Learning a General Clause-to-Clause Relationships for Enhancing Emotion-Cause Pair Extraction

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Abstract
Emotion-cause pair extraction (ECPE) is an emerging task aiming to extract potential pairs of emotions and corresponding causes from documents. Previous approaches have focused on modeling the pair-to-pair relationship and achieved promising results. However, the clause-to-clause relationship, which fundamentally symbolizes the underlying structure of a document, has still been in its research infancy. In this paper, we define a novel clause-to-clause relationship. To learn it applicably, we propose a general clause-level encoding model named EA-GAT comprising E-GAT and Activation Sort. E-GAT is designed to aggregate information from different types of clauses; Activation Sort leverages the individual emotion/cause prediction and the sort-based mapping to propel the clause to a more favorable representation. Since EA-GAT is a clause-level encoding model, it can be broadly integrated with any previous approach. Experimental results show that our approach has a significant advantage over all current approaches on the Chinese and English benchmark corpus, with an average of 2.1% and 1.03%.

Keywords: Emotion-Cause Pair Extraction, clause-to-clause relationship, EGAT, Activation Sort

1. Introduction
Recently, fine-grained understanding of emotional clause level [1 2 3] has gained increasing attention from the research community, especially a surge of research to determine the cause of emotional expression in text [4 5 6 7].
Emotion-Cause Pair Extraction (ECPE) \cite{8} is a new task that extracts all emotion clauses coupled with their cause clauses from a given document. For understanding simplicity, we following Wei et al. \cite{9}, Chen et al. \cite{10} abstract the process of ECPE as four separate modules: word-level encoding, clause-level encoding, pair-level encoding, and pair extraction. The first three parts separately model the word-to-word relationship, clause-to-clause relationship, and pair-to-pair relationship.

For the pair-to-pair relationship, there have been numerous works \cite{11,12,13,14,15} to contribute particular advantages with their different networks. However, for the clause-to-clause relationship, most approaches use BiLSTM and only Wei et al. \cite{9} adopts GAT \cite{16}. From Thost and Chen \cite{17}, Shen et al. \cite{18}. BiLSTM relatively neglects the remote clause, and GAT loses the sequential information. As a result, clause-level encoding is a fundamental yet under-explored part of the ECPE process. And this imbalance is intelligible because pair-level encoding has an exclusive direct influence on the pair extraction.

Moreover, from the findings of linguistics and psychologic: Mann and Thomp-son \cite{19}, Marcu \cite{20} have proposed that clauses or sentences are often indicative of an underlying structure of one document; Ruusuvuori \cite{21} has provided support that the emotion of clauses tends to be constant in a sentence. More recently, Wu et al. \cite{22} has argued that the entire event is usually across a set of clauses in a sentence. Huang et al. \cite{23} has exploited general grammatical conventions to
span-encode sentences and clauses, demonstrating the existing grammatical information contained in sentences and clauses. Hence, advances in the clause-to-clause relationship, specifically the knowledge of whether the clause spans a sentence, are available for distinguishing Emotion-Cause Pair (ECP) from the other non-ECPs.

To this end, we define a novel clause-to-clause relationship, as shown in Figure 1. Proceeding from the sentence attributions of two observed clauses, we delimit clause-to-clause relationships as:

- **Outer-clause relationship**: The two observed clauses are in different sentences.
- **Inter-clause relationship**: The two different observed clauses are in the same sentences.
- **Intra-clause relationship**: The two observed clauses are the same clause (self-influence).

Furthermore, Chen et al. [24], Shi et al. [25] argued that the clause representations can be integrated with the prediction sequence of two subtasks named emotion extraction and cause extraction to achieve improvement. Nevertheless, due to the fine-grained relationship representation defined by ours mismatching the binary-classification prediction sequence, such the straightforward integrating hides the clues to emotions. Chen et al. [26] has reformulated binary classifiers as 7-classifier and 4-classifier to fine the grain but at the loss of generality.

Considering this problem, and effectively empowering all approaches to utilize our defined relationship’s knowledge, we propose a clause-level encoding model for ECPE, instead of contributing an end-to-end model. Our model, composed of Enhanced GAT and Activation Sort, is called EA-GAT, which can be easily applicable to all existing approaches. Enhanced GAT is a multi-mask GAT proposed to learn our new defined clause-to-clause relationship. The Activation Sort is a radical but valid pre-processing trick for achieving grain consistency.

Specifically, Enhanced GAT yields a clause representation through separately modeling the attention of 3 types of relationships. And the Activation Sort is fed with emotion/cause prediction sequences and outputs the auxiliary information for the second Enhanced GAT module. It widens the gap among predictions via sort-based mapping, which can explore different relationships of clauses beyond the polarity prediction. Finally, EA-GAT produces a more favorable clause representation for subsequent pair-level encoding.

To gauge the generality of our clause encoding model, we conduct comprehensive experiments comparing with all published ECPE methods. And we perform
intrinsic contrast experiments of the adjacency matrix to obtain insight into how EAGAT grasps the clause relationship. Furthermore, we construct a new benchmark of the English dataset via leveraging the RECCON proposed for Causal Emotion Entailment task.

Our main contributions can be summarized as follows:

• To the best of our knowledge, we are first to define the clause-to-clause relationship and develop a multi-mask attention to learn their representation.

• We proposed the EA-GAT model, which can more effectively work in the clause-level encoding part of ECPE than networks adopted by previous methods.

• We conduct our comprehensive evaluation on the standard Chinese dataset and a newly introduced English dataset, which demonstrates that our method can be generally embedded into all existing approaches and significantly outperforms their original performance, including the state-of-the-art work.

The remainder of this paper is organized as follows: in Section 2 we briefly introduce the related works; in Section 3 we formalize the task; in Section 4 we describe our proposed method; in Section 5 we present the details and data of the experiments; in Section 6 we analyze the results and limitations; in Section 7 we conclude of the proposed work.

2. Related Works

The process of ECPE task has been carried out in 3 encoding parts and 1 extraction part, as shown in Table 1. In word-level encoding, word representation adopts pre-training with word2vec [35] toolkit or BERT [36]. Moreover, almost all approaches adopt BiLSTM to model the relationship between clauses in clause-level encoding. But pair-level encoding has attracted substantial interest from numerous researchers, in which Fan et al. [11] has transformed ECPE into a procedure of directed graph structure and adopted a transition-based model to identify the semantic relationship between emotions and causes; Wei et al. [9] has used the RankNN with an RBF kernel function for the pair-level encoding. Specifically, they proposed a GAT to capture the underlying relationship among different clauses via designing a full-connected graph; Chen et al. [27] has adopted GNN framing pairs as nodes to learn the pair-level representation.

And to alleviate the loss of information by binary classification, Chen et al. [26] used a more fine-grained tagging scheme that combines emotion labels and
Table 1: 4 parts of existing approaches. There are different networks for encoding the pair-to-pair representations whereas clause-level encoding sharply lacks effective research.

| Model     | word-level encoding | clause-level encoding | pair-level encoding | clause extractions |
|-----------|---------------------|-----------------------|---------------------|--------------------|
| Inter-EC  | word2vec            | BiLSTM                | Logistic regression | Rank model         |
| RankCP    | word2vec/BERT       | BiLSTM                | Transformer         |                    |
| ECPE-2D   | word2vec/BERT       | BiLSTM                | Transition Model    |                    |
| TDGC      | word2vec            | BiLSTM                | CNN                 |                    |
| IE-CNN    | word2vec            | BiLSTM                | GCN                 |                    |
| PairGCN   | word2vec/BERT       | BiLSTM                | Local Searcher      |                    |
| SLSN      | word2vec            | BiLSTM                | Joint MLP Model     |                    |
| JointNN   | BERT                | BiLSTM+attention      | Sliding window      |                    |
| MLL       | word2vec            | BiLSTM                | Aggregation         | Linear             |
| CPAM      | word2vec            | BiLSTM                |                     | 3-level filters    |
| RSN       | word2vec/BERT       | BiLSTM                |                     | PTF-based model    |
| MASTM     | word2vec            | BiLSTM                |                     | Adversarial model  |
| PTF       | word2vec/BERT       | BiLSTM                |                     | MOO                |
| CL-ECPE   | word2vec            | BiLSTM                |                     | Semantic Aware Graph |
| BERT+     | BERT                | BiLSTM                |                     | BiGRU              |
| MGSAG     | word2vec/BERT       | BiLSTM                |                     |                    |
| SAP-ECPE  | word2vec            | BiLSTM                |                     |                    |

More recently, the clause-level relationship between emotions and causes has gained significant attention due to its effectiveness in real-world applications. Kumar and Jain [38] has replaced the traditional technique for rule-based semantic analysis work on sentence-level with the ECPE-BERT model to recognize emotion in psychological texts. And Ghosh et al. [39] has proposed a pre-trained transformer-based ECPE model to address the problem of cause annotation and cause extraction for emotion in suicide notes datasets. Furthermore, inspired by recent advances in ECPE task, Halat et al. [40] has analyzed the causes leading to a negative statement via ECPE model, to improve the recognition of hate speech and offensive language (HOF).

Of 4 parts of the ECPE process, our model, as a clause-level encoding method, is broadly applicable to all existing works well, reserving the crucial components of each work and exploiting the clause-to-clause relationships.
3. Task Definition

Given a document $D = (c_1, c_2, \ldots, c_{|D|})$ where $D$ is the number of clauses and the $i$-th clause $c_i = (\omega_1^i, \omega_2^i, \ldots, \omega_{|c_i|}^i)$ is a word sequence, the goal of ECPE is to extract a set of emotion-cause pairs (ECPs) in $D$:

$$P = \{\ldots, (c^e_i, c^c_j), \ldots\}$$ (1)

where $(c^e_i, c^c_j)$ is an ECP consisting of $i$-th clause $c^e_i \in D$ as emotion clause and $j$-th clause $c^c_j \in D$ as corresponding cause clause. Additionally, the input of our method is $(c_1, c_2, \ldots, c_{|D|})$ outputting from word-level context encoding, and the output of our method is clause representation $(h^e_{c_1}, h^e_{c_2}, \ldots, h^e_{c_{|D|}})$. Note that the pair representation $P_{i,j}$, the input of pair-to-pair encoding, is contacted by clause representation $h^e_{c_i}$ and $h^e_{c_j}$, which is entirely different from clause representation and not developed in this paper.

4. Methodology

The main framework of EA-GAT consists of hierarchical Enhanced GAT modules and Activation Sort modules. The overview is shown in Figure 2. Enhanced GAT is used to process clauses under the clause-to-clause relationship defined in Section 4.1 and Activation Sort enlarges the spread of predictions weighting of negative samples to form the new adjacency matrix for Enhanced GAT. Furthermore, an additional sort loss is adopted to evaluate the performance of the whole framework.
4.1. Building Clause-to-Clause Relationship

In the tokenizer, 3 sentence-ending dot marks, “.”, “?” and “!” are denoted by a token <period>. For notational consistency, we also add <period> to the beginning and the end of a document. Hence, for any sentence $S$, one can partly define a unique sequence order on a document $D = (<period>, c_1, c_2, \ldots, <period>, c_i, \ldots, c_j, <period>, \ldots, c_{|D|}, <period>)$, such that all clauses between two contiguous <period> belong to the same $S$. Then, a document can also be denoted by $D = (S_1, S_2, \ldots, S_n)$, where $n$ is one less the number of <period>.

We formalize the clause-to-clause relationship by the multi-mask matrix $M \in \mathbb{R}^{\left|D\right| \times \left|D\right|}$ as follows:

$$M_{i,j} = \begin{cases} 2, & S_i \neq S_j \\ 1, & S_i = S_j \land c_i \neq c_j \\ 0, & c_i = c_j \end{cases} \quad (2)$$

where $M_{i,j}$ denotes the relationship type from $c_j$ to $c_i$. There are 3 diverse values $(2, 1, 0)$ that separately represent outer-clause relationship, inter-clause relationship, and intra-clause relationship.

4.2. Enhanced Graph Attention

Given a clause embedding $D = (c_1, c_2, \ldots, c_{|D|})$ generated by word-level encoding, we design Enhanced GAT to instantiate the information aggregation of clauses.

Specifically, for each clause, self-attention aggregates information from neighboring clauses to learn the updated attention weight as follows:

$$A_{ij}^{(0)} = \frac{\text{LeakyReLU}(e_{ij}^{(0)})}{\sum_{k \in |D|} \text{LeakyReLU}(e_{ik}^{(0)})} \quad (3)$$

$$e_{ij}^{(0)} = W_{i_{row}}^{(0)} \overrightarrow{c_i} + W_{j_{col}}^{(0)} \overrightarrow{c_j} \quad (4)$$

Where $A_{ij}^{(0)}$ represents the adjacency matrix modeled by graph attention, the superscript $(0)$ denotes the first E-GAT module ($(1)$ denotes the second), and $A_{ij}^{(0)}$ measures the importance of influence of the $j$-th clause on the $i$-th clause, $W_{row}^{(0)}$ and $W_{col}^{(0)}$ are the learnable parameters in the graph attention.

Considering the multi-mask $M$, the primary clause representation $h$ is the sum of 3 types of relationship attention operators:
\[
h = \sum_{m=0,1,2} eLU(A_m^{(0)}DW_m^{(0)})
\] (5)

\[
A_m^{(0)} = \begin{cases} 
  A_{i,j}^{(0)}, & M_{i,j} = m \\
  0, & M_{i,j} \neq m
\end{cases}
\] (6)

Where the \( W_m^{(0)} \) denotes the learnable parameters for each mask value \( m \). Following the strategy of other ECPE approaches which performs two individual subtasks named emotion/cause extractions, the probabilities of each clause for the two subtasks are computed as follows:

\[
\hat{y}^e = \text{Sigmoid}(W_e h + b_e)
\] (7)

\[
\hat{y}^c = \text{Sigmoid}(W_c h + b_c)
\] (8)

Where \( \hat{y}^e \) and \( \hat{y}^c \) are prediction sequences of emotion/cause extraction, \( W_e, W_c \), \( b_e \) and \( b_c \) are learnable parameters of two linear layers.

4.3. Activation Sort

We use prediction sequences \( \hat{y}^e \) and \( \hat{y}^c \) to generate an enhanced adjacency matrix. Because as an individual subtask, \( \hat{y}_{i}^e \) denotes the probability that the \( i \)-th clause is an emotion clause. Similarly, \( \hat{y}_{j}^c \) denotes the probability that the \( j \)-th clause is the cause of a certain emotion clause. For an ECP \((c_{i}^e, c_{j}^c)\), it should more possibly consist of the \( c_{i}^e \) with a higher \( \hat{y}_{i}^e \) and the \( c_{j}^c \) with a higher \( \hat{y}_{j}^c \).

But the ground truth sequences \( y^e \) and \( y^c \) are binary, Chen et al. \[26, 10\] have provided the supports of which framing emotion/cause extractions as binary classification partly ignores the relationship from cause to a specific emotion.

In order to make emotion/cause predictions more efficient to indicate the relationship among all clauses, especially non-ECPs. We design a trick processing the emotion/cause predictions to provide EGAT auxiliary information as part of input. In the output of each EGAT module, We sort all predictions in \( \hat{y}^e \) and \( \hat{y}^c \) to expand the differences, which contributes to the next EGAT to generate more favorable adjacency. Our sort approach named ActivationSort is operated as follows:

\[
\hat{r}_{i}^{e} = \text{label}[\text{argsort}(\hat{y}^e)]
\] (9)
\begin{equation}
\hat{r}_j^c = label[arg\text{sort}(\hat{y}^c)]
\end{equation}

\begin{equation}
label = [1, 2, 3, \ldots, |D|]
\end{equation}

Specifically, we decreasingly sort the $\hat{y}^e$ and $\hat{y}^c$, and separately give each $\hat{y}^e_i$ and $\hat{y}^c_j$ a serial number $\in [1, |D|]$ according to the sorting position, use this serial number as an index, and make the value of the corresponding index in the $label$ assigned to $\hat{y}^e$ and $\hat{y}^c$. We design the $label$ as a sequence of natural numbers not containing 0, which can distinguish the difference between each prediction. A sort position embedding is adopted for $\hat{r}^e$ and $\hat{r}^c$ to regulate magnitude order. And after experimental trying, We also defined an alternative $label$ sequence as follows:

\begin{equation}
label[i] = 2^i (i = \lfloor \log_2 |D| \rfloor - \lfloor \log_2 |D| - i + 1 \rfloor)
\end{equation}

We exemplify this equation by a document with 10 clauses, the value of $label$ is [1, 1, 1, 2, 2, 2, 4, 4, 8]. In this way, $\hat{r}^e$ and $\hat{r}^c$ have more visible differences compared with the original prediction sequence close to [0, 0, 0, 0, 0, 0, 0, 0, 1, 1] (two positive example clauses).

Note that: (i) there are countless $label$ sequences that can expand the difference not be put forward; (ii) compared with popular activation functions such as $sigmoid$ or $tanh$, ActivationSort can not only expand the distance among non-ECPs after normalization but also narrow down the distance between ECPs and non-ECPs; (iii) the gradient stopping caused by argsort is a benefit to eliminate the negative impact of $Loss_{non-ECP}$ on $P^0_{pair}$ (detail shown in Section 4.5); (iv) in the pre-output of subtasks, $\hat{y}^e$ and $\hat{y}^c$ reserve the original prediction sequences.

4.4. Enhanced GAT with Activation Sort

After sorting $\hat{y}^e$ and $\hat{y}^c$, activated clause-level relationship (adjacency) matrix $e_i^{(1)}$ is denoted as:

\begin{equation}
e_i^{(1)} = W_i^{(1)} \hat{r}_i^e + W_j^{(1)} \hat{r}_j^c
\end{equation}

\begin{equation}
A_{i,j}^{(1)} = \frac{\text{LeakyReLU}(e_{i,j}^{(1)})}{\sum_{k\in|D|} \text{LeakyReLU}(e_{i,k}^{(1)})} + A_{i,j}^{(0)}
\end{equation}

Where $W_i^{(1)}$ and $W_j^{(1)}$ are learnable parameters that separately represent the correlation of clauses in $\hat{r}_i^e$ and $\hat{r}_j^c$. Under a hypothesis that $\hat{y}^e$ and $\hat{y}^c$ are close
to ground truth sequences $y^e$ and $y^c$ (from the empirical result of Section 5.4, it is a relatively weak hypothesis), $A^{(1)}$ depicts a learnable clause-to-clause relationship adjusted by the emotion/cause ground truth.

Then we feed $A^{(1)}$ into the Enhanced GAT again, aiming to generate the clause representation $h^{(1)}$ as follows:

$$h^{(1)} = \sum_{m=0,1,2} eLU(A_m^{(1)}D_{m}^{(1)})$$

where $h^{(1)}$ is the output as enhanced clause representation that can be used in the follow-up pair-level encoding and extraction. The empirical case in Section 5.6 holds the interpretability of $h^{(1)}$ and $h$. On the whole, starting with the 2-th EGAT, each adjacency matrix will be added the auxiliary information from the output of the previous EGAT. We denote the layers of EGAT as $l = 2, 3, \ldots, L$, the clause representation of each EGAT can be written as:

$$h^{(l)} = \sum_{m=0,1,2} eLU(A_m^{(l)}D_{m}^{(l)})$$

$$A_{ij}^{(l)} = \frac{\text{LeakyReLU}(e_{i,j}^{(l)})}{\sum_{k \in |D|} \text{LeakyReLU}(e_{i,k}^{(l)})} + A_{ij}^{(l-1)}$$

4.5. Optimization

![Diagram](image)

Figure 3: The forward processing and back propagation processing of our model (We only show the first and second layers of EGAT).

Generally, ECPE task is optimized by 3 cross-entropy errors: $\text{Loss}_e$, $\text{Loss}_c$ and $\text{Loss}_{pair}$, where $\text{Loss}_e$ and $\text{Loss}_c$ measure $\hat{y}^e$ and $\hat{y}^c$. $\text{Loss}_{pair}$ measures the output of pair prediction sequence.

$$\text{Loss}_e = \sum_{l=1}^{L} \sum_{i \in |D|} - (P^{l}_{y_i^e} \log(1 - P^{l}_{\hat{y}_i^e})) + (1 - P^{l}_{y_i^e}) \log P^{l}_{\hat{y}_i^e})$$

10
\[
\text{Loss}_c = \sum_{l=1}^{L} \sum_{i \in |D|} -(P_{y_{i}}^l \log (1 - P_{\hat{y}_{i}}^l) + (1 - P_{y_{i}}^l) \log P_{\hat{y}_{i}}^l) \tag{19}
\]

\[
\text{Loss}_{\text{pair}} = \sum_{l=1}^{L} \sum_{i,j \in |D| \times |D|} -(P_{y_{i,j}}^l \log (1 - P_{\hat{y}_{i,j}}^l) + (1 - P_{y_{i,j}}^l) \log P_{\hat{y}_{i,j}}^l) \tag{20}
\]

In addition, we propose sort loss measure the performance that the \( h' \) exceeds \( h \) as follows:

\[
\text{Loss}_{\text{sort}} = \sum_{l=2}^{L} \max(0, P_{y_{i,j}}^{l-1} - P_{\hat{y}_{i,j}}^{l-1}) + 0.05 \tag{21}
\]

where \( P_{y_{i,j}}^{l-1} \) is the prediction of the labeled clause pair (ECP), \( P_{y_{i,j}}^{l-1} \) is the output from \( h^{l-1} \), and \( P_{y_{i,j}}^{l} \) is the output from \( h^{l} \). \( \text{Loss}_{\text{sort}} \) ensures that \( P_{y_{i,j}}^{l} \) is more effective than \( P_{y_{i,j}}^{l-1} \), and ultimately ensures that \( A^{(l)} \) is more effective than \( A^{(l-1)} \).

Note that \( \text{ActivationSort} \) has no gradient as shown in Figure 3, so \( \text{Loss}_{\text{sort}} \) only measures the parameters after \( \text{ActivationSort} \) in forward, and the parameters of the previous Enhanced GAT module not be affected. Due to the characteristics of \( \text{Loss}_{\text{sort}} \), which increases \( P_{y_{i,j}}^{l-1} \) and also inhibits the improvement of \( P_{y_{i,j}}^{l-1} \). It is gradient stopping that can prevent the deviate gradient descent of the \( \text{Loss}_{\text{sort}} \) from conflicting with the other three losses.

5. Experiments

Extensive experiments are conducted to verify the generality and effectiveness of our model on the Chinese ECPE dataset proposed by Xia and Ding [8] and the English RECCON dataset (ECPE-like task) proposed by Poria et al. [3]. And we use the same metrics named \( F_1 \) score for evaluating Chinese corpus following Xia and Ding [8] and \( \text{avg} F_1 \) score (the average of \( F_1 \) scores for both positive and negative examples) for evaluating English corpus following Poria et al. [3].

5.1. Dataset

Xia and Ding [8] constructs the Chinese dataset based on the ECE corpus [41] and publishes the word segmentation version without periods. But to help reproduction and discussions, we refer to the ECE corpus and complete the “.”, “?” and “!” to state the end of a sentence.
| dataset | document | sentence | clause | ECP  |
|---------|----------|----------|--------|------|
| Chinese | 1945     | 8075     | 28727  | 2156 |
| English | 1106     | 5513     | 11104  | 5380 |

Table 2: Statistics of two datasets, where ECP stands for the emotion-cause pair.

Figure 4: Frequency diagram of sampling in contiguous 10 index of documents, where horizontal axis denotes the rate of sample numbers of 10 documents group, vertical axis stands for the correspond frequency.

| Statistic | fold1 | fold2 | fold3 | fold4 | fold5 | fold6 | fold7 | fold8 | fold9 | fold10 |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------|
| mean      | 342.78| 323.11| 353.30| 338.88| 340.09| 369.71| 326.13| 321.85| 336.10| 338.4  |
| std       | 257.62| 246.80| 257.40| 251.27| 258.12| 246.92| 248.42| 239.52| 236.03| 239.5  |
| skew ($\times 10^4$) | 1.71 | 2.17 | 1.66 | 2.39 | 2.07 | 1.14 | 2.45 | 2.21 | 2.04 | 2.11 |
| kurt ($\times 10^5$) | -1.49 | -1.49 | -1.49 | -1.49 | -1.49 | -1.49 | -1.49 | -1.49 | -1.49 | -1.49 |
| std (Figure.1) | 0.086 | 0.086 | 0.084 | 0.077 | 0.082 | 0.091 | 0.080 | 0.083 | 0.086 | 0.086 |

Table 3: Statistic in random 10-fold, we summarize the mean value, standard deviation, skewness and kurtosis of the test dataset document-ids. Additionally, we add the standard deviation of the sample frequency.
While the Chinese ECPE corpus is a well-known and pioneering dataset for the ECPE task, it increasingly reveals some limitations that complicate the current works. Sparsity is the most concerning point. Statistically, in ECPE corpus, a document involves 14.32 clauses, 3.56 sentences but 1.11 labeled pairs. And following the original splits, id-continuous samples are grouped together, when many long and complete documents are divided into 2-5 id-continuous samples. Hence, the sample variance is too numerically large and the feature distribution is substantially different between the train split and test split. Under the random initialization, the trivial solution exists, leading to an unstable learning process. Some works conditionally avoid this by deleting several samples from train split, while we adopt an alternative strategy that more makes sense. We initial the learnable parameters of our model with a pre-trained model from few-shot learning with 800 samples in train split.

Besides, the English dataset is about dyadic conversations. So we define all utterances from the same speaker belong to a sentence. The details of two datasets are shown in Table 2. It has the almost 17 times less ratio of non-ECPs to ECPs than ECPE datasets. So although it is a neonate in the exploitation, it is more potential for relationship discovery and construction. But the original split is 3-fold, and the test dataset uses a contiguous sample strategy making us concerned about whether the bias exists to noise the experiment. To this end, we conduct a random 10-fold split for our and subsequent research. Table 3 demonstrates that our split is stochastic in the document distribution and provides the crucial statistics. Figure 4 visualizes the sampling frequency in each 10-contiguous samples, which indicates that our sampling is also independent.

In order to obtain statistically credible performance, we evaluate our approach 10 times with different data splits by separately following Xia and Ding [8], Poria et al. [3]. Additionally, we perform one sample $t-$test with $p<0.01$ to ensure the significance.

5.2. Implementation Details

We replace the clause-level encoding part of all existing approaches with our model, with reservation of the other strategies and hyperparameters of corresponding existing approaches, besides the dimensions of E-GAT set to 768. For instance, when we embed our model into RankCP, we keep the layer of GAT with 2, learning rate with 0.001, weight decay with 1e-5, and the RBF kernel with $\sigma_K = 1$. As the same as the word embedding of corresponding dataset baseline, we use
$BERT_{\text{Chinese}}$ pre-trained model[^1] word vectors pre-trained from Chinese Weibo[^2] for the experiment without BERT in the Chinese dataset, and $RoBERTa_{\text{base}}$ pre-trained model[^3] in the English dataset.

And our entire codes and dataset splits are shared[^4]. Because the initial check-point models take up too much storage space. We will publish them to Github after the final version.

5.3. Baselines

We compare our model with almost all published works, which can be divided into two categories: one is standard baselines following the benchmark Xia and Ding [^8], the other one is designed some auxiliary annotation or proposed extra data samples. We detailed them as follows:

**Inter-EC.** A two-step method proposed by Xia and Ding [^8] is the first to extract emotions and causes separately. And then to form an ECP, it train a binary classifier to filter out ECPs and non-ECPs.

**RankCP.** A GAT-based method [^9] tackles ECP prediction from a ranking perspective, adopting a graph attention network to propagate information among clauses.

**ECPE-2D.** A transformer-based method [^12] to construct a pairs matrix and achieve the interaction between ECPs by leveraging a 2D transformer module.

**TDGC.** A transition-based method [^11] formulated the ECPE task as a set of actions and transitions with directed graph construction.

**PairGCN.** A GCN-based method [^27] constructed the influence relationships among candidate pairs by regarding pairs as nodes.

**SLSN.** A local search method [^28] extracted the local ECPs by two novel cross-subnetwork of symmetric subnetworks separately.

**SAP.** A relative position method [^23] extracted ECPs by defining the spans of two clauses among all pairs to achieve better performance.

**RSN.** A recurrent-based method [^24] performs multiple rounds of inference to recognize emotion clauses, cause clauses, and emotion-cause pairs iteratively.

**JointNN.** A self-attention-based method [^29] adopted BERT as word-level encoder and proposed a joint attention model for pair-level encoding.

[^1]: http://github.com/huggingface/pytorch-pretrained-BERT
[^2]: http://www.aihuang.org/p/challenge.html
[^3]: https://huggingface.co/roberta-base
[^4]: https://drive.google.com/file/d/1S_l59YYf0XiS1HAPz39Y3g9GdqTcpcG/view?usp=sharing
**MLL.** A slide window method [50] employs an emotion-pivoted cause extraction framework and a cause-pivoted emotion extraction framework.

**CPAM.** A new benchmark [10] determined whether or not an ECP has a causal relationship given some specific context clauses in a corresponding improved dataset via manual annotation.

**IE-CNN.** A new benchmark [26] proposed a new tagging strategy including four causal identity labels and seven emotion type labels.

**BERT+.** A BERT-based model [33] achieved better performance following the benchmark as CPAM.

**CL-ECPE.** A new contrastive benchmark [32] used adversarial samples as new datasets to perform the pair extraction.

**MGSAG.** A new benchmark [34] incorporated fine-grained and coarse-grained semantic representation by extracting keywords.

### 5.4. Overall Results

As shown in Table 4, for evaluating the generality and effectiveness of our model in ECPE dataset, we embed our model to 8 existing approaches without BERT and 7 approaches with BERT to summarize the performances on three tasks (emotion extraction, cause extraction, pair extraction). In approaches without BERT, the word2vec is adopted in word embedding, while the pre-training BERT model fine-tuned is adopted for approaches with BERT.

Overall, our model generally outperforms the traditional clause-level encoding model (BiLSTM or GAT) in all published approaches. Note that our model does not adopt any plug-in technology, so these results demonstrate that our clause-level encoding model is better than all existing clause-level encoding model. Besides, our model significantly improves the performance of graph-based neural network baselines (i.e., RankCP with 3.12% raise without BERT and 3.28% with BERT, PairGCN with 3.24% raise without BERT and 2.55% with BERT), which indicates that our model leverages the unique advantages GNNs enjoy such as the use of part neighboring nodes for aggregation. And in the graph-agnostic works, TDGC with 2.25% and 2.3% improvement, Inter-EC with 2.92%, JointNN with 4.65%, RSN with 1.8% and 2.13% improvement. These works entail a more straightforward pair-level encoding than those with complex downstream models such as a hybrid encoding for both clause-level and pair-level. Although our model advances less in these hybrid encoding works due to the part of superposition in clause relationship learning, this result reassures that clause representation orienting to clause-to-clause relationship defined by ours is effective.
Table 4: Performance comparison in ECPE Chinese corpus for replacing the clause-level encoding of all existing approaches with our model (+Ours). Except for RANKCP with GAT and JointNN with BiLSTM+attention for clause-level encoding, the other approaches above adopt BiLSTM to model the clause representation. Results significantly show that our model is more effective than original networks of all existing approaches.

Moreover, to further evaluate the performance in other language or text genres corpus, as shown in Table 6, we conduct the experiments on the English conversation dataset named RECCON for the causal emotion entailment task that is same as ECPE task. Due to the different text genres, the results in the RECCON are a little different in increments but demonstrate that the relationship proposed by ours made our model broadly applicable.

To further indicate the generality of our clause-level encoding method, we tested the performance in other benchmarks in Table 5 by replacing their clause-level encoding model with ours. From Table 5, CPAM+Ours and BERT++Ours perform better than other benchmarks under the unique conditional annotation

| Category | Model | emotion extraction(%) | cause extraction(%) | pair extraction(%) |
|----------|-------|------------------------|---------------------|--------------------|
|          |       | P R F1                 | P R F1              | P R F1             |
| Inter-EC | +Ours | 82.89 81.94 82.41±1.67 | 72.69 62.54 67.23±1.58 | 69.00 61.05 64.69±2.09 |
| RankCP   | +Ours | 86.16 85.87 87.00±1.65 | 72.82 74.35 73.58±2.94 | 69.54 68.91 69.22±2.53 |
| ECPE-2D  | +Ours | 85.12 82.20 83.58±1.14 | 72.72 62.98 67.38±1.60 | 69.60 61.18 64.96±1.95 |
| TDGC     | +Ours | 81.55 84.93 83.21±1.73 | 68.91 69.55 69.22±2.12 | 68.02 65.21 66.59±2.09 |
| PairGCN  | +Ours | 86.39 73.31 79.31±1.66 | 71.06 62.41 66.45±1.95 | 68.68 61.18 64.96±1.95 |
| SLSN     | +Ours | 84.06 79.80 81.81    | 69.92 65.88 67.78   | 68.36 62.91 65.45   |
| SAP      | +Ours | 86.74 80.69 82.67±1.33| 73.53 64.21 68.55±2.03| 70.00 63.68 66.69±1.79|
| RSN      | +Ours | 86.88 87.43 87.07    | 73.62 65.54 69.26   | 72.15 63.77 67.62   |
| JointNN  | +Ours | 86.31 81.58 83.83    | 70.11 64.42 67.09   | 71.18 64.92 66.45±1.95|
| RANKCP   | +Ours | 85.59 79.12 82.23±1.63| 72.39 64.29 68.10±2.59| 71.56 62.93 66.97±2.31|
| ECPE-2D  | +Ours | 89.20 89.99 90.57    | 74.61 77.83 76.15   | 71.19 76.34 73.60   |
| TDGC     | +Ours | 88.25 84.56 86.37±2.51| 70.11 64.42 67.09   | 71.18 64.92 66.45±1.95|
| PairGCN  | +Ours | 86.31 81.58 83.83    | 70.11 64.42 67.09   | 71.18 64.92 66.45±1.95|
| MLL      | +Ours | 86.08 91.91 88.86±1.86| 73.36 69.34 71.23   | 72.92 65.44 68.89   |
| RSN      | +Ours | 86.14 89.22 87.55    | 73.62 65.54 69.26   | 72.15 63.77 67.62   |
| PairGCN  | +Ours | 88.57 82.69 85.67±2.62| 79.01 68.28 73.27   | 76.92 67.91 72.02   |
| MLL      | +Ours | 86.08 91.91 88.86±1.86| 73.82 78.12 76.30   | 77.00 72.35 74.52   |
| RSN      | +Ours | 86.14 89.22 87.55    | 77.27 73.98 75.45   | 76.01 72.19 73.93   |

Table: Performance comparison in ECPE Chinese corpus for replacing the clause-level encoding of all existing approaches with our model (+Ours). Except for RANKCP with GAT and JointNN with BiLSTM+attention for clause-level encoding, the other approaches above adopt BiLSTM to model the clause representation. Results significantly show that our model is more effective than original networks of all existing approaches.

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To further indicate the generality of our clause-level encoding method, we tested the performance in other benchmarks in Table 5 by replacing their clause-level encoding model with ours. From Table 5, CPAM+Ours and BERT++Ours perform better than other benchmarks under the unique conditional annotation
| model | Scores (%) |          |          |          |
|-------|------------|----------|----------|----------|
|       | P         | R         | F1       |          |
| CPAM  | 61.95     | 78.65    | 69.29    |          |
| +Ours | 60.72±1.51| 84.33±2.35| 72.60±1.94|          |
| IE-CNN| 81.86     | 64.96    | 66.86    |          |
| +Ours | 82.44±3.81| 68.92±2.27| 67.41±2.56|          |
| BERT+ | 65.03     | 82.07    | 72.54    |          |
| +Ours | 66.41±1.24| 84.67±3.34| 75.41±2.14|          |
| CL-ECPE| \         | \        | 81.95    |          |
| †     | \         | \        | 82.21±0.79|          |
| MGSAG | 87.17     | 77.12    | 75.21    |          |
| +Ours | 86.82±1.89| 81.53±2.05| 76.39±1.58|          |

Table 5: The statistics of 5 methods with auxiliary annotation, extra data or samples.

| Category | Model | emotion extraction(%) | cause extraction(%) | pair extraction(F1(%)) |
|----------|-------|------------------------|---------------------|------------------------|
|          |       | F          | R          | P          | R          | F1         | pos | neg | avg |
| with     |       |            |            |            |            |            |      |      |     |
| RoBERTa  | RankCP| 90.70      | 62.48      | 73.96±2.98| 79.62      | 57.73      | 66.92±1.44| 51.45 | 97.06 | 74.26±1.13|
| +Ours    | 90.08 | 64.41      | **75.08±3.82**|            | 79.00      | **60.76** | **67.07±1.45**| **52.56** | **97.14** | **74.85±1.46**|
| ECPE-2D  | 72.17 | 41.33      | 52.56±1.92 | 81.44      | 61.49      | 54.83±3.65 | 51.07 | 97.11 | 74.09±2.02 |
| +Ours    | 88.57 | 59.11      | **70.90±1.29**| 82.59      | 63.81      | **71.99±4.35**| 53.75 | 97.37 | **75.56±1.87**|

Table 6: Performance comparison in RECCON English corpus, due to lacking word vectors pre-trained with word2vec toolkit, we cancel the experiment without RoBERTa.

dataset their enjoy. Hence, tagging the causal relationship and adding negative samples benefit our model to model the clause-to-clause relationship. And CL-ECPE improves least among all benchmarks. We infer that the adversarial samples introduce more confounders in clause-to-clause relationship. The same situation occurs in IE-CNN benchmark which introduces more relation-agnostic lable types.

5.5. Ablation Study

To explore the contribution of E-GAT, Activation Sort, and Loss sort, 3 sets of ablation experiments with the same baseline on 2 datasets are conducted. In Table 7, we investigate results under the following cases: removing the Loss sort function; replacing Activation Sort with a tanh function; both above cases; and replacing E-GAT with GAT. One observes that replacing E-GAT leads to the highest degradation in performance while modifying Loss sort and Activation Sort yields fewer losses. And this situation occurs in the two subtasks of RECCON corpus more sharply. There are two reasons we surmise. One is that in the ECPE corpus, the number of sentences of each sample is as 2.075 times as the number in RECCON, where the fewer sentences yield a more favorable attention distribution. The other one is that the ratio of ECP to non-ECP in RECCON is 1 : 10.31 too much more than 1 : 174.44 in ECPE to not need to widen the gap among the non-ECPs. In a word, they all indicate that clause (utterance) relationship is the
Table 7: Ablation analysis on RANKCP embedded with EA-GAT. To facilitate discussion, we show the experiment in ECPE corpus with BERT and experiment in RECCON dataset without BERT why both have the most obvious gap in the 4 ablation settings. C, E, and P stand for cause extraction, emotion extraction, and pair extraction. Then cn and en denote the Chinese corpus and English corpus.

| task | Model       | cn: F1(%) | en: avgF1(%) |
|------|-------------|-----------|--------------|
| C    | Ours        | 79.18     | 53.1         |
| -Loss_sort                    | -0.19    | -1.81       |
| -Sort                          | -0.88    | -3.26       |
| -Loss_sort-Sort                | -1.11    | -4.91       |
| -E-GAT                        | **-2.66** | **-6.44**   |
| E    | Ours        | 92.16     | 60.92        |
| -Loss_sort                    | -0.65    | -0.63       |
| -Sort                          | -0.88    | -1.12       |
| -Loss_sort-Sort                | -1       | -1.18       |
| -E-GAT                        | **-1.51** | **-7.07**   |
| P    | Ours        | 76.88     | 67.33        |
| -Loss_sort                    | -0.6     | -0.86       |
| -Sort                          | -0.81    | -1.33       |
| -Loss_sort-Sort                | -1.07    | -1.05       |
| -E-GAT                        | **-2.73** | **-2.14**   |

5.6. Case Analysis

To further illustrate how our model improves the performance, we inspect the matrix computed from BiLSTM, GAT, E-GAT (A(0)), and EA-GAT (A(1)) of the test dataset given by the “RankCP+Ours with BERT” model in ECPE dataset with one visualization shown in Figure 5.

In BiLSTM, all non-ECPs have almost zero weight except the row where the emotion clause is located and the column where the cause clause is located. It indicates that BiLSTM fails to identify whether pairs such as (5,7) (5,8) are correct ECPs.

In GAT, the relationship weights between non-ECPs are different, but the weight distribution is concentrated near the emotion/cause clauses, and the non-ECPs far away from the ECPs still lack effective weight evaluation.

In A(0) (E-GAT), what is different from the above two is, the weight distribution is not concentrated near the specific row and column or area, but is markedly distinguished to 3 parts via 3 sentences. And unlike the above two, the weights of (5,7) and (5,8) are significantly lower than the correct ECP such as (5, 4), this is because weights of (5,6), (6,7), and (7,8) are not high, which indicates that there is no reverse causal influence from 8-th clause to 5-th clause.
Figure 5: Adjacency matrices of BiLSTM, GAT, $A^{(0)}$ and $A^{(1)}$
In $A^{(1)}$ (EA-GAT), it is obvious that there is a series of stepped weight distributions, such as $(2, 1)(3, 2)(4, 3)(5, 4)$, which matches the fact that most clauses are the cause of the next clause in the document. This result corroborates the theory of Mann and Thompson [19], Marcu [20], who state that when the clause relationship is aligned with the reasoning process (in this case, multi-mask attention and activation sort), the model learns to exploit underlying semantic structure more easily.

5.7. Sensitivity Analysis

In this section, we further investigate how the different activation tricks and the layer $l$ would affect the performance. In addition, we also analyze the sensitivity in between the long document and short document.

![Figure 6: The results of different layers of EGAT and activation tricks under the baseline of RankCP with BERT.](image)

| category | Approach | P(%) | R(%) | F1(%) |
|----------|----------|------|------|-------|
| <15      | RANKCP   | 70.96| 76.33| 73.55 |
|          | Ours     | 74.68| 79.81| 77.15 |
| >=15     | RANKCP   | 72.38| 74.93| 73.63 |
|          | Ours     | 73.94| 79.76| 76.72 |

Table 8: Comparative results for documents with 2 sets of clause numbers

In Figure 6 we conducted a set of contrasts with the layers of EGAT ($l$) up to 4 and four activation strick: #2 sort following Equation 12, #1 sort following Equation 11, Sigmoid activation function; and tanh activation function. From Figure 6 there are three observation: (i) Activation Sort(#2 sort and #1 sort) both achieved better performance than activation functions (sigmoid and tanh), which collaborate the standpoint in Section 4.3 that popular activation functions can not wipe the distance among non-ECPs. (ii) #2 sort achieved the best performance,
which indicate that Equation 12 is better designed to highlight the weights of ECPs. (iii) $l = 2$ is sufficient to yield the most effective clause representation while $l = 1$ is not due to lacking of Activation Sort.

And to analyze the performance of EA-GAT to length of documents, we divided the entire dataset into approximately equal 2 parts as shown in Table 8, one for documents with less than 15 clauses and the other one with more than or equal to 15 clauses. Then RANKCP is used as the baseline for comparison. In the category more than 15, RANKCP shows better performance, while our model increases $3.09\%$ but shows less performance comparatively to the short documents. It demonstrates that the EA-GAT network is more suitable for documents with a short number of clauses.

6. Results and Discussion

Results are shown in Table 4, 6, 7 and Figure 3, and we have following observations:

- **EA-GAT is effective.** Both under word embedding with BERT and word2vec (without BERT), the $F_1$ score of pair extraction significantly improve by $2.35\%$ and $1.89\%$ averagely. Moreover, the $F_1$ score of cause extraction improve by $1.77\%$ and $2.75\%$ respectively in BERT and without BERT and the $F_1$ score of emotion extraction improve by $1.17\%$ and $0.89\%$. The most improvement occurs in cause extraction which indicates that traditional graph-based or recurrence-based model is insufficient for clause-to-clause representation learning. And it is interesting to see that cause extraction is enhanced more in word2vec embedding and emotion extraction more in BERT embedding. We consider that emotion extraction depends on word embedding more. But they both demonstrate that our model can achieve better predictive power by strengthening one of or both subtasks.

- **EA-GAT is general.** We detail our comprehensive empirical evaluation from 3 different angles to support the generality of our model: (i) our model is integrated with 10 standalone baselines with an averagely improve $2.14\%$ in pair extraction and $0.98\%$, $2.65\%$ in emotion/cause extraction separately; (ii) both in Chinese narrative corpus and English conversation corpus, our model has significant advantage with $2.1\%$ and $1.03\%$ on average respectively; (iii) from the 3 different upstream word embedding methods (word2vec, BERT, and RoBERTa), our model substantially surpasses all the baselines with $1.89\%$, $2.35\%$, and $1.03\%$ average improvement respectively.
While the EA-GAT is generally applicable in ECPE task, there are some limitations of EA-GAT.

Activation Sort is a radical framework/strategy. We define it as radical, not because it stop the gradient, but because it maps a clause pair into fixed distribution. Institutionally, stopping the gradient of a intermediate result absolutely destroy the whole back propagation. But practically, as the one of the inputs of the second E-GAT module, it is affected by two types of loss functions. One is the task loss including emotion prediction loss, cause prediction loss and pair prediction loss which measure the predictive power. According to the input $A^{(0)}$, the word encoding part can learn a favorable $A^{(0)}$ representation for prediction losses. Identically, $\hat{y}^e$ and $\hat{y}^e$ is the input of the second E-GAT also the output of the first E-GAT, which could lead to that $\hat{y}^e$ and $\hat{y}^e$ lose the purity of thier own prediction results of subtasks. Such a unnecessary conflict more substantially occur in sort loss. Hence, if we used the traditional activation function (i.e., RelU or tanh) to replace the Sort mapping, we also had to make $\hat{y}^e$ and $\hat{y}^e$ lose gradients.

What we think that it is imperfect is, for each document, we define a invariant sequence order for mapping though there are some alternative sequences in Section 4.3. In this case, each document has a fixed clause relationship level that should not be the same. In other words, this is our most concerned problem: how to construct a clause relationship? The clause relationship, a unique structure to each document, indicate that which clauses are irrelevant to the observed clause and which are closely related. Like a priori knowledge for a neural network to learn the unique structure among clauses rather than a full-linked structure that learn a clause representation from all the other clauses. For this perspective, the clause-level relationship defined by ours is a breakthrough which fine the grain of clause relationship from the whole document to sentence. And we attempt to advance the grain to the single clause via Sort mapping, while the performance of Sort is not as satisfying as clause-level relationship.

7. Conclusion

In this paper, we have defined the new and systematic clause-level relationship for the ECPE task. And to exploit this relationship, we have developed EA-GAT, a GAT-based model with multi-mask attention and activation mapping. It produces an effective clause representation by aggregating the information from different clause-to-clause relationships and incorporating the sort position embedding of subtask prediction sequences to achieve grain consistency. With comprehensive experiments in the two emotion-cause datasets named ECPE and RECCON, the
generality and effectiveness of our model are demonstrated. Furthermore, we conduct the ablation studies and case analysis to show that clause-level encoding is an integral contributor to the ECPE task.

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