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ARTICLE

Joint Feature Encoding and Task Alignment Mechanism for Emotion-Cause Pair Extraction

Shi Li and Didi Sun*

College of Computer and Control Engineering, Northeast Forestry University, Harbin, 150040, China

*Corresponding Author: Didi Sun. Email: sundidi@nefu.edu.cn

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ABSTRACT

With the rapid expansion of social media, analyzing emotions and their causes in texts has gained significant importance. Emotion-cause pair extraction enables the identification of causal relationships between emotions and their triggers within a text, facilitating a deeper understanding of expressed sentiments and their underlying reasons. This comprehension is crucial for making informed strategic decisions in various business and societal contexts. However, recent research approaches employing multi-task learning frameworks for modeling often face challenges such as the inability to simultaneously model extracted features and their interactions, or inconsistencies in label prediction between emotion-cause pair extraction and independent assistant tasks like emotion and cause extraction. To address these issues, this study proposes an emotion-cause pair extraction methodology that incorporates joint feature encoding and task alignment mechanisms. The model consists of two primary components: First, joint feature encoding simultaneously generates features for emotion-cause pairs and clauses, enhancing feature interactions between emotion clauses, cause clauses, and emotion-cause pairs. Second, the task alignment technique is applied to reduce the labeling distance between emotion-cause pair extraction and the two assistant tasks, capturing deep semantic information interactions among tasks. The proposed method is evaluated on a Chinese benchmark corpus using 10-fold cross-validation, assessing key performance metrics such as precision, recall, and F1 score. Experimental results demonstrate that the model achieves an F1 score of 76.05%, surpassing the state-of-the-art by 1.03%. The proposed model exhibits significant improvements in emotion-cause pair extraction (ECPE) and cause extraction (CE) compared to existing methods, validating its effectiveness. This research introduces a novel approach based on joint feature encoding and task alignment mechanisms, contributing to advancements in emotion-cause pair extraction. However, the study's limitation lies in the data sources, potentially restricting the generalizability of the findings.

KEYWORDS

Emotion-cause pair extraction; interactive information enhancement; joint feature encoding; label consistency; task alignment mechanisms

1 Introduction

Emotion-Cause Pair Extraction (ECPE) is a field of study that extracts emotion-cause pairs with causal relationships from diverse data sources [1]. With the rapid growth of social networks, users increasingly post comments online, and the emotions and corresponding causes expressed in these comments provide valuable information for various applications, such as opinion monitoring and comment mining [2]. Due to its significance, emotion-cause pair extraction has gained popularity as a research area in recent years. Previous research on ECPE has emphasized the internal relations within emotion-cause pairs or clauses, as they offer semantic and contextual information about the sentence during the extraction process. The extraction of inaccurate emotion clauses and emotion-cause pairs, however, results from this research's disregard for the causal information between emotion-cause pairs and clauses. Additionally, previous studies have concentrated on the individual predictions of the assistant and emotion-cause pair extraction tasks, ignoring the informational interactions across the tasks. This has led to difficulties in preserving predictive consistency between tasks. To overcome these problems, emotion-cause pair extraction using joint feature encoding and task alignment mechanisms improves the accuracy of emotion-cause pair extraction, strengthens information interaction between tasks, and allows for a deeper comprehension of the contextual semantics and causal information within sentences.

Traditional emotion-cause pair extraction techniques primarily employ sequential coding to learn internal relationships within emotion-cause pairs or clauses through a predefined order [1]. However, for the emotion-cause pair extraction task, the causal relationship between emotion clauses and cause clauses is crucial for identifying potential emotion-cause pairs. Sequential coding, unfortunately, disregards information about the interrelationships between clauses [2]. In this context, extracting and efficiently analyzing the causal relationships within clause contexts can reveal more detailed information about the categorization of clause pairs. Furthermore, the emotion-cause relationship is essential for extraction and information interaction between the two assistant tasks. Analyzing this relationship can provide valuable clues. Despite this, most prior research on emotion-cause pair extraction considers ECPE and the assistant tasks (CE: extracting cause clauses from documents, and Emotion Extraction (EE): extracting emotion clauses from documents) as two distinct extraction tasks that cannot share relevant information, resulting in inconsistent sentence prediction.

For instance, in Table 1, sentence (c7) is identified as an emotion clause in emotion-cause pairs during the ECPE process. However, it is not labeled as an emotion clause in the context of EE [3]. Consequently, the labeling consistency between emotion-cause pair extraction and the assistant task cannot be assured [4–8]. To address this issue, the labeling consistency can be further enhanced by facilitating information exchange between the emotion-cause pair extraction and the assistant tasks.

Table 1: Examples of inconsistent label predictions for emotion-cause pair extraction and ancillary tasks (emotion extraction and cause extraction). Green is the color of cause clauses, and yellow is the color of emotion clauses. Red is the color of wrong predictions

Document	Pairs (c_i, c_j)	Ground-truth
(c1) Combined with this evidence as well as the characteristics of the case, (c2) that Meng may have been killed, (c3) when the police contacted the residents of Nanyuan Village, (c4) and they discovered that Meng was playing mahjong at a mahjong parlor across his house the day before the incident, (c5) and through questioning,	ECPE: (c7, c6) EE: ( ) CE: (c6)	ECPE: (c7, c6) EE: (c7) CE: (c6)

(Continued)

Table 1 (continued)

Document	Pairs (c_i, c_j)	Ground-truth
(c6) they found that Wang was the only one who had gone out in the same village and whose whereabouts were unknown, (c7) which aroused the suspicion of the police.		

This paper proposes an emotion-cause pair extraction method based on a Joint Feature Encoding and Task Alignment (JFTA) mechanism to address the limitations of existing studies. Traditional methods either lack the ability to simultaneously model extracted features and feature interaction information or suffer from inconsistent label predictions between emotion-cause pair extraction and independent assistant tasks, such as emotion extraction and cause extraction. The JFTA approach leverages feature information obtained from emotion-cause pairs and clauses to capture causality through feature interaction. Additionally, it utilizes the sharing of interrelated information to reduce the labeling distance between emotion-cause pair extraction and assistant tasks, thereby improving prediction accuracy. This novel approach contributes to the advancement of emotion-cause pair extraction research by overcoming the shortcomings of conventional methods. To achieve this objective, the proposed methodology employs a Bidirectional Encoder Representation from Transformers (BERT) as a document encoder to generate clause representations. Subsequently, a heterogeneous undirected graph and a relational graph convolutional network are used to model the multiple relationships between emotion-cause pairs and clauses. Finally, task alignment is achieved by minimizing the bi-directional Kullback-Leibler (KL) divergence between the emotion-cause pair extraction and the product of emotion extraction and cause extraction output distributions, ensuring uniformity of the label space across all tasks.

The experimental results, evaluated on a public Chinese benchmark corpus [1], demonstrate the effectiveness of the technique proposed in this study. The main contributions of this paper are as follows:

1) Heterogeneous undirected graphs and Relational Graph Convolutional Networks (RGCN) are employed to modelling the diverse relationships among emotion-cause pairs and clauses, facilitating the learning of causal connections between sentences during the encoding process.

2) This paper introduces a task alignment mechanism that effectively captures the information interactions between tasks, obtains deep semantic information, and further narrows the labeling distance between ECPE and the combination of EE and CE. This ensures labeling consistency across these related tasks.

3) This study validates the approach's performance through a comprehensive series of ablation experiments, hyper-parameter tuning, and additional tests. The benchmark dataset's experimental results demonstrate the effectiveness and superiority of the proposed method in comparison to prior techniques.

The remaining content of this article is organized as follows: Section 2 provides an overview of relevant work on the topic. Section 3 introduces the proposed model and provides a detailed definition of the task. Section 4 describes the comprehensive experiments conducted and analyzes the results, discussing the implications of the findings. The article is concluded in Section 5, which summarizes the main insights and contributions of the study.

2 Related Works

The identification of sentiment polarity [9–12] and emotion categories [1,13] is part of the well-established field of sentiment and opinion analysis in natural language processing [13–15]. A more recent advancement in emotion detection techniques is Emotion cause analysis (ECA). Based on the emotion and cause extraction elements, several subordinate tasks revolve around the ECA theme, including emotion-cause extraction (ECE) [1–2,16–17] and ECPE [3,9,11].

The ECE task, originally presented by Xia et al. [1], is a word-level cause labeling task that has been the subject of numerous investigations using rule-based approaches [16,18–19] and machine learning methods [20]. Chen et al. [18] redefined the ECE problem as a sentence-level extraction task, suggesting that clauses may be the optimal information unit for identifying reasons. Subsequently, a related study [2] created a benchmark dataset for the ECE task using Sina News to develop a Chinese emotional causes dataset. Following the completion of this task, various studies have proposed conventional machine learning techniques [21–23]. Recently, deep neural networks have been employed in several studies to accomplish this task [24–28]. Despite its significant research value [21,22], the ECE task has two distinct limitations. First, the process of manually annotating emotions prior to cause extraction constrains its practical applicability. Second, this approach fails to consider the interaction among emotions and causes.

To overcome these limitations, Xia et al. [1] established a pioneering task in emotion cause analysis called ECPE. This endeavor aims to extract from a target document a set of phrase pairs containing emotions and their corresponding causes. The ECPE task presents a greater challenge than the ECE task, as it necessitates a comprehensive understanding of the text's content and structure to extract emotions, causes, and emotion-cause pairs. The two-step strategy employed to address the ECPE challenge [1] utilizes a binary classifier to pair the emotion and cause clauses extracted in the initial steps. While this pipeline design offers simplicity and intuition, it suffers from two significant drawbacks: error propagation from step one to step two and the substantial computational requirements of the two-step technique [28–30]. To mitigate these shortcomings, recent work predominantly solves the ECPE problem using an end-to-end deep learning framework. This structure consists of three primary segments: emotion-cause pairings and sentence prediction, word-level encoders, and clause-level encoders. The word-level encoder typically employs a shared bi-directional LSTM [11–15], while the clause-level encoder utilizes a Transformer encoder [11], a convolutional neural network (CNN) [19], or a bi-directional LSTM [11–15]. During the final prediction phase, the majority of current approaches employ softmax classifiers [11–15] to determine whether a potential emotion-cause pair constitutes the correct emotion-cause pair. Existing approaches tackle the ECPE task from various perspectives, including ranking [16], sequence labeling [17,18], link prediction [19], multi-label learning [13], multi-task learning [12,20], directed graph construction [25], symmetric local search [18], event context [23], and graph neural networks [24]. However, most end-to-end methods employ sequential coding, whereby the task-specific attributes are acquired in a predetermined order. Sequential coding exposes the paired encoder and the clause encoder to different quantities of information, as information only moves unidirectionally from the emotion/cause clause encoder to the paired encoder [7,8]. Consequently, if the emotion/cause clause encoder produces an inaccurate forecast, it substantially distorts the pair's prediction.

In contrast, the joint encoding strategy has gained increasing attention in multi-task learning [31–34]. This approach solves the sequential coding problem described above by balancing the flow of information between emotion-cause clauses, cause clauses, and emotion-cause pairings. It also effectively extracts the causal relationships between sentences in ECPE tasks [35]. The efficacy of joint coding stems from its facilitation of communication between the paired encoder and the emotion/cause clause encoder. As causality plays a crucial role in determining the compatibility of emotion and cause, the clause encoder, during the encoding process, may prioritize the assessment of clause pairing suitability over the mere extraction of emotion or cause information.

Moreover, as the two assistant task modules in the task flow and the ECPE module should intuitively concur on phrase recognition, adjusting the labeling distance between the tasks is crucial for the overall performance of the ECPE. Specifically, the CE module should predict a sentence as a non-causal clause when the ECPE module has identified it as such. However, this labeling consistency cannot be assured because most of the previous ECPE research (e.g., Yan et al. [7], Ding et al. [4], Wang et al. [8], Bing et al. [9]) was conducted in a mutually independent manner.

While prior multi-task learning frameworks effectively learn features for individual tasks, they face limitations in simultaneously modeling extracted features and their interactions or ensuring consistent label predictions across emotion-cause pair extraction and independent assistant tasks, such as emotion extraction and cause extraction. To address these challenges, this paper has proposed a novel approach that leverages a joint feature encoding and task alignment mechanism. This method efficiently captures the complex interactions between clauses and balances the information flow between tasks, ultimately enhancing the overall performance of emotion-cause pair extraction.

3 Methodology

This section provides a comprehensive description of our approach, which encodes both pairs and clauses while modeling the causal relationships between clauses through a RGCN. The bi-directional alignment of ECPE with EE and CE is achieved through a task alignment mechanism. The structure of the proposed approach is illustrated in Fig. 1.

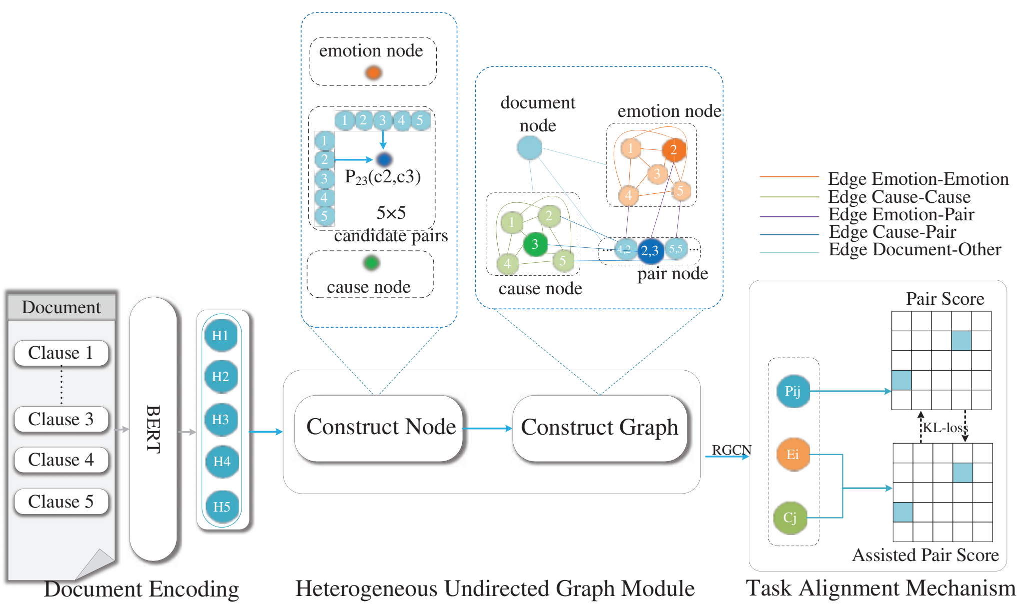

Figure 1: The architecture of the proposed JFTA model. The model incorporates an encoder, a heterogeneous graph for concurrent modeling of specific features and inter-feature interaction data, a classifier, and a task alignment mechanism to ensure label prediction consistency between ECPE and assistant tasks

Given a document $D = (c_1, c_2, \ldots, c_N)$ containing N clauses, where the i-th clause $c_i = \left(w_1^i, w_2^i, \ldots, w_M^i\right)$ is consists of M words. The objective of the ECPE task is to identify and extract all emotion-cause pairs from the given document D:

$$P = \left\{\ldots, \left(c_i, c_j\right), \ldots\right\} (1 \leq i,j \leq N) \tag{1}$$

where c_i and c_j are paired to denote emotion clauses and cause clauses.

The ECPE task consists of two assistant tasks: CE and EE. If any pair $\left(c_i, c_j\right)$ holds, the clause c_i is an emotion clause, which can be defined as follows:

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

where $y_i^{emo} = 1$ indicates that c_i is an emotion clause, the extraction process for cause clauses is identical to that for emotion clauses.

3.1 Document Encoding

Given a document $D = (c_1, c_2, \ldots, c_N)$ containing N clauses, we input D into the pre-trained BERT [26]. To be more precise, we aggregate all clauses into a single input by appending a [SEP] token at the end and prepending a [CLS] token at the beginning of each clause. Subsequently, we perform average pooling of token representations, excluding [CLS] and [SEP], within each clause to represent the clauses. Thus, a document consisting of N clauses can be expressed as:

$$H = \{h_1, h_2, \ldots, h_N\} \tag{3}$$

where $h_i \in \mathbb{R}^d$ and d is the hidden state size in the BERT model.

The representation of pairs is obtained through expression (4). This process involves constructing a matrix of candidate pairs M, connecting the relevant two clauses in the matrix, and projecting them with a learnable relative position embedding. The candidate pairing matrix M is $|n| \times |n|$. For a given candidate pair $\left(c_i, c_j\right) \in M$, its representation $h_{ij} = [h_i, h_j]$ is obtained by connecting the corresponding clause representations and projecting them using learnable relative position embeddings. The connection operation is denoted by $[,]$.

$$p_{ij} = W_p h_{ij} + b_p + r_{i-j} \tag{4}$$

where p_{ij} denotes pairs using c_i as the emotion clause and c_j as the cause clause, W_p and b_p are learnable parameters, and r_{i-j} is the relative positional embedding. A hyperparameter α is set as the local window ($|i - j| \leq \alpha$) to restrict the quantity of pairs.

3.2 Heterogeneous Undirected Graph Module

To address the issue of information interaction between pairs and clauses, as well as to capture the causal relationships between them, we construct a heterogeneous undirected graph model. This graph effectively manages the relationships both within and between clauses and pairs. The graph consists of four distinct types of nodes: emotion, cause, pair, and document. We employ separate nodes for emotion clauses and cause clauses, as the information about emotion and causation is typically conveyed using different phrases within clauses. Moreover, we incorporate pair nodes in the graph to represent the causal relationship among emotion clauses and cause clauses. This design ensures a balanced flow of information between clauses and pair nodes. To provide global information, such as topics, we also include document nodes in the graph to serve as hubs for other nodes. Furthermore, we establish five types of edges in the graph to more precisely represent the relationships between nodes:

1) Edges between Clauses (Edge Emotion-Emotion and Edge Cause-Cause): The proposed graph structure incorporates two distinct types of edges between clauses: emotion-emotion and cause-cause [24]. These interconnections guarantee that all emotion and cause nodes are comprehensively linked, enabling each node to exchange contextual information with other pertinent nodes. This design facilitates effective communication and context sharing among the relevant components of the graph.

2) Edges Between Clauses and Pairs (Edge Emotion-Pair and Edge Cause-Pair): This study also defines two types of edges between clauses and pairs: emotion clause-pair and cause clause-pair [24]. These connections enable all pair nodes to directly connect to the corresponding emotion and cause nodes. They serve as the primary mechanism for pair nodes to interact with clause nodes, facilitating the transmission of causal information from emotion and cause nodes to pair nodes. Furthermore, pair nodes and these linkages can be utilized by emotion and cause nodes for communication.

3) Edges between Document and Other Nodes (Document-Other Edges): The document node forms connections with all other nodes, enabling the transmission of global information about the entire document to these nodes [24]. This mechanism serves a dual purpose: it facilitates the dissemination of pertinent information while effectively filtering out noise from disconnected nodes.

Furthermore, each node class incorporates self-loop edges, which contribute to the preservation of the node's features during interactions. Subsequently, the features of each node's neighbors are integrated using an RGCN [29] on a heterogeneous undirected graph. The initialization of the emotion nodes and cause nodes is set using clause representations as follows:

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

where $H_E^{(0)}$ represents an emotion node, while $H_C^{(0)}$ represents a cause node. Subsequently, the pair node is initialized with the pair representation:

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

Additionally, the document nodes are initialized by the average the representations of all clauses within the pooled document:

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

Following graph construction, we apply the RGCN to the generated graph. Each node u is characterized by the following equation:

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

$$t_u^{(l+1)} = s_u^{(l)} + \sum\nolimits_{r\in R} \sum\nolimits_{v\in N_r(u)} \frac{1}{|N_r(u)|} W_r^{(l)} h_v^{(l)} + b_r^{(l)} \tag{9}$$

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

where R represents various edge types, l is the RGCN's l-th layer, $W_s^{(l)}$, $b_s^{(l)}$, $W_r^{(l)}$, and $b_r^{(l)}$ are the learnable parameters, $N_r(u)$ is the neighbor of node u connected to the edge of type r. $ReLU$ is the Rectified Linear Unit activation function.

As the final step, the last hierarchical representation of all nodes, obtained after θ layer of convolutional computation, is utilized as their ultimate feature representation.

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

3.3 Task Alignment Mechanism

To mitigate the label prediction inconsistency between the emotion-cause pair extraction task and the assistant tasks, this study employs a task alignment mechanism. This approach learns the label distance between emotion-cause pair extraction and the combination of emotion extraction and cause extraction during the training phase. By increasing the information interaction between tasks, the model achieves improved label prediction consistency.

After obtaining the representations of all nodes, we apply a multilayer perceptual machine (MLP) to predict emotion-cause pairs.

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

where the MLP consists of two fully connected layers and the $ReLU$ activation function among them, and σ represents the sigmoid activation function.

To evaluate the performance of ECPE, we employ a binary cross-entropy loss function to calculate the loss:

$$\mathcal{L}_p = -\sum_i^N \sum_j^N y_{ij}^p \log \left(\hat{y}_{ij}^p \right) \tag{13}$$

where y_{ij}^p represents the truthful label.

To enhance the efficacy of clause nodes in learning emotion and cause information, we introduce two assistant tasks [26]: CE and EE. These tasks are designed to assist clause nodes in capturing essential contextual information within clauses. The probabilities for these tasks are computed as follows:

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

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

where $\hat{y}_i^e$ and $\hat{y}_j^c$ denote the probabilities of expressing the emotion and cause clauses respectively, σ is the sigmoid activation function. W_e, W_c, b_e, and b_c are learnable parameters.

Two ancillary tasks experience corresponding losses:

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

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

where y_i^e and y_j^c represent the truthful labels.

As previously mentioned, the predictions from EE and CE may not align with those from ECPE. This discrepancy can lead to emotions identified by ECPE not being recognized by EE, hindering model optimization. To address this problem, we introduce an alignment mechanism that synchronize the prediction scores of ECPE with those of the assistant tasks during training. The process of generating the assisted pair score is shown in Fig. 2. Initially, we utilize emotion score $\hat{y}_i^e$ and cause score $\hat{y}_j^c$ to calculate the preliminary score for the assisted-pair $\sqrt{\hat{y}_i^e \hat{y}_j^c}$. It is important to note that the predictions based on EE and CE do not permit the formation of pairwise matched causal relationships. Consequently, we computed the assisted-scores $\tilde{y}^p_{ij}$ for emotion-cause pairs as follows:

$$\tilde{y}^p_{ij} = \alpha_{ij}\sqrt{\hat{y}^e_i\hat{y}^c_j} \tag{18}$$

where α_{ij} $\left(0 \le \alpha_{ij} \le 1\right)$ is a soft mask score for an assisted-pair that reduces the fraction of assisted-emotion-cause pairs in the pre-assisted-pair score. The value of α_{ij} is determined by the following equation:

$$t_{ij} = \frac{\left(v^e_i\right)^T v^c_j}{\sqrt{d}} \tag{19}$$

$$\alpha_{ij} = \frac{exp\left(t_{ij}\right)}{\sum_j^N exp\left(t_{ij}\right)} \tag{20}$$

where v^e_i and v^c_j are obtained by linear functions of E_i and C_j, respectively. d denotes the dimensions of v^e_i and v^c_j.

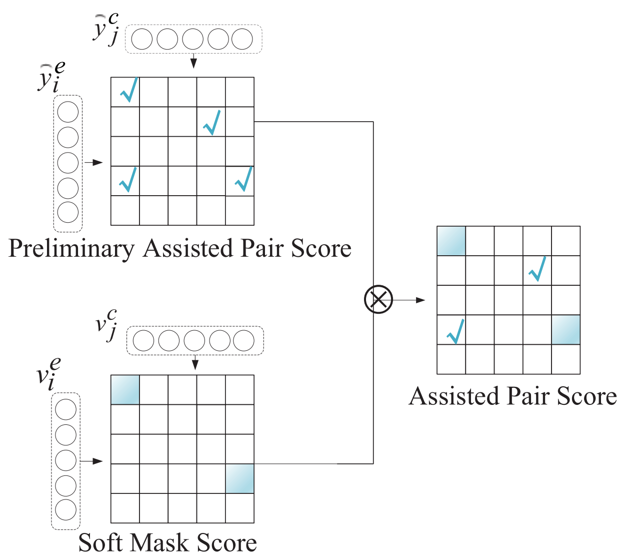

Figure 2: Generation of assisted pair score in the task alignment mechanism. The "√" indicates candidate emotion-cause pairs. The blue grid indicates blocked pairs

The difference among the assisted emotion-cause pair score $\tilde{y}^p_{ij}$ acquired from EE and CE and the actual emotion-cause pair score $\hat{y}^p_{ij}$ obtained from ECPE, is minimized using KL Divergence:

$$\begin{aligned}\mathcal{L}_{KL} &= \frac{1}{2}\sum_i^N\sum_j^N\left(KL\left(\tilde{y}^p_{ij}||\hat{y}^p_{ij}\right) + KL\left(\hat{y}^p_{ij}||\tilde{y}^p_{ij}\right)\right)\\ &= \frac{1}{2}\left(\sum_i^N\sum_j^N\left(\tilde{y}^p_{ij}\log\left(\frac{\tilde{y}^p_{ij}}{\hat{y}^p_{ij}}\right) + \hat{y}^p_{ij}\log\left(\frac{\hat{y}^p_{ij}}{\tilde{y}^p_{ij}}\right)\right)\right)\end{aligned} \tag{21}$$

3.4 Optimization

The model is trained using a cross-entropy loss function. The final loss function comprises ECPE and a weighted sum of EE, CE, and task alignment mechanisms. The total loss of in model is represented by the sum of the weights of $\mathcal{L}_p$, $\mathcal{L}_e$, $\mathcal{L}_c$, and $\mathcal{L}_{KL}$:

$$\mathcal{L} = \mathcal{L}_p + \lambda(\mathcal{L}_e + \mathcal{L}_c + \mathcal{L}_{KL}) \tag{22}$$

where λ is the hyperparameter.

4 Experimental Results and Analysis

This section employs publicly available datasets to evaluate the efficacy of the proposed JFTA model for ECPE using Relational Graph Convolutional Networks (RGCNs) and task alignment mechanisms. The following subsections present the experimental methodology, results, and an ablation study to assess the model's performance and key components.

4.1 Dataset

We evaluated the proposed model using the ECPE corpus described by Xia et al. [1], which is derived from the Chinese Affective Causes Corpus [8]. Table 2 presents the key details of this benchmark dataset. The corpus consists of 1945 Chinese documents sourced from Sina Metropolis Newspaper, including 1746 documents with one emotion-cause pair, 177 documents with two emotion-cause pairs, and 22 documents with more than two emotion-cause pairs. For the evaluation, we randomly selected 90% of the data for training and 10% for testing, employing 10-fold cross-validation. The primary task is ECPE, with two subtasks: EE and CE, consistent with prior research [3–7]. We assessed the model's performance using precision (P), recall (R), and F1 score (F1) metrics.

Table 2: Statistical data on datasets

Item	Number
Document with one emotion-cause pair.	1746
Document with two emotion-cause pairs.	177
Document with more than two emotion-cause pairs.	22

4.2 Implementation Details

The pre-trained BERT model was employed as the embedding layer, with the hidden layer size set to 768. The default parameter settings for BERT-base-Chinese were utilized. The hyperparameters α and θ were assigned values of 3 and 4, respectively, for the training parameters. The value of 1.2 was selected for λ. The AdamW optimizer [30] was applied during the training process, with a learning rate of 1e−5. To mitigate overfitting, a dropout of 0.2 was incorporated into the training process [36]. The batch size for the experiments was maintained at two, and the training was conducted for thirty-five epochs. All experiments were performed using the PyTorch-1.9.0 platform on an Ubuntu 18.04 system, with Intel Xeon Platinum 8255C CPUs employed in the hardware configurations.

Baseline Models

The efficacy of the proposed model is assessed by comparing it to the following baseline approach:

1) ECPE-2Steps [1] (2019) employs a two-step strategy for extracting emotion-cause pairs. It involves three distinct models with varied learning configurations: Indep, Inter-CE, and Inter-EC.

2) ECPE-2D [4] (2020) introduces a novel method that seamlessly integrates the representation, linking, and prediction of emotion-cause pairings using an end-to-end approach based on a window-constrained 2D converter. However, the effectiveness of this integration relies significantly on the manually selected window size.

3) ECPE-MLL [25] (2020) employs a sliding window mechanism to simplify the ECPE task. To enhance the robustness of the extraction process, this technique simultaneously performs cause-centered emotion extraction and emotion-centered cause extraction by integrating two joint frameworks.

4) RankCP [26] (2020) addresses the ECPE problem from a ranking perspective, employing kernel-based relative position embedding and graph attention networks to enhance the representation and ranking of emotion-cause pairs.

5) PTN [27] (2023) is characterized by the application of a pairwise labeling framework, facilitating the exhaustive and uniform extraction of emotion-cause pairs.

6) MGSAG [28] (2022) is a graph-based model that uses fine-grained semantic-aware graphs to investigate the dependencies between clauses and keywords. Additionally, it models the relationships between clauses by employing coarse-grained semantic-aware graphs.

7) MMN [37] (2023) proposes the Modularized Mutuality Network (MMN) to capture reciprocity in relationships. The MMN architecture consists of three key components: Interposition-aware Encoders, a Mutual Refinement Module, and a Bi-regularized Pairwise Predictor. The Interposition-aware Encoders account for the relative positioning of elements, while the Mutual Refinement Module facilitates the reciprocal refinement of representations. Finally, the Bi-regularized Pairwise Predictor leverages bidirectional regularization to predict reciprocal relationships accurately. This modularized approach effectively addresses the challenges associated with modeling reciprocity in complex systems.

8) GANU [38] (2023) proposes a model that utilizes multi-granularity information, including word-, clause-, and document-level data. The architecture consisted of a foundational encoder, followed by a multi-head attention module designed to process affective and causal cues. Additionally, it incorporates a graph attention network featuring a cross-graph co-attention mechanism. The final component is a neural classifier that makes predictions based on the processed data.

9) GAT-ECPE [39] (2024) introduces a knowledge-guided graph attention network to facilitate interactions across various activities. The model's guiding principle is inter-sentence dependency graphs, which enable the aggregation of features between pairs of phrases. This approach leverages the relational information encoded in the dependency graphs to enhance the extraction of emotion-cause pairs.

4.3 Main Result

Table 3 presents the results of the ECPE task and its two subtasks, EE and CE, after 130 h of model training. Performance is evaluated using precision (P), recall (R), and F1 score (F1). JFTA demonstrates significant advantages over previous approaches, particularly in the primary ECPE task and the secondary CE task. We attribute the key role in information interaction to JFTA's joint encoding approach and alignment mechanism, which enable bidirectional information flow and balance between pairs, clauses, and tasks. Our approach achieves a 1.03% F1 improvement on the dataset compared to MMN, the best-performing baseline. While MGSAG excels in EE by utilizing an emotion lexicon, its poor CE performance leads to a decrease in overall ECPE performance, revealing an imbalance between the tasks. CE is generally more challenging, as sentiment expressions often contain a single keyword, whereas cause expressions involve multiple words and require deeper textual understanding. For CE, our method achieves a 0.62% F1 improvement. The enhancements in CE and ECPE are primarily attributed to our joint feature encoding approach and task alignment mechanism, which effectively model specific feature information, capture interaction information between features, and balance label prediction information among the EE, CE, and ECPE tasks. The performance on the ECPE task is improved overall as a result of this balance.

Table 3: Comparison of results between our proposed method and existing studies with the same dataset

Model	EE			CE			ECPE		
	P	R	F1	P	R	F1	P	R	F1
Indep	83.75	80.71	82.10	69.02	56.73	62.05	68.32	50.82	58.18
Inter-CE	84.94	81.22	83.00	68.09	56.34	61.51	69.02	51.35	59.01
Inter-EC	83.64	81.07	82.30	70.41	60.83	65.07	67.21	57.05	61.28
ECPE-2D	86.27	92.21	89.10	73.36	69.34	71.23	72.92	65.44	68.89
ECPE-MLL	86.08	91.91	88.86	73.82	79.12	76.30	77.00	72.35	74.52
RankCP	91.23	89.99	90.57	74.61	77.88	76.15	71.19	76.30	73.60
PTN	85.09	91.59	88.19	74.87	77.90	76.31	76.41	72.40	74.30
MGSAG	92.08	92.11	92.09	79.79	74.68	77.12	77.43	73.21	75.21
MMN	90.37	87.85	89.07	79.01	75.54	77.21	76.11	73.96	75.02
GANU	86.34	89.72	87.91	74.10	74.64	74.33	72.95	71.02	71.89
GAT-ECPE	90.98	91.03	90.99	76.17	78.72	77.34	72.65	77.52	74.92
JFTA	90.13	88.80	89.44	78.78	77.01	77.83	76.41	75.81	76.05

4.4 Ablation Study

This ablation study aimed to validate the efficacy of the task alignment mechanism and the significance of edges and nodes in heterogeneous graphs with diverse relationships. Table 4 presents the results of the ablation analysis for edges and nodes in heterogeneous networks with various relations, while Table 5 demonstrates the outcomes of the task alignment mechanism.

Table 4: Results of the ablation study of heterogeneous undirected graphs

Approach	ECPE	EE	CE
JFTA	76.05	89.44	77.83
-w/o E-C-C	75.09	88.78	77.10
-w/o E-C-P	75.01	88.75	76.75

Table 5: Results of the ablation study of the task alignment

Approach	ECPE	EE	CE
JFTA	76.05	89.44	77.83
-w/o ECPE→ assistant tasks	75.37	88.66	77.36
-w/o assistant tasks→ ECPE	75.24	88.55	77.26
-w/o KL	74.85	89.07	77.24

4.4.1 Effects of Heterogeneous Undirected Graphs

-w/o E-C-C: To replace the cause-cause and emotion-emotion clauses (-w/o E-C-C), we utilize an edge type. The removal of these two types of edges significantly diminishes our model's performance on the CE and EE tasks. Consequently, this deterioration leads to a decline in the overall performance of the ECPE task. This alteration disrupts the equilibrium between EE and CE, causing the framework to prioritize EE while neglecting CE, which is the primary objective among the three goals. Our analysis of the experimental results in Table 4 reveals that the elimination of E-C-C results in a 0.96% decrease in the F1 score of ECPE. Moreover, a substantial performance decline occurs in both emotion extraction and cause extraction, underscoring the importance of emotions or causes nodes to exchange contextual information with other associated nodes.

-w/o E-C-P: We remove the edges of the emotion clause-pair and the cause clause-pair (-w/o E-C-P) and replace them with another edge. Table 4 demonstrates that this modification leads to a more significant performance deterioration in the ECPE task compared to the removal of clause-clause-edges (-w/o E-C-C), with a 1.04% decrease in the F1 score for ECPE. The elimination of E-C-P edges renders emotion and cause extraction more independent, complicating the extraction of emotion information from emotion clauses and cause information from cause clauses. This lack of distinction hinders the model's ability to effectively extract and utilize causal information, emphasizing the importance of pair node and clause node interactions in transferring causal information from emotion and cause nodes to pair nodes.

4.4.2 Effects of Task Alignment Mechanisms

This study commenced by examining the influence of the directionality of the task alignment mechanism on performance. The initial approach involved utilizing unidirectional alignment to modify the predictions for the ECPE task and its two assistant tasks: emotion extraction and cause extraction. The results revealed a decline in performance across all three tasks when employing unidirectional alignment. Specifically, the F1 scores, which serve as a measure of a test's accuracy, were found to be lower for each task under these conditions.

Moreover, we investigated a scenario in which the task alignment mechanism was completely eliminated, corresponding to a bidirectional alignment setting. In this context, the F1 scores for all three tasks—ECPE, EE, and CE—underwent a considerable decline. Remarkably, the ECPE task demonstrated the most profound decrease in F1 scores, highlighting the critical role of task alignment in achieving optimal performance in emotion-cause pair extraction.

These findings emphasize the paramount significance of inter-task label space alignment within our model. The marked decrease in performance, especially in the ECPE task, when the alignment mechanism is modified or eliminated, corroborates the imperative of preserving a resilient bidirectional alignment. This bidirectional alignment plays a pivotal role in guaranteeing the efficacious integration and coordination of predictions across tasks, consequently elevating the overall model performance.

4.5 Hyperparameter Discussion

This section examines the influence of the hyperparameter values θ and λ.

4.5.1 Effects of the Value of θ

We analyze the effect of different θ values on the performance of the ECPE task, as shown in Fig. 3. The experimental results demonstrate that the model achieves optimal performance on the ECPE task when the number of RGCN layers is set to 4. However, the model's performance deteriorates when the θ values are either above or below 4. This phenomenon may be attributed to excessive smoothing [33–35]. Specifically, when the value of θ surpasses 4, it implies an increase in the number of RGCN layers. This can result in the over-mixing of features from different node classes, which diminishes the discriminative capability and leads to a degradation in ECPE performance. Furthermore, the incorporation of additional layers introduces a greater number of trainable parameters, potentially leading to overfitting issues.

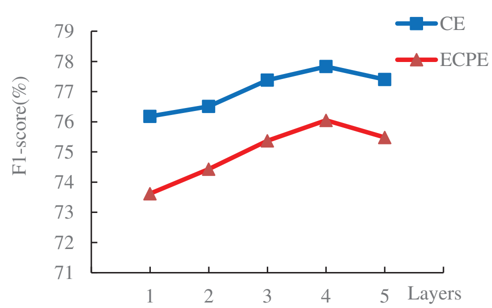

Figure 3: The influence of different θ

4.5.2 Effects of the Value of λ

The final loss function employed in training the model is a compound of multiple loss functions, including emotion-cause pair extraction loss, emotion extraction loss, causes extraction loss, and task alignment loss, each assigned a corresponding weight. Consequently, determining the optimal weights for maximum model performance presents a challenge. To address this, we conducted hyperparametric experiments to exploring the effects of different loss weights by setting the value of λ to 0.8, 1.0, 1.2, and 1.4. This section assesses the impact of various lambda values on the model's performance experimentally. Fig. 4 illustrates the experimental outcomes, clearly indicating that the model achieves optimal performance on CE and ECPE when λ is set to 1.2. However, when the λ value deviates from 1.2, either higher or lower, the model's performance deteriorates significantly. Based on these findings, we selected a λ value of 1.2 for our model.

Figure 4: The influence of different λ

4.5.3 Case Study

Table 6 presents a comparative case study analysis of the prediction outcomes generated by the MGSAG model and our proposed model. The objective is to elucidate the advantages of the JFTA model through a direct comparison of the results obtained from both approaches.

Table 6: A case study experiment was conducted using MGSAG and our proposed model. In the table, cause clauses are highlighted in green, while emotion clauses are denoted in yellow. Clauses that serve the dual purpose of representing both causes and emotions are indicated in blue

Document	Predicted pairs		
	Gloden	MGSAG	JFTA
(c1) The reporter was informed by Xinqiao Hospital of the Third Military Medical University on 16th,	(c5, c4)	(c5, c4)	(c5, c4)
(c2) that uremic patient Cheng Xia risked her life to give birth to a 5 kg healthy baby boy,	(c6, c6)	(c5, c6)	(c6, c6)
(c3) I have this life is given by my mother,			
(c4) and now I have a baby too,			
(c5) I'm so lucky,			
(c6) and thank all those who have helped me,			
(c7) still lying in the hospital bed of Cheng Xia,			
(c9) said in a weak voice.			
(c1) 29th afternoon,	(c4, c3)	(c9, c8)	(c4, c3)
(c2) a number of citizens reflected in the newspaper,			
(c3) there is a woman standing on the electric tower tottering,			
(c4) the villagers and passers-by were extremely anxious,			
(c5) everyone for her safety a sweat,			
(c6) the police and firefighters rushed to the scene,			
(c7) the woman has climbed to the top of the high-voltage towers,			

The first example's document comprises two emotion-cause pairings: one pair with identical emotion and cause clauses, and another pair consisting of (c5, c4). The MGSAG model identifies two pairs: (c5, c4) and (c5, c6), with the latter being an erroneous identification. However, our model accurately detects both genuine emotion-cause pairs, indicating its superior performance in capturing the causality between emotions and their corresponding causes.

In the second example, a pair of emotion-cause (c4, c3) exists within the document. However, the MGSAG model inaccurately identifies (c9, c8) as an emotion-cause pair. This error may stem from the MGSAG model's imprecise selection of context window clauses, resulting in an incorrect extraction of the emotion-cause pair. Conversely, our approach demonstrates superior accuracy in causal and contextual reasoning by successfully identifying the correct emotion-cause pair.

5 Conclusion

This publication examines the work on ECPE. We propose a model that simultaneously encodes features of emotion-cause pairs and clauses to obtain causal information. This approach addresses two key issues in ECPE research: the imbalance of feature interactions between pair and clause encoders, and the lack of shared interrelated information between the ECPE task and assistant tasks. To capture deeper semantic information and enhance ECPE performance, we employ a task alignment technique that minimizes the labeling discrepancy between the ECPE task and assistant tasks. Experiments conducted on the ECPE benchmark data confirm the effectiveness of our method, with results showing an F1 score of 76.05% for ECPE, a 1.03% improvement over the state-of-the-art method, and an F1 score of 77.83% for CE, a 0.49% improvement over the state-of-the-art method. To avoid introducing noise, future research will concentrate on adapting the model to different languages and domains and dynamically incorporating contextual information depending on the causal requirements of emotion-cause pairs.

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