

Overview and future prospects of emotion-cause pair extraction

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Abstract. Emotion-Cause Pair Extraction (ECPE) is a crucial task in sentiment analysis, aiming to analyze emotions expressed in text and their underlying causes in a reasonable, correct, and efficient manner. It primarily addresses challenges arising from human-machine dialogue and finds application in big data analysis for processing emotion-related text content. The main objective of ECPE is to extract emotion-cause pairs. Currently, this task is evolving rapidly and can be applied to both single-modal and multimodal scenarios. Its core mission remains focused on extracting, combining, and screening emotion-cause pairs. The primary research question is how to enhance the accuracy of ECPE further. This paper presents a comprehensive review of existing literature, summarizes the current development process of ECPE, and envisions the future direction of this task.

Keywords: Emotion-Cause Pair Extraction, Multimodal Learning, Conversation-Based Emotion-Cause Pair Extraction (ECPE), Sentiment Analysis, Machine Reading Comprehension.

1. Introduction

In the field of natural language processing, the classification of human emotions has been considered an important and challenging problem for a very long time. Due to the prevalence of emotional features in sentences, a significant number of tasks involving text analysis require emotion classification. Take, for example, the compilation and examination of user feedback on popular websites, as well as reviews of films and other media. This type of data is extremely important to the AI's ability to comprehend and improve the quality of human life. Therefore, one of the most important tasks for integrating AI into human civilization is the analysis of human emotions that are embedded in language. However, there is a disconnect between the methods that are being used and the requirements of the program.

Emotion extraction (EE) from written text was the initial goal of the researchers who started looking into this problem many years ago when they began their investigation. However, simply extracting emotions was not adequate for the majority of applications, as these applications required additional information about the emotions, such as their sources. As a result, the emotion cause extraction (ECE) task was proposed, and its earliest missions date back to the year 2010. Early attempts at emotion cause extraction had as their primary focus the determination of the factors that contributed to particular feelings [1]. The researchers Lee et al. concentrated on isolating feelings and the factors that correspond to those feelings in pairs [1]. Nevertheless, complicated texts frequently involve a number of different feelings and a number of different reasons, which may not line one-to-one, and sometimes the author

will conceal the causes. As a direct consequence of this, the Emotion-Cause Extraction (ECE) task eventually morphed into the Emotion-Cause Pair Extraction (ECPE) task.

The previous ECE assignment has been transformed into the current ECPE endeavor. When dealing with large-scale datasets, the typical ECE tasks required emotions to be specified manually, which made the procedure inefficient. Ding and Xia proposed a more refined ECPE assignment to be carried out in the year 2020 in order to overcome this issue. In accordance with the typical notion of natural language processing (NLP) tasks, the original solutions for ECPE involved step-by-step processing. Specifically, emotion phrases and cause clauses were individually extracted, merged, and filtered in order to create the proper emotion-cause pairings. However, this two-step process was plagued with substantial errors, which led to poor accuracy and made it difficult to enhance performance. As a consequence of this, some researchers continued to work on perfecting the two-step approach, while others turned their attention to research methodologies that cover the entire process. These innovative approaches utilized a wide variety of methodologies, including sequence marking, graphs, neural networks, and graph neural networks, each of which had their own distinct set of benefits and drawbacks. In addition to that, researchers have also investigated ECPE tasks that are based on dialogue.

This paper aims to summarize the progress made in ECPE. Through the examination of crucial literature, we seek to identify the future development and application directions of ECPE. The significance of this paper lies in its effort to compile and organize the context, facilitating subsequent researchers and interested parties in comprehending existing research outcomes and the latest advancements in this field, providing valuable insights and guidance.

2. Related Works

In recent times, the ECPE task has come to be regarded as an important research topic, which has attracted a large amount of attention. We have separated the existing ECPE approaches into two categories: single-modal and multi-modal methods, which are also referred to as text-based ECPE and dialogue-based ECPE, respectively. The majority of methods to the burgeoning field of research known as dialogue-based ECPE build upon the foundations established by text-based ECPE activities. Text-based ECPE tasks can be roughly categorized into three types: two-step, end-to-end, and the machine reading comprehension (MRC) technique.

The two-step method, which demonstrates clear logic and excellent efficiency, was the initial suggestion. It has served as the basis for numerous later improvement versions since its introduction. Nevertheless, it has cascading failures during the transitions between steps. In order to find a solution to this problem, the end-to-end technique was developed.

The end-to-end method makes use of a number of models for both the pre-training and the actual training, and the training itself cannot be split up into separate steps. On the other hand, it has an increased performance and a pretty high level of accuracy.

On a different path, the MRC method and QA method were explored, attempting to transform the ECPE task into a mature MRC task and utilize MRC methods to solve ECPE.

Text-based ECPE activities have developed throughout time, resulting in solutions that are both more diversified and more effective. Researchers have been talking about the ECPE task based on dialogue material in order to broaden the scope of this work so that it can be applied to a larger variety of contexts. ECPE activities that are based on dialogue, as opposed to text-based ECPE tasks, function in multimodal contexts, which adds an additional layer of complication to the task. But in addition to that, it broadens the applicability of ECPE.

In addition, an important study that deserves to be mentioned is one in which researchers constructed an English-based dataset in order to investigate sentiment analysis activities carried out in a wide variety of languages all over the world [2]. The researchers wanted to make significant advances in the processing of the English language, and they were successful to a noteworthy degree.

3. Emotion-Cause Pair Extraction

3.1. Text-based ECPE tasks

3.1.1. Two Step Method.

The earliest ECPE task was proposed in 2019 [2]. At that time, the simplest two-step classification method was employed. The first step involved extracting emotions and causes from the text, while the second step focused on matching and screening the extracted emotions and causes to find the correct emotion-cause pairs. However, this method introduced cascading errors that accumulated during step-by-step extraction, significantly affecting results.

To address the ECPE problem while still using a two-step treatment method, some researchers explored alternative approaches. For instance, Chen X et al. reprogrammed the two-stage task and integrated reinforcement learning methods [3]. In this setup, the first stage aims to find the emotion clause, while the second stage retrieves the cause for the sentiment clause. Importantly, the two-stage task exhibits strong correlation, reducing the cascading errors associated with the traditional two-step method

To further enhance sentiment analysis within the existing two-step processing framework, Xia et al. proposed a novel end-to-end approach known as ECPE-Two-Dimensional (ECPE-2D) [4]. They introduced a fresh concept of representing emotion-cause pairs in a two-dimensional scheme. Below, we will provide a brief overview of the end-to-end approach.

3.1.2. End-to-End Method.

Sequence Label-Based Method: Building upon the end-to-end model, researchers shifted their mission objectives. Cheng Z et al. proposed a unified sequence labeling method [5] that enables the extraction of emotion-cause pairs through a single pass of sequence labeling. This method broadened the development path of ECPE. The sequence labeling method utilizes a special set of unified labels, and they designed a unified target-oriented sequence-to-sequence model to ensure the normal functioning of the unified label model.

In the context of sequence labeling-based extraction methods, further experiments were conducted by Chuang Fan et al., who employed label serialization [6] for extraction. They extended the sequence labeling task to multitasking by designing a multi-task sequence tagging framework. This framework incorporates distance tagging for encoding and improves information interaction between the two auxiliary tasks (emotion extraction and cause extraction). The results from the two auxiliary tasks are used to summarize deviations to enhance the final effect.

Method Based on Supervised Learning and Unsupervised Learning: Supervised learning, a common machine learning training method, is also applied to ECPE. In 2023, Guimin Hu et al. discovered the potential of sentiment prediction and utilized it to enhance the efficiency of emotion-cause pair extraction, introducing an end-to-end ECPE method called Emotion Prediction Oriented ECPE (EPO-ECPE) [7]. They employed a synchronization mechanism with true-pair-supervised and false-pair-supervised methods to reinforce the strong dependence between sentiment prediction and the extraction of emotion-cause pairs, achieving favorable results. Unsupervised learning also proves effective, as exemplified by contrastive learning. In 2022, Zhang S et al. proposed a novel model named Contrastive Learning with Adversarial Samples for Emotion-Cause Pair Extraction (CL-ECPE) [8] to improve extraction accuracy through contrastive learning and adversarial training to obtain contrasting features in the text.

Graph-Based Method: Graphs are widely used models capable of solving various practical problems. To address issues related to position-insensitive data in existing methods, some researchers proposed the Multi-Granularity Semantic Aware Graph model (MGSAG) [9], which combines statement characteristics across different granularities. This effectively eliminates the influence of position insensitivity on sentiment analysis.

Neural Network-Based Method: Neural networks have proven essential in various machine learning tasks, with several researchers employing them to address the ECPE problem. One key area of investigation involves the attention mechanism in neural networks. In 2023, Siyang Z et al. introduced a mixed attention mechanism [10]. They utilized the BERT method in pre-training to obtain global and local characteristics of the text through encoding Bi-GRU and LSTM, respectively, and fused them to enhance the integrity of the semantic features of the text.

Additionally, convolutional neural networks, often known as CNNs, were investigated. The SEE-3D model was developed as a consequence of a method that researchers presented utilizing 3D Convolutional Neural Networks to measure emotional intensity and similarity [11]. This was done in an effort to increase the accuracy of ECPE. By merging similar emotional traits between neighboring documents, they were able to continuously enhance the effectiveness of the model. Additionally, during the extraction step for emotion-cause pairs, successful strategies such as frequency modulation utilizing BERT's method and a new pre-training method referred to as Emotion-Cause Relationship between Clauses Prediction (ECRP) were proposed by Rui Fan et al. The work of data extraction is made easier by first decomposing the information into clause pairs. In addition, Wu Z and colleagues came up with a novel framework that they called the Pairwise Tagging Framework (PTF). Its purpose was to achieve global optimization by integrating all subtasks by means of neural networks [13]. This enabled the framework to effectively train previously established methodologies and models to a greater extent.

Graph Neural Networks Based Method: Graph attention networks (GATs) are essentially graph neural networks and have been widely used with positive outcomes in enhancing existing emotion-cause pair extraction models. Chen S and Mao K proposed a cross-graph co-attention mechanism for the extraction of emotion-cause pairs [14], utilizing a cross graph containing emotion and cause graphs. This cross-graph co-attention mechanism facilitates multi-granular text analysis. Cao Q et al. introduced a textual Emotion-Cause Pair (ECP) causal relationship detection method (GAT-ECP-CD) fused with graph attention network (GAT) [15]. In this approach, a Bi-directional Long Short-Term Memory (Bi-LSTM) network is combined with GAT pre-training to better capture features of clauses in the document, which are then processed by GAT.

Emotion-Cause Pair Feature Extraction model (ECPFE) was designed by Fan C et al. [16] using Bi-LSTM, which learns valuable features in semantics, enhances learning skills, and increases location awareness. The BERT model and the graph attention network are combined in this approach in order to improve the representation learning ability of emotion-cause pair relationships. In addition, Graph Convolutional Neural Networks (GCNNs), which were inspired by convolutional neural networks, have powerful skills in processing irregular data, which is beneficial for the complicated and irregular texts in ECPE. A unique Pair-Based Joint Encoding (PBJE) network was proposed by Liu J et al. [17], which generates pairs and clause features simultaneously in order to describe the causal relationship in phrases. They make use of GCNN in a flexible manner in order to capture the relationship that exists between these pairs and clauses, which considerably improves the overall performance and semantic feature capture.

Multitasking Model Based Method: Earlier auxiliary jobs concentrated their attention largely on the extraction of feelings and the extraction of causes. ECPE's effectiveness was gradually increased as a result of multitasking learning, which saw ongoing improvements in multitasking ability. A filtering model and a mutual-aid single-task model were proposed by Shi J et al. to improve the extraction of emotion-cause pairings [18]. This was accomplished by improving two auxiliary tasks. By attaching clause position information, they were able to improve composite jobs. In a similar vein, Chen F. and colleagues came up with the idea of a recurrent synchronization network [19] to improve the interaction between auxiliary activities. The goal of this network was to promote synchronization and interactivity between the three auxiliary tasks that were already in place, so effectively boosting collaboration among numerous tasks. Shang X and colleagues came up with the idea for a new relationship network that they called the Modularized Mutuality Network (MMM) [20]. This network would capture and increase the interoperability of many jobs, which would lead to improved performance.

Deep Networks Based Method: Deep networks have been widely used to solve various problems, but most studies have been limited to modeling the relationship between affective clauses and cause clauses, lacking exploration of the statistical dependence between them. Guimin Hu et al. introduced the comprehensive concept of mutual information (MI) [21], finding MI through information differences between affective-cause pairs and emotion-non-cause pairs and identifying the probability distribution. This approach transforms the ECPE problem into a statistical problem, yielding promising results for accuracy. Additionally, the use of special encoders in deep networks proved beneficial. Wei Fan et al. improved the coding method, focusing on sequential information between the emotion clause and the cause clause through a three-level long-short term memory (LSTM) network [22].

3.1.3. MRC Method and QA Method

Machine reading comprehension (MRC) involves machines answering questions based on given text and is a classic subject with a wide range of applications. During the study of the ECPE topic, researchers discovered that converting ECPE tasks into MRC tasks is highly cost-effective. The MRC method is relatively mature and efficient. Chang T et al. utilized the ECPE text as an input to the MRC and employed pre-trained models for processing [23]. The question "which sentences cause emotions?" was posed in this approach, utilizing an MRC model with superior performance and exceptional capabilities at this stage.

MRC tasks are often related to Question-Answer (QA) and human-machine dialogue. While MRC typically employs a single round of question and answer to address problems, QA involves multiple rounds. Consequently, researchers have either attempted to improve the MRC method or directly employed the QA method for multi-round processing. In recent studies, Cheng Z et al. proposed a new paradigm for the ECPE task, combining the strengths of the MRC and QA methods, and casting the task as a two-turn machine reading comprehension (MRC) task [24]. Similarly, Zhou C et al. introduced reading tasks, such as the document-level machine reading comprehension (MRC) task, and the Multi-turn MRC framework with Rethink mechanism (MM-R) [25]. Furthermore, Nguyen H et al. attempted to transform the sentiment analysis task into a question-answering task, utilizing the BERT method to address it, achieving favorable results [26].

3.2. Conversation-Based ECPE Tasks

Apart from the existing research directions, there is another intriguing avenue to explore, which involves the ECPE problem in multimodal situations [27]. In essence, it pertains to the analysis of emotion-cause pairs in dialogues. This presents a unique question unlike regular text-based queries. Building upon the existing ECPE task between documents, Wei Li et al. sought to combine it with the conversational sentiment analysis task, giving rise to a new task: emotion-cause pair extraction in conversations (ECPEC) [28]. They even developed a new dataset named Conv-ECPE and proposed a novel two-step analysis framework. Similarly, in the context of ECPE research within conversations, some researchers argue that the existing methods are too simplistic to extract as many emotion-cause pairs as possible. In response, Soyeop Yoo et al. introduced a label-based emotion-cause pair extraction model applied to ECPEC using the beginning-inside-outside (BIO) tagging method [29].

The perfecting of emotion-cause pair extraction in conversations could lead to further advancements in AI research. In the current cutting-edge research on Chat-GPT, the processing and analysis of conversational text content play a crucial role, signifying that ECPE issues will continue to hold significant importance. Moreover, existing conversations have been largely confined to text conversations. However, dialogues can be extended to encompass other modalities such as voice or even video. By expanding to audio, video, and real-time dialogues, ECPE can achieve more efficient results, paving the way for new progress in human-machine dialogue. This may well be the future development direction of this topic.

4. Conclusions

In conclusion, the research presented above highlights the significance of Emotion-Cause Pair Extraction (ECPE) in the domain of natural language processing. ECPE plays a crucial role in extracting text information from documents or conversations and has great potential in the field of textual sentiment analysis. Various existing methods and improvements have been discussed, demonstrating the promising nature of textual sentiment analysis research. The research ideas and application value of ECPE will undoubtedly contribute to the advancement of sentiment analysis research. The next pressing research direction should be conversation-based ECPE, which will become a pivotal driver in human-machine conversations.

Furthermore, it is worth noting that previous ECPE studies have predominantly focused on the Chinese language, considering the complexity of Chinese textual sentiment analysis. However, it is expected that this topic will gradually extend to encompass more languages in the future. Thus, research on ECPE in English deserves our attention. Some researchers have already built an English-based dataset to explore sentiment analysis tasks across a broader range of languages worldwide, and we eagerly await further advancements in this direction.

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