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Semantic Decision Internal-Attention Graph Convolutional Network for End-to-End Emotion-Cause Pair Extraction

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ABSTRACT

Emotion-cause pair extraction is an emergent natural language processing task; the target is to extract all pairs of emotion clauses and corresponding cause clauses from unannotated emotion text. Previous studies have employed two-step approaches. However, this research may lead to error propagation across stages. In addition, previous studies did not correctly handle the situation where emotion clauses and cause clauses are the same clauses. To overcome these issues, the authors first use a multitask learning model that is based on graph from the perspective of sorting, which can simultaneously extract emotion clauses, cause clauses and emotion-cause pairs via an end-to-end strategy. Then the authors propose to convert text into graph structured data, and process this scenario through a unique graph convolutional neural network. Finally, the authors design a semantic decision mechanism to address the scenario in which there are multiple emotion-cause pairs in a text.

KEYWORDS

Emotion-Cause Pair Extraction, Graph Neural Network, Information Extraction, Multitask Learning

INTRODUCTION

In emotion-cause extraction (ECE), the underlying causes that lead to the emotional polarity of texts are extracted. Since ECE was proposed, it has received widespread attention in natural language processing (Lee et al., 2010). ECE has great significance for customer evaluation analysis and public opinion monitoring. For example, in terms of business, it can combine the work of Alharbi et al. (2020) to better analyze users' satisfaction with suppliers and help facilitate the decision-making process of the consumer (Abayomi-Alli et al., 2021; Guebli & Belkhir, 2021). However, emotion labels are required in ECE, and emotion annotation is quite labor intensive, thus limiting the applicability of ECE in practice (Gui et al., 2016; Gui et al., 2017). To address this limitation, the emotion-cause pair extraction (ECPE) task was proposed (Xia & Ding, 2019). ECPE is a new task in which emotion clauses and the corresponding cause clauses in unannotated emotion texts are identified. This involves

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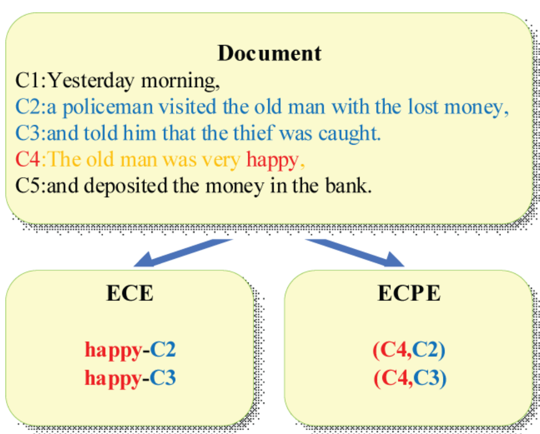
two main subtasks. The first subtask is extracting the emotion and cause clauses from the unannotated emotion text. The second subtask is matching the emotion clauses with the corresponding cause clauses and removing the nonexistent causal relationships. An example that demonstrates the difference between the ECE task and the ECPE task is presented in Figure 1. The objective of ECE is to track two corresponding cause clauses: "C2 A policeman visited the old man with the lost money" and "C3 and told him that the thief was caught". In the ECPE task, the objective is to extract all pairs of emotion clauses and cause clauses ("C4 The old man was very happy" and "C2 A policeman visited the old man with the lost money" and "C4 The old man was very happy" and "C3 and told him that the thief was caught"). From the above comparison, we find ECPE to be much more challenging. For ECPE, the authors' model must be able to identify the structure and content of the text and then accurately extract the corresponding emotion-cause pairs from the text.

Xia and Ding (2019) proposed a two-step framework for the ECPE task. In the first step, a multitask long short-term memory (LSTM) is used to extract emotion clauses and cause clauses. Then, a classifier is used to filter out negative candidate clause pairs. However, in a two-step approach, any misclassification from the first step is magnified in the second step. To overcome this drawback related to error propagation, the framework of emotional cause clause extraction should be considered as an integral framework. Hence, the authors propose a one-step framework, which is referred to as the semantic decision internal-attention graph convolutional network (SIGCN). This end-to-end approach can extract both the emotion-clause and the cause clause, thus avoiding the propagation of errors across stages.

Fan et al. (2020) transformed the task into a process that is similar to analyzing the construction of a directed graph. However, LSTM still has the disadvantage of long-range dependence when capturing the hidden state of the clause (Shi et al., 2015; Geng et al., 2020). Graph convolutional networks (GCNs) have made breakthrough progress in addressing long-range dependencies (C. Zhang et al., 2019; M. Zhang et al., 2018). A GCN treats each clause as a node in a graph and identifies the hidden state that contains the semantic structure of the text through the information transfer between each pair of nodes.

However, GCN suffers from excessive smoothness of nodes, which causes the network to lose the unique characteristics of each node in the information transmission process. In response to these two problems, the authors pre-process the serialized text to generate graph structured data, and then the authors improve the traditional GCN to effectively reduce the impacts of long-range dependence and excessive smoothing of nodes. The core improvement is that when information is transferred

Figure 1. Example that demonstrates the differences between ECE and ECPE



between nodes, the dot product internal attention mechanism is added for each node while preserving the semantic structure of the text. Using this approach, the authors finally obtain a self-aware global hidden state. And this global hidden state can effectively combine the semantic information of the context to build a more perfect semantic space. Meanwhile, the authors have considered the importance of position information. However, a single linearly correlated weight reduction method is often adopted for traditional position information, and the authors design a position buffer that is based on the positions of the clauses (when the clause position is closer, the change rate of the position weight is smaller).

In addition, previous methods have flaws in processing scenarios in which the text contains multiple emotion-cause clause pairs, and emotion clauses are often used as the subject to select the cause clauses without giving each clause equal consideration. For example, in Figure 1, only "C4 The old man was very happy" and "C2 a policeman visited the old man with the lost money" may be chosen as an emotion-cause clause pair, and the pair "C4 The old man was very happy" and "C3 and told him that the thief was caught" may be ignored. The authors believe that this is caused by the unequal status of the emotion-clause and the cause clause in the semantic space. To solve this problem, the authors design an efficient processing method, which the authors refer to as semantic decision analysis (SDA). In this method, each clause can be given equal status and is combined with the clause that has the highest degree of relevance to it. SDA not only selects the cause clause from the perspective of the emotion clause but also dynamically selects the emotion clause with the cause clause as the subject, thereby simultaneously mining the deeper semantic information of the clause and avoiding omissions caused by using emotion clauses as the subject of decision-making.

SIGCN consists of five major parts. The first part is the embedding layer, which is used to obtain the clause feature sequence for subsequent processing. The second part is the graph-hidden layer, which obtains the hidden state from the graph structured data by a special graph convolutional neural network. The third part is the semantic decision layer, which is used to address the special scenario in the dataset from a new perspective. The fourth part is the position-embedding layer, which is used to import position information by combining position buffers. The fifth part is the emotion-cause pair prediction layer.

The main contributions of this study are summarized as follows:

1. The authors propose converting text into graph-structured data and then using a graph convolutional network that incorporates internal attention within the dot product and applies it.
2. To address the special scenario in the dataset, the authors propose SDA to analyze the deep semantic information of text from the perspective of mutual prediction and learning between cause and emotion clauses. At the same time, the authors design a position buffer when introducing position information into the clause hidden state.
3. The authors use a one-step multitask network from a sequence perspective. The experimental results demonstrate that this network outperforms the state-of-the-art methods overall on all tasks.

BACKGROUND

The main objective of ECE is to extract cause clauses that may elicit emotions in a piece of text. Previous studies on this task are divided into three main groups according to the approaches that were used. The first group of studies used rule-based approaches; for example, Chen et al. (2010) proposed a method that is based on linguistic construction, and Gao et al. (2015) proposed a method that is based on an emotional lexicon (Huang et al., 2014). The studies in the second group are based on common sense methods (e.g., Russo et al. (2011) proposed a method that is based on knowledge). The studies in the last group are based on traditional machine learning methods (Alias Balamurugan et al., 2011; Xu et al., 2018); Ghazi et al. (2015) proposed a method that is based on conditional random fields (CRFs) (Tran et al., 2017), and Xu et al. (2017) applied a structural support vector machine (SVM).

However, these methods rely on the manual extraction of features. Given the continuous increase in the scale of data and the growth of the data dimensions, manual feature extraction is labor intensive and time-consuming.

In recent years, the deep neural network method has been applied to generate effective sentence features without manual extraction; hence, it has attracted increasing attention (Graves & Schmidhuber, 2005; Liu et al., 2018). Gui et al. (2017) innovatively transforms ECE into a reading comprehension task. Ding et al. (2019) proposed a model that is based on the neural network architecture for encoding three elements (the text content, the relative position and the global label). Li et al. (2019) proposed to combine LSTM and convolutional neural network (CNN) to complete the ECE task (Srinivasanet al., 2019). Chen et al. (2018) proposed a hierarchical convolution neural network (Hier-CNN) for emotion cause detection to deal with the feature sparse problem through a clause-level encoder. Xia et al. (xxxx) proposed an ECE framework, namely the RNN-transformer hierarchical network, for simultaneously encoding and classifying multiple clauses. Fan et al. (2019) used hierarchical neural models and knowledge-based regularization methods to extract emotional causes. The model was creatively proposed to integrate discourse context information and constrain parameters through a sentiment lexicon and common knowledge.

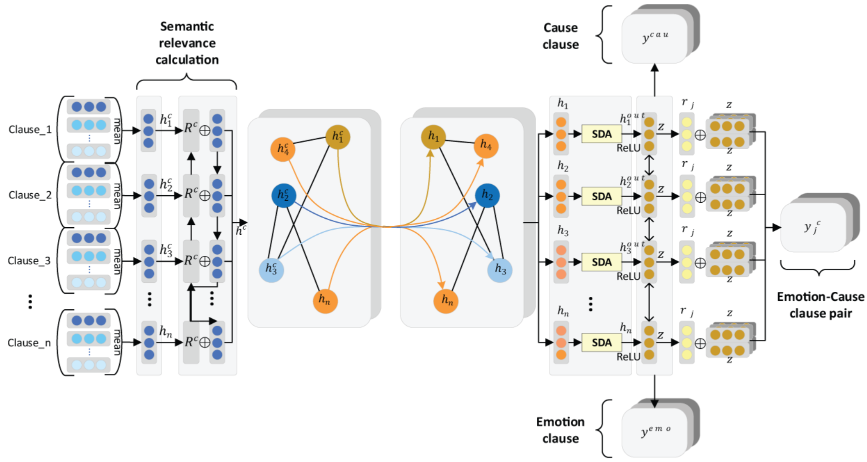
All of the above studies on the extraction of emotional causes rely on artificially labeled emotion annotations, and emotion labeling requires substantial time and money (Devillers et al., 2005; Tafreshi & Diab, 2018). Therefore, the application of emotion cause extraction is limited in practice. Xia and Ding (2019) proposed a novel task that is based on ECE, namely, emotion-cause pair extraction (ECPE), which does not require emotion annotation. The objective of ECPE is to extract emotion clauses and corresponding cause clauses from text (Sailunaz et al, 2018). Xia et al. (2019) proposed a method for extracting emotion clauses and cause clauses, combining emotion clauses and cause clauses into clause pairs and filtering the correct emotion-cause clause pairs by training a classifier (Yang et al., 2007; Sebe et al., 2002).

However, in the previous two-step methods, error is propagated across stages. Fan et al. (2020) proposed a model that mitigated the error propagation across stages and transforms the task into a process that is similar to the construction of an analytical directed graph. Wei et al. (2020) solved the problem of error propagation from another perspective and proposed a one-step neural network method that emphasizes cross-sentence modeling. Dai and Yubin (2020) proposed an Emotional Dilation Gated CNN (EDGCNN) model, aiming to extract emotion-cause pairs for sentiment analysis. Ding et al. (2020) proposed two 2D representation schemes for modeling emotion-cause pairs. However, when capturing the hidden state of the text, the above method still cannot effectively handle multiple pairs of emotion-cause pairs, and the clause pairs consist of two identical clauses. Therefore, the authors propose a semantic decision mechanism and a graph convolutional network that incorporates internal attention to resolve these problems. The authors also use a one-step framework based on the work by Wei et al. to eliminate the error propagation across stages. In addition, the importance of position information is demonstrated, and the authors establish a position buffer.

PROPOSED METHODOLOGY

The authors propose a one-step framework that builds on the foundation of that in, namely, SIGCN, and its overall structure is illustrated in Figure 2. SIGCN consists of five major parts. The first part is the embedding layer, which is used to obtain the clause feature sequence for subsequent processing. The second part is the graph-hidden layer, which first converts embedded data into graphic structured data and is then used to obtain the hidden state from the graph structured data by a special graph convolutional neural network; this layer is based on DGL (Chen et al., 2011). The third part is the semantic decision layer, which is used to address the special scenario in the dataset from a new perspective. The fourth part is the position-embedding layer, which is used to import position information by combining position buffers. The fifth part is the emotion-cause pair prediction layer,

Figure 2. Overall architecture of semantic decision internal-attention graph convolutional network



which is used to predict emotion-cause clause pairs. Meanwhile, to better understand the argument the authors describe some annotations and acronyms in Table 1.

Embedding Layer

Given a text $T = \{c_1, c_2, \ldots, c_n\}$ that is composed of n clauses, for each clause $c_i = \{c_1^t, c_2^t, \ldots, c_m^t\}$ that contains m words, the authors utilize BERT to preprocess word embeddings and obtain the clause feature sequence $h_i = \{h_1^t, h_2^t, \ldots, h_m^t\}$, and the lengths of c_i and h_i are both m. The conversion of input c_i is expressed as follows:

Table 1. Annotations and acronyms annotation table

Annotations and Acronyms	Annotation
ECE	emotion-cause extraction
ECPE	emotion-cause pair extraction
SDA	semantic decision analysis
h^c	feature sequence of the text
$H^{(l)}$	the last GCN layer's updated clause representations
y_i^{emo}	the likelihoods that the i -th clause is an emotion clause
y_i^{cau}	the likelihoods that the i -th clause is a cause clause
r_{ij}	the absolute position weight between the hidden states of the clause

$$h_i^t = BERT\left(c_i^t\right) \tag{1}$$

Then the authors average the feature sequence of each clause to obtain the average feature of the clause. Finally, the authors obtain the feature sequence of the text $h^c = \left\{h_1^c, h_2^c, \ldots, h_n^c\right\}$. The process is as follows:

$$h_i^c = mean\left(h_1^t, h_2^t, \ldots, h_m^t\right) \tag{2}$$

Graph-Hidden Layer

The authors believe that in ECPE tasks, it is necessary to fully combine the context to determine whether a sentence has the potential to become a candidate emotion-cause clause. In this layer, the authors rely on the semantic relations between different clauses to build a semantic map, and the interaction relationship between different clauses is used to improve the overall semantic space. After obtaining the features of the clauses in the text, the authors fully utilize the interactive relationships between clauses. The authors propose the use of the k-nearest neighbor (KNN) approach to construct a graph structure for the text (Geng et al., 2018; Chen et al., 2011). The authors identify a special case where the emotion clause and the cause clause are the same clause. In response to this case, the authors propose a graph convolutional neural network with dot product internal-attention. The construction of the authors' graph-hidden layer depends on DGL package (Chen et al., 2011). The authors use the output of embedding layer h^c as the input of the graph-hidden layer. The authors use KNN to calculate the degree of association between each h_i^c in h^c and all other hidden states in the semantic space. The calculation process is as follows:

$$R_i^c = knn\left(h^c\right) \tag{3}$$

$$R^c = \left\{r_1^{c-i}, r_2^{c-i}, \ldots, r_n^{c-i}\right\} \tag{4}$$

The authors take out the r_{v1}^{c-i} and r_{v2}^{c-i}, which are most closely connected to h_i^c from R_i^c. Then the authors construct graph-structured data based on r_{v1}^{c-i}, r_{v1}^{c-i}, and h_i^c. The authors define the graph structured data as $G_i = \left\{u_i, u_{v1}, u_{v2}\right\}$, for hidden sequence h^c that contains n $G_i.u_i$ represents the feature of the current node. u_{v1} and u_{v2} represent the two nodes that are connected to point u_i in the graph. Finally, from the original feature sequence h^c, the authors obtain the graph-structured data G that fit the authors' model.

In the next step, the authors will use the graph convolutional neural network that incorporates dot product internal-attention to obtain the hidden state, which contains the relevance of the clauses. The hidden state update process of each node is as follows:

$$h_i^{(l+1)} = ReLU\left(\sum\nolimits_{j \in \mathcal{N}(i)} \alpha_{i,j} h_j^{(l)}\right) \tag{5}$$

where $\mathcal{N}\left(i\right)$ is the set of its one-hop neighbour (which contains two nodes in the text in the authors' case); $h_j^{(l)}$ represents the hidden state in l -th layer of the graph neural network. $\alpha_{i,j}$ is the attention score between node i and node j, and the calculation process of $\alpha_{i,j}$ is as follows:

$$\alpha_{i,j} = softmax\left(e_{ij}^{l}\right) \tag{6}$$

$$e_{ij}^{l} = r_j^{c-i}\left(W_i^{(l)} h_i^{(l)}\right)^T \cdot W_j^{(l)} h_j^{(l)} \tag{7}$$

$W_i^{(l)}$ and $W_j^{(l)}$ transform the hidden states of nodes i and j such that they are of the same dimension. When computing the hidden state similarity e_{ij}^{l}, the authors use the dot product internal-attention, which can help the model increase its attention to itself to address the special scenarios where emotion clause and cause clause are the same clause. The l -th graph neural network layer is represented in matrix form as follows:

$$H^{(l)} = ReLU\left(\sum\nolimits_{j \in \mathcal{N}\left(i\right)} A^{(l)} H^{(l)}\right) \tag{8}$$

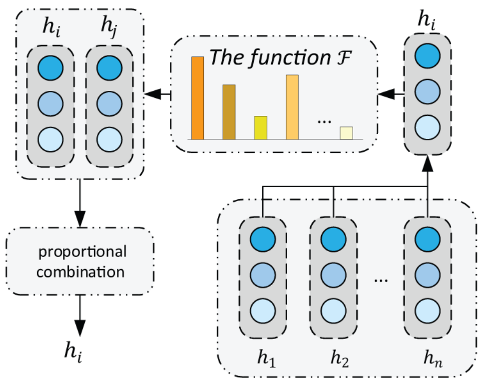
The first layer's input $H^{(0)} = \left\{h_1^c, h_2^c, \ldots, h_n^c\right\}$ is the output of the embedding layer, and $\left[A^{(l)}\right]_{ij} = \alpha_{i,j}^{(l)}$. The l layers used to model relationships between clauses, the last layer's updated clause representations, is $H^{(l)} = \left\{h_1, h_2, \ldots, h_n\right\}$.

Semantic Decision Layer

In this layer, in order to further use of emotion-clause and cause clause indicates the fact that each other, the authors use a semantic decision mechanism to the deep semantic information of text mining. The authors give each sentence equal status, and active combination by each clause and its correlation is the deepest meaning of the sentence to excavate the deep semantic information contained in each sentence.

The semantic decision layer consists of multiple identical single structures. Each single structure uses the clause hidden state as the core element to perform semantic decision analysis on clauses. A single structure is divided into n semantic decision analysis units (SDA) according to the same principle *(n* is the number of clauses in the text). Multiple SDA can give each clause equal status. Then for each clause, the clause with the deepest connection to it is selected. Through this special mechanism, the authors give each clause an equal opportunity and fully utilize the global semantic structure of the text. SDA not only predict the cause clause from the perspective of the emotion clause; they also dynamically predict the emotion clause with the cause clause as the subject; therefore it can avoid the cause clauses that may be omitted when only the emotion clause is used as the core of the selection. This method addresses scenarios in which there are multiple emotion-cause pairs in the text. The SDA units are illustrated in detail in Figure 3.

Figure 3. Semantic decision analysis units



In the next step, the authors will describe the SDA units in detail according to Figure 3. The authors input the result of the graph-hidden layer $\left\{h_1, h_2, \ldots, h_n\right\}$ to semantic decision analysis units. Then after a series of transformations, the semantic decision result $\left\{h_1^{out}, h_2^{out}, \ldots, h_n^{out}\right\}$ is obtained. The process is as follows:

$$r_i^t = \sum_{j=1}^{n} h_j \cdot \mathcal{F}\left(h_i, h_j\right) \tag{9}$$

$$\mathcal{F}\left(h_i, h_j\right) = \frac{\exp\left(h_i^{\top} \cdot h_j\right)}{\sum_{k=1}^{n} \exp\left(h_i^{\top} \cdot h_k\right)} \tag{10}$$

where r_i^t is the tailored clause-level feature, and the function $\mathcal{F}$ represents the correlation between h_i and h_j as follows:

$$h_i^{out} = r_i^t \cdot h_i + h_i \tag{11}$$

Then the authors feed the output of SDA to the $ReLU$ and generate c_i as follows:

$$z = ReLU\left(w_{out}^{\top} h^{out} + b^{out}\right) \tag{12}$$

where h^{out} is the set of h_i^{out}, and $w_{out}^{\top}$ and b^{out} are learnable weights, Finally, the authors obtain the output sequence $\left\{z_1, z_2, \ldots, z_n\right\}$ of the graph-hidden layer. After obtaining updated clause hidden state z_i, the authors use z_i to predict whether the clause is an emotion clause or cause clause. An MLP with a logistic function σ is used to make predictions on clauses. The process is as follows:

$$y_i^{emo} = \sigma\left(w_{emo}^{\top} z_i + b_{emo}\right) \tag{13}$$

$$y_i^{cau} = \sigma\left(w_{cau}^{\top} z_i + b_{cau}\right) \tag{14}$$

where $w_{emo}^{\top}$ and b_{emo} are learnable parameters and y_i^{cau} and y_i^{emo} represent the likelihoods that the i -th clause is a cause clause and an emotion clause, respectively.

Position-Embedding Layer

The authors found that the relative position between these two clauses is important to identifying emotion-cause pairs. Therefore, the authors use relative position information into the hidden state through relative position-embedding learning. The authors posit if relative position of the two clauses in the text is too large, the probability of their forming a clause pair will be small. The authors consider each clause pair $\left(z_i, z_j\right)$, for which the relative position of the two clauses is less than or equal to a threshold β as a candidate emotion-cause pair. In addition, to distinguish the importance of the hidden features of the clause within the threshold, the authors assign weights according to the absolute positions of clauses using a curve function, which can provide a position buffer (when the clause position is closer, the change rate of the position weight is smaller). Finally, the authors obtain an $n \times n$ clause pair matrix. The position-embedding process is as follows:

$$r_{ij} = \begin{cases} r_{ij} = \cos\left(\dfrac{\pi\left|i-j\right|}{\eta}\right) & \left|i-j\right| < \beta \\ r_{ij} = 0 & \left|i-j\right| \geq \beta \end{cases} \tag{15}$$

where r_{ij} represents the absolute position weight between the hidden states of the clause. The purpose of η is to limit the clause weight within the threshold to the adjustment number of (0,1). Only if the value of r_{ij} is not 0 can the next position-embedding operation be performed. The position-embedding operation is as follows:

$$c_{ij}^{r} = \left[z_i; z_j; r_{ij}\right] \tag{16}$$

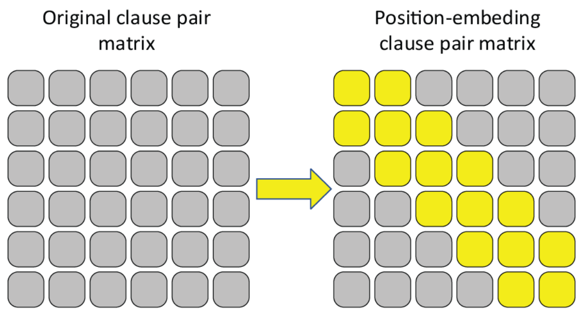
$$z_{ij}^{out} = ReLU\left(w_z c_{ij}^{r} + b_z\right) \tag{17}$$

where w_z and b_z are learnable parameters, $\left[;\right]$ represents the connection of vectors, and z_{ij}^{out} represents the i th row and j th column in the clause pair matrix. To examine the hidden layer process more intuitively, as illustrated in Figure 4, the authors present an example with a threshold of 2 and a clause matrix with 6 clauses in the text. The yellow part is the part on which to focus when the threshold is 2.

Emotion-Cause Pair Prediction Layer

This layer uses an activation function ζ to predict the likelihoods of emotion-cause clause pairs. The method used for this layer is from Wei et al. The process is as follows:

Figure 4. Examples with a threshold of two and a clause matrix with six clauses (the left is original clause pair matrix, the right is position-embedding clause pair matrix)



$$y_{ij} = \zeta\left(\left(w_p^\top z_{ij}^{out}\right) + b_p\right) \tag{18}$$

In the testing phase, the authors select the most likely emotion-cause pairs from y_{ij}, which is composed of clause c_i and clause c_j. Then the authors filter out n high probability clause pair combinations from y. The authors use the emotional dictionary method to determine whether c_k (where the authors assume that c_k is a component of a high probability clause pair (c_k, c_l)) contains emotion words. This method comes from RANKCP by Wei et al. If so, the authors consider this clause pair to be the correct emotion-cause clause pair. Via this approach, multiple emotion-cause clause pairs in the text can be extracted.

PROPOSED METHODOLOGY

Dataset and Experimental Settings

The authors used a publicly available dataset released by Xia et al. (2019). The dataset consists of 1945 texts from Sina News (Xue et al., 2014; Bai et al., xxxx). In the authors' experiment, the authors divided the data into 10 portions (10-fold cross-validation) (Fushiki, 2011). The dataset is described in detail in Table 2. For model performance comparison, the authors selected the precision P, recall R, and F-score $F1$ as evaluation metrics (Goutte & Gaussier, 2005).

The dropout is 0.3, and the position threshold is 5. The authors train SIGCN by Adam optimizer with a 0.001 learning rate, and the regularization coefficient is set to 1e-5 (Zhang, 2018; Jacobs, 1988). The embedding dimension is 768 for pretrained BERT (Devlin et al., 2018. Then the authors choose pointwise ranking loss and use ANTUSD as the basis for emotion words (Wang et al., 2016).

Table 2. Dataset description

Category	Number
one emotion-cause clause pair	1746
two emotion-cause clause pairs	177
more emotion-cause clause pairs	22
all emotion-cause clause pairs	1945

Comparison Models

To evaluate the performance of SIGCN, the authors consider 6 baseline models and design 2 ablation experiments for SIGCN (Sun et al., 2018; Glickman et al., 2005).

- **Indep:** Encodes clauses with a bidirectional LSTM network, and Indep uses two bidirectional LSTM network to extract emotion clauses and cause clauses (Graves et al., 2013; Fan et al., 2014; Xia et al., 2019).
- **Inter-CE:** Extracts cause clauses on the basis of Indep and then uses the extracted cause clauses to assist the model in extracting emotion clauses (Xia et al., 2019).
- **Inter-EC:** Extracts emotion clauses on the basis of Indep and uses the extracted emotion clauses to assist the model in extracting cause clauses (Xia et al., 2019).
- **ECPE-2D:** Uses 2D representation to express emotion-cause clause pairs. A 2D transformer is proposed to model emotion clause and cause clause (Ding et al., 2020).
- **RANKCP:** Uses a neural method that emphasizes cross-region modelling to perform end-to-end extraction (Wei et al., 2020).
- **TransECPE:** Transforms the task into a process that is similar to the construction of an analytical directed graph (Fan et al., 2020).
- **RSN:** Proposes a recurrent synchronization network that explicitly models the interaction among different tasks (Chen et al., 2022).

Ablation Experiment

- **SIGCN w/o Decision:** Evaluates the authors' model by deleting only the semantic decision process from the semantic decision layer (explore the impact of the authors' designed SDA on the overall experimental results).
- **SIGCN w/o Internal-Attention:** Evaluates the authors' model by deleting only the internal-attention from the graph-hidden layer (explore the impact of the authors' improved version of GCN and traditional GCN on the experimental results).

Table 3 shows the performances of the baseline models and SIGCN in the ablation experiments on three tasks. Compared with all baseline models, the overall performance of the authors' model is the best.

Table 3. Main results

Model	Emotion-Cause			Emotion Clause			Cause Clause			Average		
	F1	P	R	F1	P	R	F1	P	R	F1	P	R
Indep	58.18	68.32	50.82	82.10	83.75	80.71	62.05	69.02	56.73	67.44	73.69	62.75
Inter-CE	59.01	69.02	51.35	83.00	84.94	81.22	61.51	68.09	56.34	67.84	74.02	62.97
Inter-EC	61.28	67.21	57.05	82.30	83.64	81.07	65.07	70.41	60.83	69.55	73.75	66.31
ECPE-2D	72.92	65.44	68.89	86.27	92.21	89.10	73.36	69.34	71.23	77.52	75.66	76.41
RANKCP	73.60	71.19	76.30	90.57	91.23	89.99	76.15	74.61	77.88	80.11	79.01	81.39
TransECPE	73.74	63.07	67.99	87.16	82.44	84.74	75.62	64.71	69.74	78.84	70.07	74.17
RSN	73.93	76.01	72.19	87.55	86.14	89.22	75.45	77.27	73.98	78.98	79.80	78.46
SIGCN w/o decision	72.89	70.85	75.10	90.29	90.84	89.77	77.27	76.51	78.11	80.15	79.40	80.99
SIGCN w/o attention	73.05	73.21	74.49	91.80	90.12	90.04	76.42	77.41	77.81	80.42	80.25	80.78
SIGCN	74.50	73.01	76.20	90.94	91.81	90.14	77.84	77.42	78.42	81.09	80.75	81.59

Regarding the pipelined models, SIGCN significantly outperforms Indep and Indep's variants Inter-CE and Inter-EC in terms of the three metrics for each task. The F1 score of SIGCN is at least 16.32%, 15.49%, and 13.22% higher than the above-mentioned models, respectively. This may be because error propagation across stages occurs in two-step models, whereas this problem is alleviated in the one-step SIGCN model. It also shows that the one-step model is more suitable than the two-step model for emotion-cause clause pair extraction.

In comparison with other joint models, the authors observe that overall, the one-step model outperforms the two-step models that are considered above. Then, the authors compared SIGCN with three one-step models (ECPE-2D, RANKCP, and TransECPE) in detail. SIGCN outperforms ECPE-2D on three tasks in terms of eight metrics, and the authors posit that this is because the feature extraction ability of SIGCN's special graph neural network is stronger than that of the 2D transformer module. In terms of capturing global text relevant features, the neural network for graph structure conversion significantly outperforms the transformer module.

Although the SIGCN is based on RANKCP, overall, the authors' model outperforms RANKCP, and breakthroughs are realized in seven metrics on three tasks using the authors' model. The authors obtain better results on the emotion-cause extraction task than RANKCP due to SIGCN's excellent performance in terms of cause clause extraction. The authors attribute this to the semantic decision layer giving every clause the same opportunity, which can help SIGCN analyze the cause clauses from the perspective of deep semantics and better handle the scenarios where the text contains multiple emotion-cause clause pairs. The authors' model outperforms TransECPE in terms of all metrics on three tasks, and the overall performance of RSN is significantly worse than SIGCN. Compared with TransECPE, in emotion clause extraction and cause clause extraction, the authors' model realizes P values that are 9.37% and 12.71% higher, respectively. TransECPE analyses directed graphs to complete the task (Koncel-Kedziorski et al., 2019).

However, the long-range dependency problem of TransECPE and RSN, which is due to the use of LSTM to capture the hidden state, causes the model to lose important clause information (Song et al., 2018 Yang et al., 2020). The authors alleviate this problem through graph-structured information transmission. Ultimately, SIGCN realizes state-of-the-art performance on these three tasks.

Ablation Study

The ablation experiment was conducted mainly to evaluate the influences of various components of the network on the overall performance of the network. Table 3 presents the results of the authors' ablation experiments on SIGCN. The authors observe a 1.61% decrease in F1 when using this network model without decisions compared to SIGCN, and without dot product internal attention, a 1.45% decrease in F1 is observed. To explore the reasons for the overall poor performance, the authors conducted a more detailed analysis of the experimental data. As illustrated in Figure 5, the authors can observe that the emotion clause and cause clause are the same clause, accounting for approximately 24%. Therefore, the advantage of dot product internal attention is demonstrated in this case. The experimental data in Table 3 also further prove the satisfactory performance of this attention mechanism. In addition, the authors find that the occurrence rate of multiple emotion-cause clause pairs in the same text is close to 10%. Therefore, due to the suitable processing of the semantic decision layer in this case, SIGCN obtains better results than SIGCN w/o decision.

Evaluation on Emotion-Cause Extraction

Since SIGCN is a multitask framework, the authors regard that performance on the emotion-cause extraction task is also important for SIGCN evaluation. The authors further examine SIGN by comparing it with some existing methods for the emotion-cause extraction task. The methods are as follows:

Figure 5. Ratios of two special cases in the dataset to the overall. same clause represents that the emotion clause and the cause clause in the pair are the same clause. one pair represents only one emotion-cause pair in a text.

- **RB:** A rule-based system for emotion-cause extraction for manually defined linguistic rules (Lee et al., 2010).
- **MULTI-KERNEL:** Present a new event-driven emotion cause extraction method using multi-kernel SVMs (Gui et al., 2016).
- **CANN:** Encodes the input representation of the clauses with Bi-LSTM based on co-attention, which is then further fed into convolutional layers for information extraction (Li et al., 2018).
- **RTHN:** Proposes a joint emotion-cause extraction framework consisting of an RNN-based word-level encoder for encoding multiple words in each clause and a Transformer-based encoder for learning correlation between multiple clauses (Xia et al., xxxx).
- **ECJD:** Uses relative positions in emotion detection as prior knowledge for cause detection to improve detection performance (Hu et al., 2020).
- **FSS-GCN:** Proposes a graph convolutional network based on clause dependencies to fuse semantic information, which automatically selects participate clause for emotion-cause analysis (Hu et al., 2021).

From Table 4, it is shown that SIGCN outperforms the existing approaches on the emotion-cause extraction task. The F1 is at least 25.41% and 10.32% lower for RB and MULTIKERNEL, respectively, than SIGCN. SIGCN outperforms CANN and RTHN on the emotion-cause extraction task for three metrics. Both CANN and RTHN use the traditional serialized neural network LSTM when extracting the hidden state of the text, while SIGCN uses graph-structured data to capture the

Table 4. Results on the emotion-cause extraction task

Emotion Cause Extraction	F1	P	R
RB	52.43	67.47	42.87
MULTI-KERNEL	67.52	65.88	69.27
CANN	72.66	77.21	68.91
RTHN	76.77	76.97	76.62
ECJD	72.28	67.04	69.40
FSS-GCN	77.14	78.61	75.72
SIGCN	77.84	77.42	78.42

hidden state. Therefore, the authors posit that the graph neural network has a large advantage in extracting the interactive relationships of different clauses. SIGCN outperforms ECJD in terms of all metrics on the task. The authors observe a 5.56% decrease in F1 when using ECJD compared to SIGCN. The authors attribute this to the SDA, which gives every clause the same opportunity, allowing SIGCN to screen useful clauses for the task. SIGCN outperforms FSS-GCN in terms of two metrics on the emotion-cause extraction task. The authors posit that this is due to the synergistic effect of the internal attention and the semantic decision analysis units. Most of the above methods utilize known emotion clauses as model input. SIGCN does not utilize known emotion clauses as model input. It still outperforms the above methods, which further illustrates that the multitask framework SIGCN is also superior on the emotion-cause extraction task.

Effect of the Graph-Hidden Layer

To evaluate the impact of the graph-hidden layer on the overall structure of the network, the authors conduct detailed experiments in this section. First, the authors conduct related experiments on KNN-based graph-structured data and sequence-based data. The experimental results are presented in Figure 6. According to Figure 6, the performance on KNN-based graph-structured data is significantly higher than that on sequence-based data in terms of F-score and recall. However, the performance on KNN-based graph-structured data is slightly worse than that on sequence-based data in terms of precision. The overall performance on graph-structured data is better than that on sequence-based data for the two tasks. The authors posit that this is because the production of KNN-based graph-structured data involves a pre-processing operation, in contrast with that of sequence-based data. SIGCN aggregates the hidden states of neighbor nodes, and this pre-processing operation can help SIGCN better aggregate important clause information. The sequence-based data structure will cause SIGCN to pay too much attention to the two nodes before and after the sequence. Therefore, the authors posit that KNN-based graph-structured data can better help SIGCN capture the hidden states of clauses.

Effect of the Position-Embedding Layer

To explore the impact of the position-embedding layer on the overall network architecture, the authors conducted two related experiments, in which they changed the position weight to a linear correlation weight and removed the position weight. According to Figure 7, the network with position information significantly outperforms the networks without position information. This is because coherent semantic content is often expressed in the text, and the relative distances between clauses that can form clause pairs are often short. Overall, the position weight in SIGCN results in SIGCN

Figure 6. Experimental results on different structured date (the blue is graph-structured data; the red is sequence-structured data)

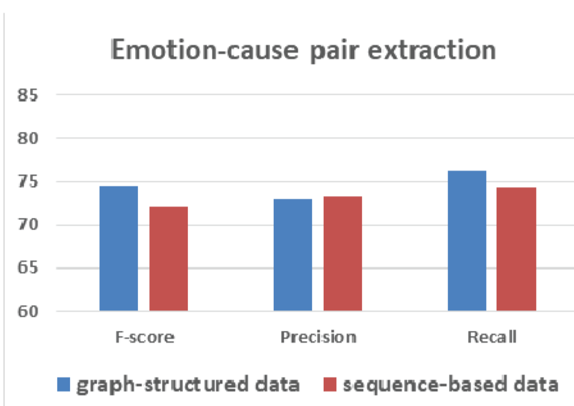
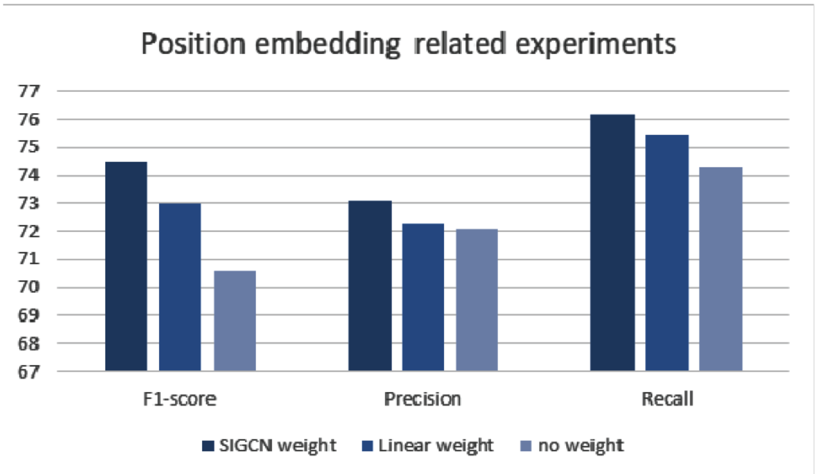


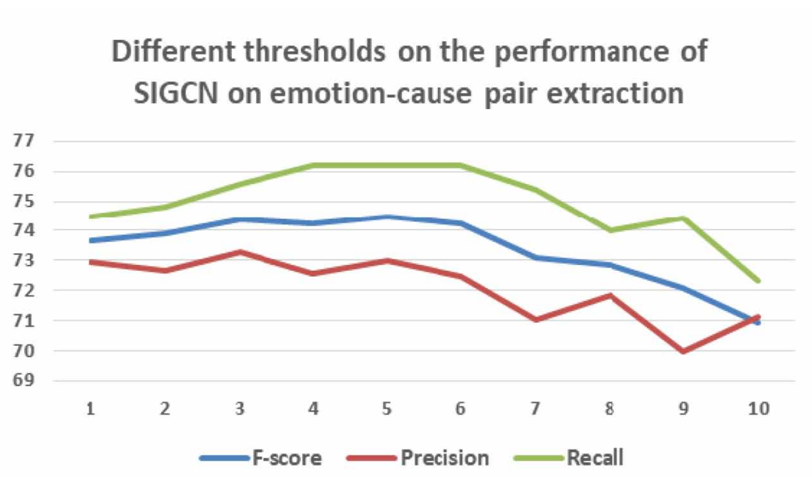
Figure 7. Experimental results on position-embedding layer (the authors selected the precision P, recall R, and F-Score F1 as evaluation metrics)



outperforming the other two experimental models. This is because the linear weight blindly reduces the weight attention by a fixed proportion, which causes a loss of information from important clause pairs. SIGCN adopts a relatively smooth position weight function with a buffer area to fully utilize the position information between clauses. In addition, to explore the impact of the buffer area on SIGCN, the authors changed the threshold and conducted related experiments. The experimental results are presented in Figure 8.

As shown in Figure 8, when the threshold is less than 5, the overall performance of SIGCN shows an upward trend, and the best result is obtained when the threshold is equal to 5. The authors posit that this is because the dataset often consists of coherent documents with complete semantic information; hence, the absolute positions of important clause information with high relevance are often close. The authors can only enlarge the threshold to a suitable value, and SIGCN can include clauses

Figure 8. Experimental results of changing the threshold (the authors selected the precision P, recall R, and F-Score F1 as evaluation metrics)



that contain important semantic information in the buffer. However, when the threshold is between 5 and 10, the overall performance of SIGCN shows a downward trend as the threshold increases. The authors posit that this occurs when the threshold is in the range of 5-10. Although clauses that contain important semantic information can be included, a threshold that is too large will increase the number of insignificant clauses in the buffer, which will generate more noise and affect the overall performance of SIGCN. Therefore, the authors select the most suitable threshold of 5 in SIGCN.

Case Study

Table 5 gives the information of four representative cases about text ID, clause number (Number), emotion clause ID (EID), cause clause ID (CID) and emotion-cause pairs (Pairs). These four cases include examples of long text, multiple emotion-cause pairs text, text with the same emotion clause, and cause clause and text with the different emotion clause and cause clause. To examine SIGCN more intuitively, the authors visualized the attention degrees of these texts in Figure 9. The abscissa and ordinate represent the indices of emotion clauses and cause clauses, respectively. Specifically, the darker the color is, the more attention the network model has focused on the corresponding clause.

As shown in Figure 9 (a), SIGCN has given clause pairs [C7, C6] the highest attention while giving lower attention to other clause pairs. The authors find that dark colors are mainly concentrated around [C7, C6], which indicates SIGCN can capture relevant deep semantic information of clauses while ignoring irrelevant information. Similarly, the authors can verify the same findings in Figure 9 (b). Specifically, the authors find that dark colors mainly surround [C7, C6] and [C13, C12] in Figure 9 (b). This further shows that SIGCN can adapt to multiple emotion-cause pair scenarios. Figure 9 (c) and Figure 9 (d) are text with the same emotion-cause clause and text with the different emotion-cause clauses, respectively. The authors find that dark colors mainly surround [C3, C3] in Figure 9 (c) and [C12, C10] in Figure 9 (d). This further shows that SIGCN can handle various special scenarios and further verifies that SIGCN has good robustness. Based on the above results, the authors can see that SIGCN can automatically learn how to selectively focus on some of the clause pairs useful for emotion-cause pair extraction tasks instead of all clause pairs in the text.

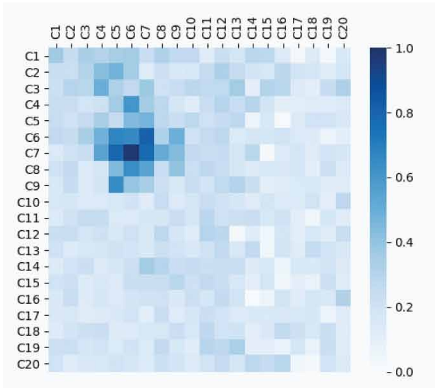
CONCLUSION

Nowadays, social networks provide a platform for people to make comments anytime and anywhere, which generates a huge amount of data. It is not enough to rely solely on manual processing of massive data, so the ECPE task has gradually become a hot research object. The ECPE task can be combined with hot events in the media to reveal different emotional objects and the causes of emotion on the basis of hot events.To provide strong support for facilitating government decision-making and preventing and resolving negative social emotions. At the same time, the ECPE also has important commercial value. For example, in e-commerce, it can help merchants to better understand the comments of commodities, improve the quality of commodities, and improve user experience. Its goal is not only to post consumer opinions, but also to provide personalized recommendations.

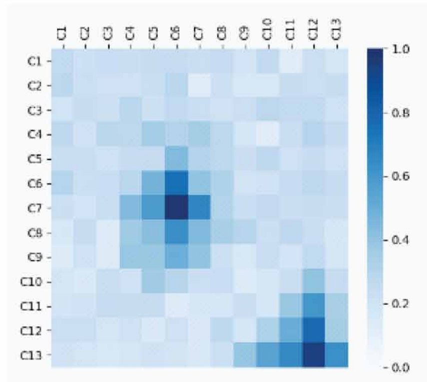
Table 5. The profile of four cases for visualization study

ID	Number	EID	CID	Pairs
66	20	C7	C6	[C7, C6]
243	13	C7, C13	C6, C12	[C7, C6] [C13, C12]
1065	13	C3	C3	[C3, C3]
57	12	C12	C10	[C12, C10]

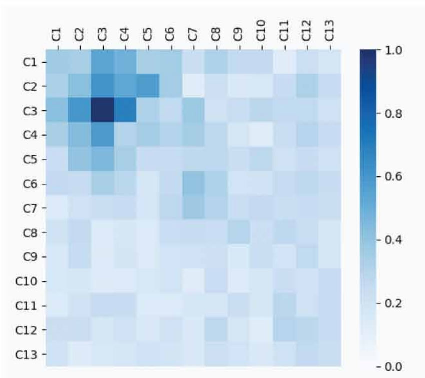
Figure 9. Visual weights for the four examples



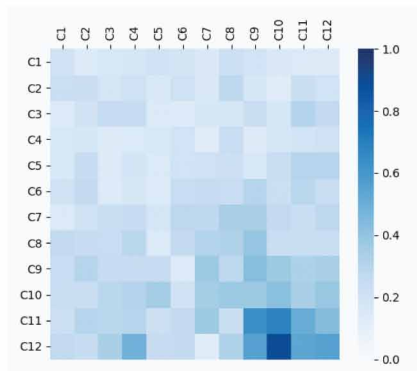
(a)



(b)



(c)



(d)

In this paper, the authors proposed SIGCN for completing the task of emotion-cause pair extraction. First, the hidden state of each clause node is captured through a variant that is based on a graph convolutional network. Then, the authors use a semantic decision mechanism that gives each clause equal status to capture the deep semantic information of each sentence. Finally, the position information is effectively integrated into a unified network architecture. Experimental data show that the overall SIGCN outperforms other models. The authors also conducted a detailed analysis of the effects of various components of SIGCN on the network.

The current emotion-cause pair extraction task is based on clauses, and the authors regard this as a coarse-grained method. In the future, the authors will explore the use of words as nodes in graph-structured data and apply a fine-grained approach to complete the emotion-cause pair extraction task.

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