

Emotion-Cause Pair Extraction as Question Answering

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Abstract: The task of Emotion-Cause Pair Extraction (ECPE) aims to extract all potential emotion-cause pairs of a document without any annotation of emotion or cause clauses. Previous approaches on ECPE have tried to improve conventional two-step processing schemes by using complex architectures for modeling emotion-cause interaction. In this paper, we cast the ECPE task to the question answering (QA) problem and propose simple yet effective BERT-based solutions to tackle it. Given a document, our *Guided-QA* model first predicts the best emotion clause using a fixed question. Then the predicted emotion is used as a question to predict the most potential cause for the emotion. We evaluate our model on a standard ECPE corpus. The experimental results show that despite its simplicity, our Guided-QA achieves promising results and is easy to reproduce. The code of Guided-QA is also provided.

1 INTRODUCTION

Emotion Cause Extraction (ECE) is the task of detecting the cause behind an emotion given the emotion annotation (Lee et al., 2010; Gui et al., 2016), see Figure 1 (Top). The text was divided into clauses and the task was to detect the clause containing the cause, given the clause containing the emotion. However, the applicability of ECE is limited due to the fact that emotion annotations are required at test time. Recently, (Xia and Ding, 2019) introduced the more challenging Emotion-Cause Pair Extraction (ECPE) task: extracting all possible emotion-cause clause pairs in a document without annotations. Figure 1 (Bottom) shows an example of the ECPE task. The input is a document of six clauses. Clauses c4 and c5 contain emotion with the emotion expressions “happy” and “worried”. The emotion c4 has two causes c3 and c2, the emotion c5 has one cause c6, so the expected output is $\{(c4, c2), (c4, c3), (c5, c6)\}$.

Why cause-effect pair extraction? We argue that *independent* extraction of cause and emotion may be ineffective. For a given document, ECPE models may predict correct cause but incorrect emotion. This makes the output *incomplete*, and subsequent processing steps less reliable (Ding et al., 2020; Wei et al., 2020; Chen et al., 2020; Yan et al., 2021). We make a toy example of two models using the document in

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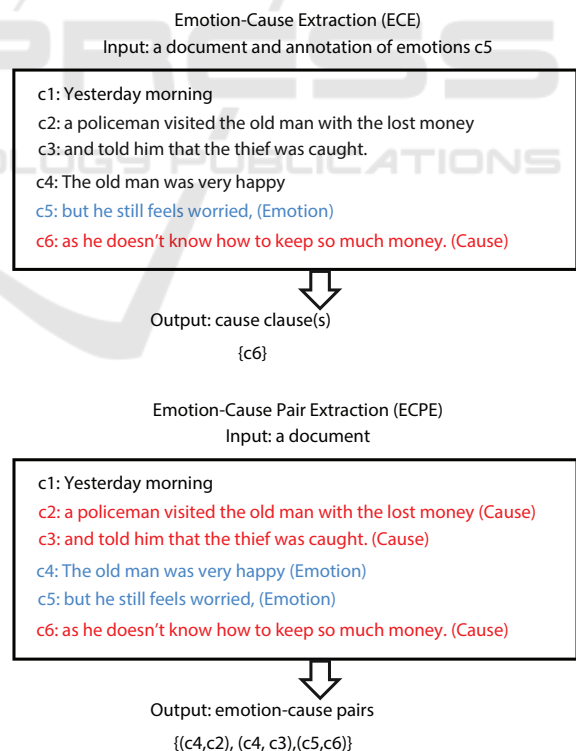


Figure 1: Illustration of ECE and ECPE tasks.

Figure 1. Model-1 predicts (c4,c1) and (c6,c3) as emotion-cause pairs. Its emotion, cause and pair ac-

curacy scores are 0.5, 0.33 and 0.0. Model-2 predicts (c4, c2) and (c6, c1) as emotion-cause pairs. Its emotion, cause and pair accuracy scores are 0.5, 0.33 and 0.33. From the perspective of the pair extraction task, Model-2 is better.

Previous studies addressed the ECPE task by using sequence labeling (Lee et al., 2010; Cheng et al., 2021), clause-level classification (Gui et al., 2016; Ding et al., 2020; Chen et al., 2020), ranking (Wei et al., 2020), or recurrent synchronization (Chen et al., 2022). The methods achieved promising results, yet the use of interaction between emotion and cause clauses is still an open question. For example, c4 and c2 share "the old man" tokens, which refer to "him" in c3; and c5 and c6 share "he", which mentions "the old man" in c2 and c4.

Based on this observation, we introduce a paradigm shift (Sun et al., 2022) for ECPE by using *span extraction*. As far as we know, (Gui et al., 2017) is the first work that uses question answering for emotion-cause detection. However, their work addresses the ECE task only, which requires the annotation of emotion for cause prediction. In contrast, our paradigm shift is applied to the ECPE task, which is more challenging and does not require the annotation of emotion for cause prediction. The paradigm bases on two hypotheses. First, information from emotion clauses can be used to infer cause clauses. Second, emotion and cause clauses share implicit interaction. The design of our model is based on these two hypotheses. For the first hypothesis, we form questions based on emotional information which is used to predict emotion clauses. For the second hypothesis, we used predicted emotion as the guided question for cause prediction. The model is trained by using the BERT-QA architecture (Devlin et al., 2018) in form of SQuAD task (Rajpurkar et al., 2016).

Our paper makes three main contributions.

- We formulate the ECPE task as a QA problem and propose a Guided-QA model to implicitly capture the relationship between emotion and cause clauses, in which the predicted emotion is used as a guided question for cause prediction. The model can capture the implicit interaction between emotions and causes with a simple but effective architecture. To the best of our knowledge, we are the first to address the ECPE task by using QA formulation.
- We evaluate our model on the standard ECPE corpus (Xia and Ding, 2019; Fan et al., 2020). Experimental results show that our approach achieves promising results compared to previous methods.
- We promote the reproducibility (Houghton et al., 2020) by providing the source code of our meth-

ods as well as rerunning publicly available source codes of the compared methods.

2 RELATED WORK

ECE and ECPE Tasks. The ECE task was formulated as sequence-labeling by (Lee et al., 2010) and refined as clause-level by (Gui et al., 2016). Recently, the more challenging ECPE task (Xia and Ding, 2019) has attracted a lot of contributions with several strong methods (Ding et al., 2020; Wei et al., 2020; Chen et al., 2020; Cheng et al., 2021; Chen et al., 2022). For example, (Ding et al., 2020) introduced ECPE-MLL, which uses a sliding window for a multi-label learning scheme. ECPE-MLL extracts the emotion and cause by using the iterative synchronized multitask learning. (Chen et al., 2022) proposed a similar approach, recurrent synchronization network (RSN), that explicitly models the interaction among different tasks. (Wei et al., 2020) presented RankCP, a transition-based framework, by transforming the ECPE problem into directed graph construction, from which emotions and the corresponding causes can be extracted simultaneously based on labeled edges. The PairGCN model (Chen et al., 2020) used Graph Convolutional Networks to model three types of dependency relations among local neighborhood candidate pairs and facilitate the extraction of pair-level contextual information.

We share the purpose of addressing the ECE and ECPE tasks with prior studies, however, instead of using classification or sequence labeling, we address the tasks with a new paradigm shift by using span extraction. It allows us to take into account the implicit interaction between emotion and cause clauses and to design a simple but effective BERT-based model for ECE and ECPE.

(Bi and Liu, 2020) derived a span-based dataset and formulated a new ECSP (Emotion Cause Span Prediction) task from (Xia and Ding, 2019) but it has not attracted much attention. The accessibility of the dataset and source code may be the reason. We leave span-based ECSP evaluation as future work.

Paradigm Shift in Natural Language Processing.

A paradigm is a general modeling framework or a family of methods to solve a class of tasks. For instance, sequence labeling is a mainstream paradigm for Part-of-speech (POS) tagging and Named entity recognition (NER). The sequence-to-sequence (Seq2Seq) paradigm is a popular tool for summarization and machine translation. Different paradigms usually require different formats of input and output,

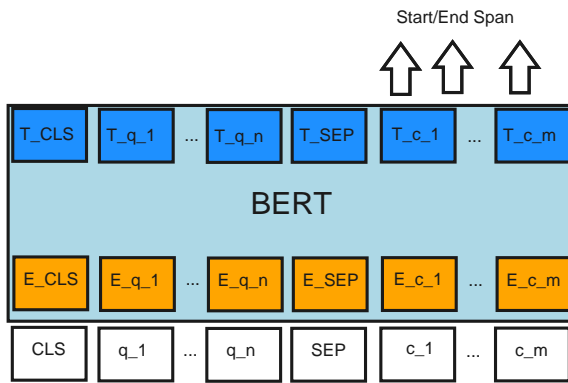


Figure 2: BERT-based extractive Question Answering.

and therefore highly depend on the annotation of the tasks.

Paradigm shift indicates the job of solving one NLP task in a new paradigm by reformulating the task along with changing the input-output formats. Paradigm shift in NLP has been explored scatteringly in recent years and with the advent of pretrained language models, it became a rising trend (Li et al., 2019; Khashabi et al., 2020). An excellent survey of paradigm shifts in NLP has been done by (Sun et al., 2022). In this work, we realize such a paradigm shift for the ECPE task, i.e., we reformulate the clause-based text classification task as span extraction.

Span-Based Extractive Question Answering. Our formulation for the tasks of ECE and ECPE relates to span-based extractive QA, which has been widely investigated (Khashabi et al., 2020). More precisely, we design our model based on the pretrained language models (PLMs) such as BERT (Devlin et al., 2018) or RoBERTa (Liu et al., 2019). This is because applying PLMs as the backbone of QA systems has become a standard procedure. For detailed information, please refer to (Devlin et al., 2018).

Figure 2 reproduced from (Devlin et al., 2018) shows how BERT is applied to the extractive QA task. Tokens of question $q = q_1, \dots, q_n$ and context $C = c_1, \dots, c_m$ are concatenated before being encoded by BERT. The contextual representations of tokens T_i are put into a feed-forward layer followed by a softmax. Each candidate span for the answer is scored as the product of start/end probabilities. The maximum scoring span is used as the prediction. The training objective is the loglikelihood of the correct start and end positions.

By casting the ECPE to QA problem, our work leverages the powerful models of the BERT family (Devlin et al., 2018) to detect clause-level emotions and causes as well as emotion-cause pairs.

3 METHOD

3.1 Problem Statement

Given a document of n clauses $d = (c_1, c_2, \dots, c_n)$, the goal of ECPE is to detect all potential emotion-cause pairs $P = \{..(c_e, c_c), ..\}$ where c_e is an emotion clause, and c_c is the corresponding cause clause (Xia and Ding, 2019). We formulated the ECPE task as a QA problem. Given a set of questions $\{q_e, q_c\}$ (q_e is for emotion and q_c is for cause) and a context document d with n clauses, the model learns to predict start and end positions of each c_e and c_c : $s_{c_e}, e_{c_e} = f(d, q_e | \Theta)$ and $s_{c_c}, e_{c_c} = f(d, q_c | \Theta)$ to form P . Θ can be learnt by using independent or guided extraction.

3.2 Independent Emotion, Cause Extraction

We first introduce a simple version of our model, Indep-QA in Figure 3. Indep-QA receives a fixed question (for emotion or cause) and then pulls out corresponding emotion or cause clauses independently.

Question Formulation. Because no emotion/cause information is provided beforehand, we have to detect them first with generic questions. It is possible to use pre-defined questions for extraction (Menge et al., 2020), however, we argue that the definition of questions is time-consuming, needs domain knowledge, and does not guarantee the semantic relationship between the questions and context documents. Instead, we use two short questions "emotion" and "cause" as an implicit indicator that provides additional information for the model. We leave the analysis of using generic questions such as "What is the emotion?" and "What is the cause?" as future work.

Learning and Prediction. Given a document d and a question ("emotion" or "cause"), we concatenated all clauses of d and the question to form a single sequence C . The sequence was fed to a pretrained language model (PLM) to obtain its hidden representations of tokens which were subsequently fed into a feed-forward layer followed by a softmax layer. Each candidate span was scored as the product of start/end probabilities. The maximum scoring span was used as the prediction.

Mapping Predicted Answer Span to Clauses. The predicted answer span may overlap with one or several clauses. We applied a span-to-clause mapping rule to determine which clauses are predicted results:

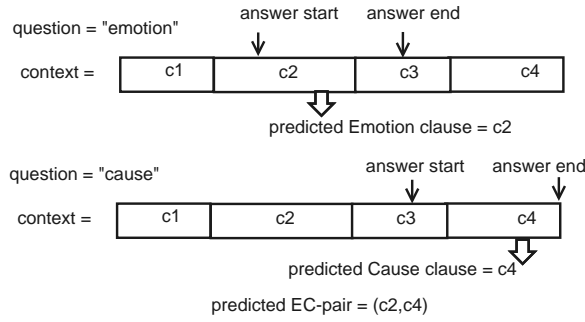


Figure 3: Independent extraction Indep-QA.

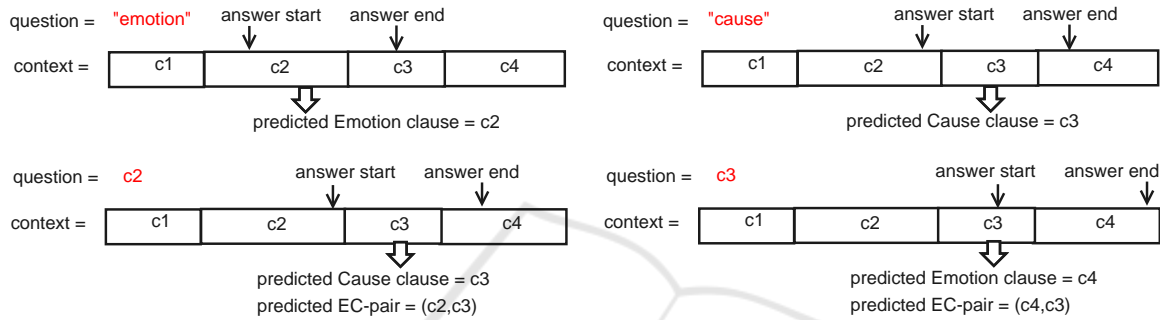


Figure 4: Guided pair extraction Guided-QA: Emotion is detected first (Left), Cause is detected first (Right).

the clause that overlaps most with the predicted span is returned. The tie is broken arbitrarily. For instance, In Figure 3, the predicted span for "emotion" overlaps with clauses c_2 and c_3 in which c_2 is more overlapped. As a result, c_2 is the predicted emotion.

EC Pair Prediction. Given predicted emotion/cause clauses c_e and c_c , Indep-QA simply predicts (c_e, c_c) as an emotion-cause pair. As illustrated in Figure 3, (c_2, c_4) is the predicted emotion-cause pair.

3.3 Guided Emotion-Cause Pair Extraction

The Indep-QA model extracts emotion/cause clauses independently but does not exploit the relationship between emotion and cause clauses, which plays an important role in the extraction of emotion-cause pairs (Ding et al., 2020; Wei et al., 2020; Chen et al., 2020; Cheng et al., 2021; Chen et al., 2022).

To better model this relationship, we introduce Guided-QA in Figure 4. The model receives an emotion question and predicts the corresponding emotion clause. Then the predicted emotion clause is used as a question for cause extraction. Compared to Indep-QA, the Guided-QA takes into account an implicit relationship from emotion for cause prediction.

The Guided-QA model shares the question formulation, hidden representation learning, and the mapping process of the Indep-QA model.

EC Pair Extraction. We used the predicted (noisy) emotion clause as the question for cause extraction. The interaction between emotion and cause happens here. The predicted emotion clause may or may not be the true one but on average, it contains much more information for the QA model than the generic question (i.e., "emotion"). Note that the predicted (noisy) emotion as the question was used for the test set only. For the training set, as the model already knows which clauses are emotion or cause, it uses the true emotion clause as the question.

By swapping the role, the model can detect cause clauses first and use the noisy causes as questions to predict the emotions. In Section 5 we compare Emotion-first and Cause-first, the two variants of Guided-QA and show that the gaps are tiny. In other word, the two variants are almost equivalent on the tested datasets.

As our QA models use the best answer span for each question, only one emotion, one cause, and one EC pair are predicted for each document which are appropriate for the ECPE dataset. We also aware that the prediction of spans should be multiple and we aim to address this limitation in future work by using mul-

tuple span extraction methods (Nguyen et al., 2021; Fu et al., 2021).

3.4 Discussion

Given a document of n clauses, existing schemes such as ECPE-MLL (Ding et al., 2020), RankCP (Wei et al., 2020) and PairGCN (Chen et al., 2020) attempt to reduce the $O(n^2)$ complexity of emotion-cause pair classification by using sliding window, transition graph techniques. However, these techniques may miss certain interaction between the emotion-cause pair and the full context in the document. BERT-based QA models with full attention between the question and the context mitigate this issue. Through QA models, the emotion-cause relationship between all clauses is implicitly learned and we can leverage the power of existing QA methods.

4 EXPERIMENTAL SETTINGS

Datasets. We followed the 10-split ECPE dataset provided by (Xia and Ding, 2019) and the 20-split TransECPE variant (Fan et al., 2020) to evaluate our methods. Each split is a random partition of the 1945 documents to train/dev/test sets with ratio 8:1:1, i.e., the train set, dev set and test set contain approximately 1556, 194 and 195 documents. On average, each document contains 14.8 clauses.

Table 1 shows the distribution of documents with different number of emotion-cause pairs. Most of the documents have only one emotion-cause pairs. This fact makes the detection of emotion/cause clauses as well as emotion-cause pairs challenging.

Evaluation Metrics. We used the precision, recall, and F1 score (Xia and Ding, 2019) as evaluation metrics for all three tasks of ECPE: emotion extraction, cause extraction and emotion-cause pair extraction. Let T_e and P_e be the number of ground-truth and predicted emotion clauses respectively, the precision, recall and F1 score for emotion are as defined as follows.

$$P_e = \frac{|T_e \cap P_e|}{|P_e|}$$

$$R_e = \frac{|T_e \cap P_e|}{|T_e|}$$

$$F1_e = \frac{2 * P_e * R_e}{P_e + R_e}$$

Metrics for cause clauses and emotion-cause pairs are defined similarly.

Implementation Details. Our model was implemented using BERT classes provided by Huggingface (Wolf et al., 2020). The model was trained in 5 epochs, with the learning rate of $5e-5$, and the batch size of 16. We used BERT (Devlin et al., 2018)¹ and RoBERTa (Liu et al., 2019)² for Chinese. All models were trained on a Tesla P100 GPU.

5 RESULTS AND DISCUSSION

Guided-QA: Emotion-First vs. Cause-First. We first compare the two variants Emotion-first and Cause-first of the Guided-QA method. Table 2 shows that the two variants have almost equivalent performance on the tested datasets except the BERT-based results on 10-split ECPE. Also, the RoBERTa-based results are consistently better than the BERT-based, 1.1 to 2.0 points. In the next section, we pick the Emotion-first scores for comparing Guided-QA with other methods.

Guided-QA vs. Indep-QA. We now compare Guided-QA and Indep-QA. For 10-split ECPE in the upper part of Table 3, the Guided-QA model is consistently better than Indep-QA for pair extraction. This is because Guided-QA takes into account the implicit interaction between emotion and cause clauses. For emotion or cause extraction, Indep-QA is competitive with Guided-QA. This is because they share the same formulation. The results in Table 4 also show similar observation.

We also confirm the performance of our model by using RoBERTa to have better analysis. The results are consistent with the model using BERT, in which Guided-QA outputs better F-scores than the Indep-QA model. It also shows that our model can be improved further by using stronger PLMs.

Guided-QA vs. Strong Baselines. We compare our model with five strong methods for ECPE: ECPE-MLL³ (Ding et al., 2020), RankCP⁴ (Wei et al., 2020), PairGCN⁵ (Chen et al., 2020), UTOS (Cheng et al., 2021), and RSN (Chen et al., 2022). For 10-split, our model using BERT follows ECPE-MLL, RankCP, and RSN. It shows that with a simple architecture, our model can output competitive results compared

¹<https://huggingface.co/bert-base-chinese>

²<https://huggingface.co/hfl/chinese-roberta-wwm-ext>

³<https://github.com/NUSTM/ECPE-MLL>

⁴<https://github.com/Determined22/Rank-Emotion-Cause>

⁵https://github.com/chenying3176/PairGCN_ECPE

Table 1: Histogram of the number of emotion-cause pairs per document.

	Number	Percentage
Documents with one emotion-cause pair	1746	89.77%
Documents with two emotion-cause pairs	177	9.10%
Documents with more than two emotion-cause pairs	22	1.13%
All	1945	100%

Table 2: Guided-QA Emotion-first vs. Cause-first on 10-split ECPE dataset and 20-split TransECPE dataset.

Model	Emotion Extraction			Cause Extraction			EC Pair Extraction		
	P	R	F1	P	R	F1	P	R	F1
10-split ECPE									
Emotion-first (BERT)	0.847	0.908	0.876	0.719	0.792	0.754	0.771	0.692	0.729
Cause-first (BERT)	0.831	0.891	0.860	0.714	0.787	0.749	0.763	0.685	0.722
Emotion-first (RoBERTa)	0.854	0.916	0.884	0.732	0.806	0.767	0.786	0.706	0.744
Cause-first (RoBERTa)	0.843	0.904	0.873	0.733	0.807	0.768	0.784	0.704	0.742
20-split TransECPE									
Emotion-first (BERT)	0.842	0.906	0.873	0.710	0.782	0.744	0.760	0.689	0.723
Cause-first (BERT)	0.833	0.897	0.864	0.713	0.785	0.747	0.761	0.690	0.724
Emotion-first (RoBERTa)	0.844	0.909	0.875	0.723	0.796	0.757	0.772	0.700	0.734
Cause-first (RoBERTa)	0.838	0.902	0.869	0.724	0.797	0.758	0.773	0.701	0.735

to complicated methods. For 20-split TransECPE in Table 4, the trend is consistent with Table 3, in which the Guided-QA model is competitive for both ECE and ECPE tasks.

Moreover, as we observe from all the compared methods, the gaps between the reported pair-f1 scores for 10-split ECPE and 20-split TransECPE are 0.023 ($=0.745-0.722$) for ECPE-MLL, 0.042 for RankCP, 0.029 for UTOS, 0.003 for Indep-QA and 0.006 for Guided-QA, i.e., largest gap in RankCP and smallest gaps in our models. Across the two settings, our models seem more robust than the compared methods.

Reproducibility. For fair comparison (Houghton et al., 2020), we also rerun publicly available source codes in the original setting. The reproduced results confirm the gaps between reproduction and original results. Compared to the reproduced results, Guided-QA using BERT is the best for EC pair extraction.

Compared to the results of reproduced methods, the Guided-QA is still better for both ECE and ECPE tasks. This confirms our hypotheses stated in Section 1. Compared to the results of strong baselines reported in papers, the F-scores of Guided-QA are still competitive. It shows that our simple model can output promising results compared to complicated ECPE methods (Ding et al., 2020; Wei et al., 2020; Chen et al., 2020; Cheng et al., 2021; Chen et al., 2022). The results from the original papers are just for reference because it seems there are gaps between the reproduced results and original results.⁶ This is be-

cause several scholars tried to reproduce the results, but it seems there are gaps between the reproduced results and original results.

For 20-split TransECPE in Table 4, the trend is consistent with Table 3. The Guided-QA is competitive for both ECE and ECPE tasks. The model using RoBERTa is still the best. After rerunning the source codes of the baselines, we found that PairGCN has the best reproducibility.

By adopting the standardized pipeline of BERT-based question answering, our models inherit its simplicity and reproducibility which may become an issue in more complex methods like RankCP.

Runtime Comparison. We also measured the running time of our model and the baselines. In Table 5, PairGCN which only uses BERT embeddings has the best running time. The other models take longer to run due to the fine-tuning of BERT models. Our model is the second best, which is much faster than ECPE-MLL. It shows that our model can balance between competitive accuracy and high speed.

6 CONCLUSION

This paper introduces a paradigm shift for the ECPE task. Instead of treating the task as the conventional formulation, we formulate the extraction as a QA problem. Based on that, we design a model which

⁶[https://github.com/Determined22/Rank-Emotion-](https://github.com/Determined22/Rank-Emotion-Cause/issues/3)

[Cause/issues/3](https://github.com/Determined22/Rank-Emotion-Cause/issues/3)

Table 3: Experimental results of different models on 10-split ECPE dataset. * indicates reproduced results.

Model	Emotion Extraction			Cause Extraction			EC Pair Extraction		
	P	R	F1	P	R	F1	P	R	F1
Indep-QA (BERT)	0.847	0.908	0.876	0.714	0.787	0.749	0.736	0.661	0.697
Guided-QA (BERT)	0.847	0.908	0.876	0.719	0.792	0.754	0.771	0.692	0.729
Indep-QA (RoBERTa)	0.854	0.916	0.884	0.733	0.807	0.768	0.761	0.683	0.720
Guided-QA (RoBERTa)	0.854	0.916	0.884	0.732	0.806	0.767	0.786	0.706	0.744
ECPE-MLL (BERT)	0.861	0.919	0.889	0.738	0.791	0.763	0.770	0.724	0.745
RankCP (BERT)	0.912	0.900	0.906	0.746	0.779	0.762	0.712	0.763	0.736
PairGCN (BERT)	0.886	0.796	0.838	0.791	0.693	0.738	0.769	0.679	0.720
UTOS (BERT)	0.882	0.832	0.856	0.767	0.732	0.747	0.739	0.706	0.720
RSN (BERT)	0.861	0.892	0.876	0.773	0.740	0.755	0.760	0.722	0.739
ECPE-MLL (BERT)*	—	—	—	—	—	—	0.688	0.752	0.718
RankCP (BERT)*	0.741	0.744	0.742	0.614	0.647	0.627	0.573	0.625	0.597
PairGCN (BERT)*	0.784	0.883	0.829	0.686	0.795	0.735	0.675	0.772	0.718

Table 4: Experimental results of different models on 20-split TransECPE dataset. * indicates reproduced results. The authors of PairGCN and RSN did not tested their models on TransECPE.

Model	Emotion Extraction			Cause Extraction			EC Pair Extraction		
	P	R	F1	P	R	F1	P	R	F1
Indep-QA (BERT)	0.842	0.906	0.873	0.713	0.785	0.747	0.730	0.662	0.694
Guided-QA (BERT)	0.842	0.906	0.873	0.710	0.782	0.744	0.760	0.689	0.723
Indep-QA (RoBERTa)	0.844	0.909	0.875	0.724	0.797	0.758	0.739	0.670	0.703
Guided-QA (RoBERTa)	0.844	0.909	0.875	0.723	0.796	0.757	0.772	0.700	0.734
ECPE-MLL (BERT)	0.847	0.899	0.872	0.705	0.770	0.736	0.749	0.698	0.722
RankCP (BERT)	0.894	0.895	0.894	0.694	0.747	0.719	0.658	0.731	0.692
UTOS (BERT)	0.865	0.829	0.849	0.742	0.708	0.728	0.710	0.681	0.691
ECPE-MLL (BERT)*	—	—	—	—	—	—	0.659	0.714	0.684
RankCP (BERT)*	0.896	0.897	0.896	0.694	0.749	0.720	0.657	0.731	0.691
PairGCN (BERT)*	0.804	0.878	0.839	0.689	0.770	0.727	0.677	0.746	0.709

Table 5: Running time (train and test) on Tesla P100.

	ECPE	TransECPE
ECPE-MLL	8.5h	17h
RankCP	3h	6h
PairGCN	42min	85 min
Indep-QA	2h30	5h
Guided-QA	2h30	5h

takes into account the implicit interaction between emotion and cause clauses. Experimental results on a benchmark Chinese dataset show that using implicit interaction of emotions and causes can achieve competitive accuracy compared to strong baselines. Future work will consider explicit interaction between emotion and cause clauses.

REFERENCES

- Bi, H. and Liu, P. (2020). Ecspp: A new task for emotion-cause span-pair extraction and classification. *arXiv preprint arXiv:2003.03507*.
- Chen, F., Shi, Z., Yang, Z., and Huang, Y. (2022). Recurrent synchronization network for emotion-cause pair extraction. *Knowledge-Based Systems*, 238:107965.
- Chen, Y., Hou, W., Li, S., Wu, C., and Zhang, X. (2020). End-to-end emotion-cause pair extraction with graph convolutional network. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 198–207.
- Cheng, Z., Jiang, Z., Yin, Y., Li, N., and Gu, Q. (2021). A unified target-oriented sequence-to-sequence model for emotion-cause pair extraction. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29:2779–2791.
- Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.
- Ding, Z., Xia, R., and Yu, J. (2020). End-to-end emotion-cause pair extraction based on sliding window multi-label learning. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 3574–3583.
- Fan, C., Yuan, C., Du, J., Gui, L., Yang, M., and Xu, R. (2020). Transition-based directed graph construction

- for emotion-cause pair extraction. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 3707–3717.
- Fu, J., Huang, X.-J., and Liu, P. (2021). Spanner: Named entity re-/recognition as span prediction. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 7183–7195.
- Gui, L., Hu, J., He, Y., Xu, R., Lu, Q., and Du, J. (2017). A question answering approach for emotion cause extraction. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 1593–1602.
- Gui, L., Wu, D., Xu, R., Lu, Q., and Zhou, Y. (2016). Event-driven emotion cause extraction with corpus construction. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1639–1649.
- Houghton, B., Milani, S., Topin, N., Guss, W., Hofmann, K., Perez-Liebana, D., Veloso, M., and Salakhutdinov, R. (2020). Guaranteeing reproducibility in deep learning competitions. *arXiv preprint arXiv:2005.06041*.
- Khashabi, D., Min, S., Khot, T., Sabharwal, A., Tafjord, O., Clark, P., and Hajishirzi, H. (2020). Unifiedqa: Crossing format boundaries with a single qa system. *arXiv preprint arXiv:2005.00700*.
- Lee, S. Y. M., Chen, Y., and Huang, C.-R. (2010). A text-driven rule-based system for emotion cause detection. In *Proceedings of the NAACL HLT 2010 workshop on computational approaches to analysis and generation of emotion in text*, pages 45–53.
- Li, X., Feng, J., Meng, Y., Han, Q., Wu, F., and Li, J. (2019). A unified mrc framework for named entity recognition. *arXiv preprint arXiv:1910.11476*.
- Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., and Stoyanov, V. (2019). Roberta: A robustly optimized bert pre-training approach. *arXiv preprint arXiv:1907.11692*.
- Mengge, X., Yu, B., Zhang, Z., Liu, T., Zhang, Y., and Wang, B. (2020). Coarse-to-fine pre-training for named entity recognition. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6345–6354.
- Nguyen, T.-A. D., Vu, H. M., Son, N. H., and Nguyen, M.-T. (2021). A span extraction approach for information extraction on visually-rich documents. In *International Conference on Document Analysis and Recognition*, pages 353–363. Springer.
- Rajpurkar, P., Zhang, J., Lopyrev, K., and Liang, P. (2016). Squad: 100,000+ questions for machine comprehension of text. *arXiv preprint arXiv:1606.05250*.
- Sun, T.-X., Liu, X.-Y., Qiu, X.-P., and Huang, X.-J. (2022). Paradigm shift in natural language processing. *Machine Intelligence Research*, 19(3):169–183.
- Wei, P., Zhao, J., and Mao, W. (2020). Effective inter-clause modeling for end-to-end emotion-cause pair extraction. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 3171–3181.
- Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., et al. (2020). Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 conference on empirical methods in natural language processing: system demonstrations*, pages 38–45.
- Xia, R. and Ding, Z. (2019). Emotion-cause pair extraction: A new task to emotion analysis in texts. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1003–1012.
- Yan, H., Gui, L., Pergola, G., and He, Y. (2021). Position bias mitigation: A knowledge-aware graph model for emotion cause extraction. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3364–3375.