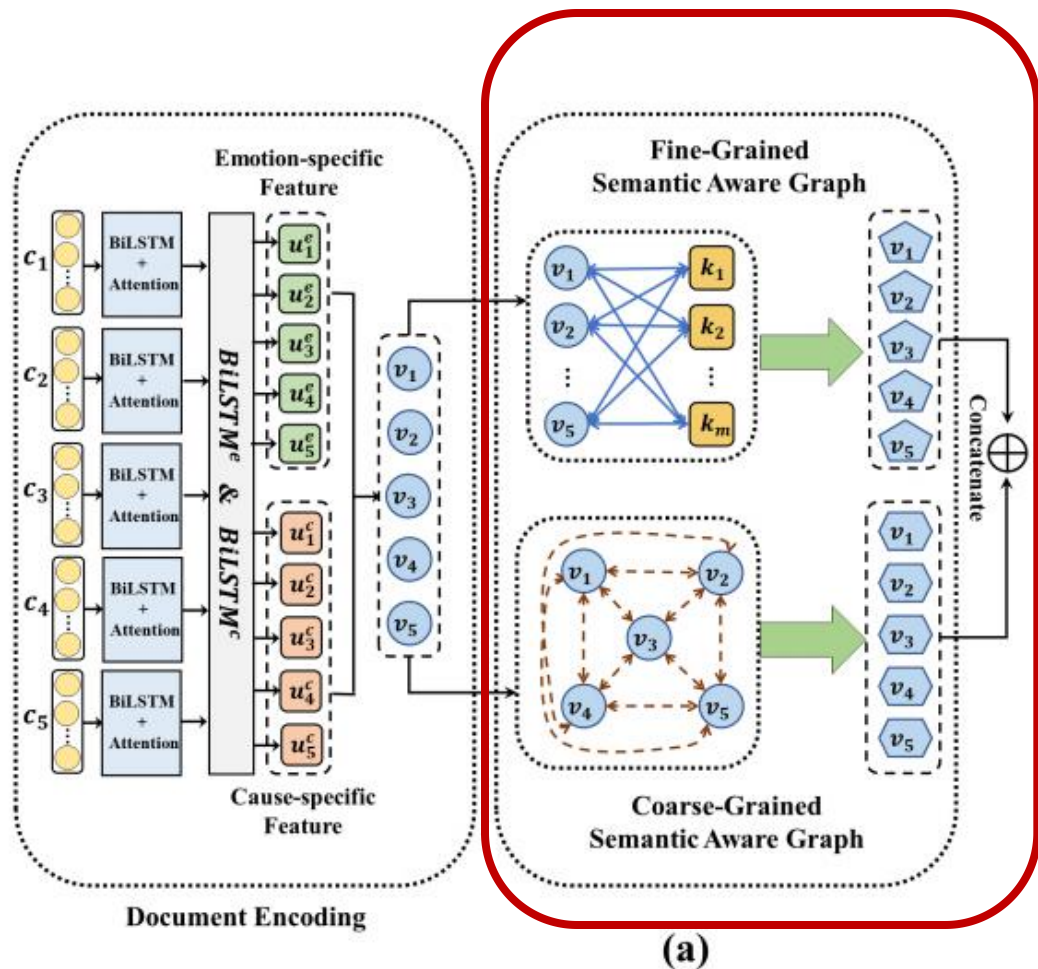
$$\mathbf{g}_i = \sigma(\mathbf{W}_g \mathbf{u}_i^e + \mathbf{b}_g), \quad (2)$$

$$\mathbf{v}_i = \mathbf{g}_i \mathbf{u}_i^c + (1 - \mathbf{g}_i) \mathbf{u}_i^e,$$

$$\hat{\mathbf{y}}_i^e = \text{softmax}(\mathbf{W}_e \mathbf{u}_i^e + \mathbf{b}_e), \quad (3)$$

$$\hat{\mathbf{y}}_i^c = \text{softmax}(\mathbf{W}_c \mathbf{u}_i^c + \mathbf{b}_c),$$

# Method



## Fine-Grained Semantic Aware Graph

$$\alpha_{ij} = \frac{\exp(w^\top [\mathbf{W}_1 \mathbf{v}_i; \mathbf{W}_2 \mathbf{k}_j])}{\sum_{t=1}^{|D|} \exp(w^\top [\mathbf{W}_1 \mathbf{v}_t; \mathbf{W}_2 \mathbf{k}_j])}, \quad (4)$$

$$\mathbf{v}_i^b = \tanh\left(\mathbf{v}_i + \sum_{j=1}^m (\alpha_{ij} \left(\sum_{t=1}^{|D|} \alpha_{tj} \mathbf{W}_3 \mathbf{v}_t\right))\right) + \mathbf{b}, \quad (5)$$

## Coarse-Grained Semantic Aware Graph

$$\mathbf{v}_i^{(t)} = \text{ReLU}\left(\sum_{j \in \mathcal{N}(i)} \alpha_{ij}^{(t)} \mathbf{W}_1^{(t)} \mathbf{v}_j^{(t-1)} + \mathbf{b}^{(t)}\right), \quad (6)$$

$$e_{ij}^{(t)} = w^{(t)\top} \tanh([\mathbf{W}_2^{(t)} \mathbf{v}_i^{(t-1)}; \mathbf{W}_3^{(t)} \mathbf{v}_j^{(t-1)}]),$$

$$\alpha_{ij}^{(t)} = \frac{\exp(\text{LeakyReLU}(e_{ij}^{(t)}))}{\sum_{k \in \mathcal{N}(i)} \exp(\text{LeakyReLU}(e_{ik}^{(t)}))}, \quad (7)$$

# Method

$$\hat{\mathbf{v}}_i = [\mathbf{v}_i^b; \mathbf{v}_i^c]$$

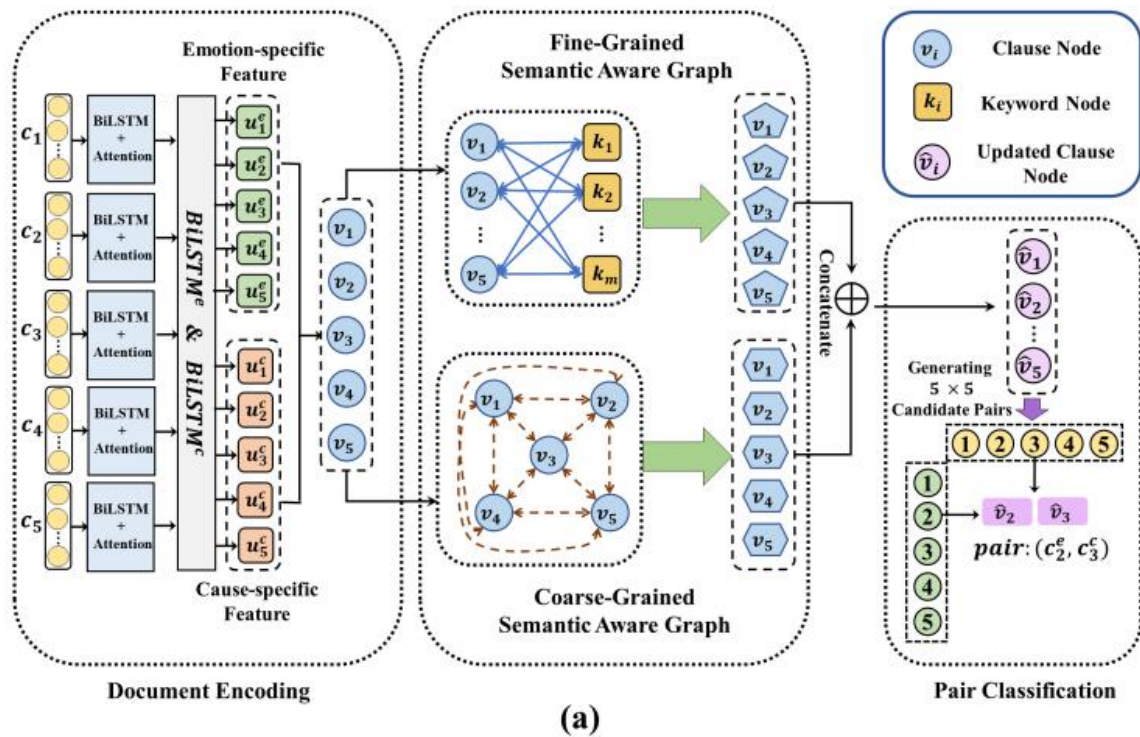
## Emotion Cause Pair Extraction

$$\hat{p}_{ij} = \text{softmax}(\mathbf{W}_p^\top \mathbf{v}_{ij}^p + \mathbf{b}_p), \quad (8)$$

$$\mathcal{L} = \mathcal{L}_{pair} + \mathcal{L}_{emo} + \mathcal{L}_{cau}. \quad (9)$$

## Emotion Extraction and Cause Extraction

$$\hat{\mathbf{E}}_i = \begin{cases} 1, & \text{if } \sum_{j=1}^{|D|} (\mathbf{E}\hat{\mathbf{C}}_{ij}) > 0 \\ 0, & \text{otherwise} \end{cases}. \quad (10)$$



# Experiments

Category	Model	Emotion Ext.			Cause Ext.			EC Pair Ext.		
		P	R	$F_1$	P	R	$F_1$	P	R	$F_1$
Position-insensitive Baselines	Indep	0.8375	0.8071	0.8210	0.6902	0.5673	0.6205	0.6832	0.5082	0.5818
	Inter-CE	0.8494	0.8122	0.8300	0.6809	0.5634	0.6151	0.6902	0.5135	0.5901
	Inter-EC	0.8364	0.8107	0.8230	0.7041	0.6083	0.6507	0.6721	0.5705	0.6128
	IE-CNN	0.8614	0.7811	0.8188	0.7348	0.5841	0.6496	0.7149	0.6279	0.6686
Position-sensitive Baselines	PairGCN	0.8587	0.7208	0.7829	0.7283	0.5953	0.6541	0.6999	0.5779	0.6321
	ECPE-2D	0.8512	0.8220	0.8358	0.7272	0.6298	0.6738	0.6960	0.6118	0.6496
	SLSN-U	0.8406	0.7980	0.8181	0.6992	0.6588	0.6778	0.6836	0.6291	0.6545
	RankCP	0.8703	0.8406	<b>0.8548</b>	0.6927	<b>0.6743</b>	0.6824	0.6698	<b>0.6546</b>	0.6610
	ECPE-MLL	0.8582	<b>0.8429</b>	0.8500	0.7248	0.6702	0.6950	0.7090	0.6441	0.6740
Our Model	<b>MGSAG</b>	<b>0.8721</b>	0.7911	0.8287	<b>0.7510</b>	0.6713	<b>0.7080</b>	<b>0.7243</b>	0.6507	<b>0.6846</b>

Table 1: Comparison of varying approaches on the original test set ( $Test_{all}$ ).



# Experiments

Model	$Test_{Bias}$	$Test_{NoBias}$
Inter-EC	0.6783	0.3318
IE-CNN	0.7666	0.3484
PairGCN	0.7246	0.3355
ECPE-2D	0.7590	0.3830
SLSN-U	0.7456	0.3978
RankCP	0.7467	0.3857
ECPE-MLL	0.7673	0.3988
<b>MGSAG</b>	<b>0.7730</b>	<b>0.4301</b>

Table 2:  $F_1$  results of varying approaches on  $Test_{Bias}$  and  $Test_{NoBias}$ , focusing on EC Pair Ext.

Model	$Test_{Bias}$	$Test_{NoBias}$	$Test_{all}$
w/o FGSAG	0.7594	0.3894	0.6519
w/o CGSAG	0.7654	0.4027	0.6529
w/o FGSAG+CGSAG	0.7264	0.3269	0.6242
<b>MGSAG</b>	<b>0.7730</b>	<b>0.4301</b>	<b>0.6846</b>

Table 3:  $F_1$  results of ablation study on  $Test_{Bias}$ ,  $Test_{NoBias}$ , and  $Test_{all}$ , focusing on EC Pair Ext.

# Experiments

Loss Function	P	R	$F_1$
$\mathcal{L}_{pair}$	0.6940	<b>0.6533</b>	0.6720
$\mathcal{L}_{pair} + \mathcal{L}_{emo} + \mathcal{L}_{cau}$	<b>0.7243</b>	0.6507	<b>0.6846</b>

Table 4: Comparison of different supervised signals for our method.

Model	$Test_{Bias}$	$Test_{NoBias}$	$Test_{all}$
w/ RW	0.7596	0.4078	0.6674
w/o EW	0.7669	0.3920	0.6686
w/o TW	0.7658	0.4271	0.6771
<b>MGSAG</b>	<b>0.7730</b>	<b>0.4301</b>	<b>0.6846</b>

Table 5: Comparative  $F_1$  results on  $Test_{Bias}$ ,  $Test_{NoBias}$ , and  $Test_{all}$  of our variant models, focusing on EC Pair Ext. “w/ RW” means using random embeddings for keyword feature initialization. “w/o EW” and “w/o TW” means removing emotion words and key phrases obtained by TextRank, respectively.

# Experiments

( $c_1$ ) When Mr. Chen drove from south to north on Yangtze River Avenue,  
( $c_2$ ) it was dark and there was no street lamp.  
( $c_3$ ) His slight was not clear.  
( $c_4$ ) He ran into a stone and overturned.  
( $c_5$ ) After that,  
( $c_6$ ) he was trapped in the car,  
( $c_7$ ) broke the window glass,  
( $c_8$ ) and climbed out of the car.  
( $c_9$ ) He said that,  
( $c_{10}$ ) because of the sudden incident,  
( $c_{11}$ ) **he was shocked and injured.**

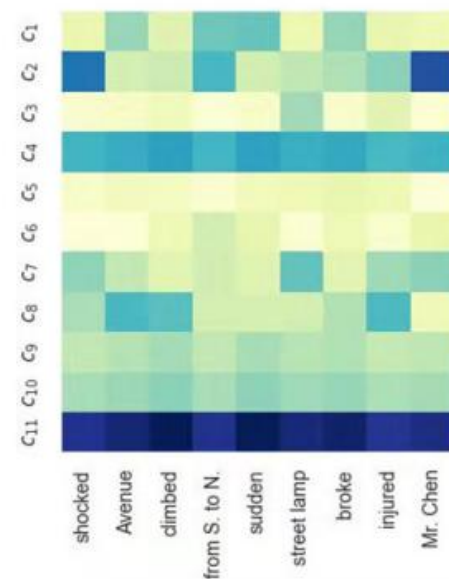


Figure 4: An example that MGSAG extracts the emotion cause pair ( $c_{11}, c_4$ ) correctly, while ECPE-MLL fails. Words shaded in yellow are keywords. The heatmap presents attention scores in the clause-keyword bipartite graph. Rows of  $c_{11}$  and  $c_4$  are the top-two darkest rows, means that keywords pay more attention to them and facilitate MGSAG to extract pair ( $c_{11}, c_4$ ) correctly.



# Thank you!



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