Apply Event Extraction Techniques to the Judicial Field

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ABSTRACT

While hearing a case, the judge must fully understand the case and make clear the disputed issues between parties, which is the cornerstone of a fair trial. However, manual mining the key of the case from the statements of the litigious parties is a bottleneck, which currently relies on methods like keyword searching and regular matching. To complete this time-consuming and laborious task, judges need to have sufficient prior knowledge of cases belonging to different causes of action. We try to apply the technology of event extraction to faster capture the focus of the case. However, there is no proper definition of events that contains types of focus in the judicial field. And existing event extraction methods can't solve the problem of multiple events sharing the same arguments or trigger words in a single sentence, which is very common in case materials. In this paper, we present a mechanism to define focus events, and a two-level labeling approach, which can solve multiple events sharing the same argument or trigger words, to automatically extract focus events from case materials. Experimental results demonstrate that the method can obtain the focus of case accurately. As far as we know, this is the first time that event extraction technology has been applied to the judicial field.

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CCS CONCEPTS

• **Information systems** → **Information extraction**.

KEYWORDS

Event Extraction; Event-type Definition; Judicial Field

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1 INTRODUCTION

The clearness of the disputed issues of a case is a crucial step in the process of hearing civil cases. The disputed issues will affect the judge's decision. Nowadays, people are relying on reading the statement of the case manually and using the keyword searching and regular matching methods to obtain the disputed issues from text materials of cases. This has many shortcomings. First, it requires lots of manpower and time. Second, different cases with different causes have different keys, which requires the staff to have a wealth of prior knowledge, which further increases the labor cost. Finally, the result depends on the care and experience of the staff and is uncertain. If we can automate the acquisition of key information, we can not only reduce human resources but also unify the understanding of the case and improve the efficiency and accuracy of the trial. However, the case statement is in the form of natural language text, and it's also difficult to obtain the complete key information of the case only by using keyword retrieval and regular matching.

We try to use the event extraction technology to obtain the key information of the case so as to accelerate the clearness of the dispute issues. But the existing definition of event types is not sufficient to cover the key information of case

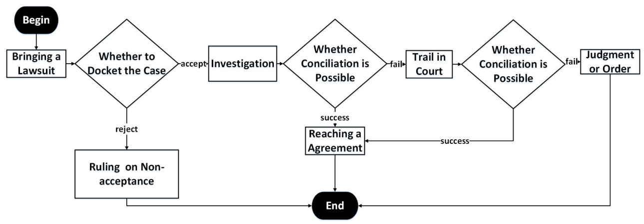

Figure 1: Formal Procedure at First Instance.

in the judicial field, so we first propose a mechanism to define the core events from the focus of each course of the case. In addition, multiple events in a single sentence often share arguments or trigger words in case materials, which can't be effectively solved by existing event extraction methods. Therefore, we propose a two-level labeling approach to solve this problem. For demonstrating the capabilities of the proposed technique, we take civil divorce cases as an example, and implement the whole process including defining core events and extracting the target events. We evaluate the accuracy of event extraction. The result shows that our methods can accurately obtain the core events and significantly improve the time spent in clarifying the focus of disputes.

The remainder of this paper is structured as follows. Section 2 introduces some basic knowledge about China's judicial litigation and some about event extraction. Section 3 introduces in detail the process of applying this method to divrce dispute cases, extracting key events and obtaining the disputes issues. Section 4 evaluates the effectiveness of this method. Finally, section 5 serves as a summary of the paper.

2 BACKGROUND

In this section, we will introduce some basic knowledge.

Formal Procedure at First Instance

The civil formal procedure at first instance of the Peoples's Republic of China includes instituting and accepting an action, pretrial preparations, court trial, suspension and termination of an action, judgments and rulings[1], as shown in figure 1. In the process, the statement of the case mainly includes the plaintiff's complaint, defendant's answer to complaint and court record.The judge mainly obtains the key information of the case on the basis of these statements, and then to clarify the focus of the dispute. Take the divorce law as an example[2]:

Divorce shall be granted if mediation fails under any of the following circumstances: ... (2)domestic violence ... (4)separation caused by incompatibility, which lasts two full years...

And a statement of complaint:

[1] *The Civil Procedure Law of the People's Republic of China(2017 Revision)*
[2] *Marriage Law of the Perple's Republic of China(2001)*

Figure 2: The sentence describes a "Meeting" event in which the trigger word "met" identifies the occurrence of a "Meeting" event, while the parameters "The chairman" and "the visiting official" are participants in the event.

In the middle and later period, ... the defendant often beat the plaintiff and caused injuries. ... Since April 1, 2016, the plaintiff and the defendant have separated.

There are domestic violence and separation. During the trial, the judge will take these key information into consideration to judge whether the allegations of domestic violence and separation are true, which have a huge impact on the judgment.

Event Extraction

Event extraction is an important technique in natural language processing. It is involved in many fields, such as question answering, information retrieval, and so on[2]. An event indicates a state transition has occurred. ACE 2005[3] defines 8 types of events which include 33 subtypes, and an event consists of a trigger that identifies the occurrence of the event and a series of parameters (including participants and attributes) that serve different roles in the event. Figure 2 shows an example of an event.

The last couple of years witnessed the success of the deep neural network models for event extraction. [1] uses convolutional neural network technology to determine the trigger words and determine the role of parameters. [3] try to find the mapping relationship between the Abstract meaning representations(AMR) structure of a sentence and the defined event types. [9], [8] use Bi-LSTM-CRF sequential model to extract sentence-level events. [6], [4] employ the graph convolutional networks(GCN) to make use of graph structures of the original sentences to detect events.

Challenges of Applying Event Extraction to Judicial Challenges

There are some challenges when applying event extraction to the judicial field:

- Event type mismatch: ACE 2005 defines only 33 event types, which don't exactly match the type of event to be concerned about when hearing a case.

[3] *https://www.ldc.upenn.edu/collaborations/past-projects/ace*

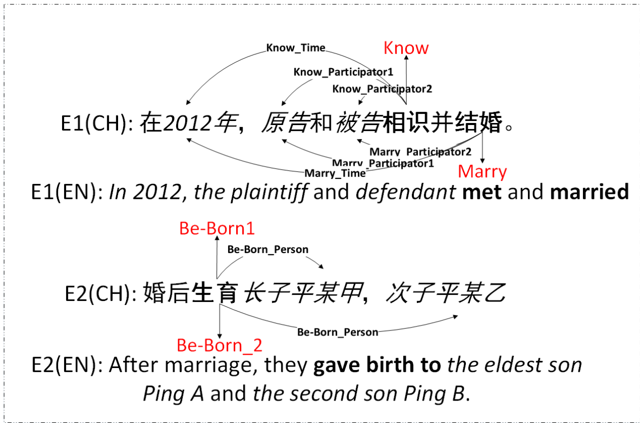

Figure 3: Examples of Multi-event in Single Sentence

- No existing data sets: Extraction technologies are experimentally verified on existing publicly available English data sets. As far as we know, this is the first time to attempt to apply event extraction technology to Chinese judicial data.
- Multiple events share parameters or trigger words in the litigation materials: In materials of cases, there are many sentences containing multiple events that share parameters or trigger words. As shown in figure 3, there are two events(bold *met* and *married*) in E1, where the two events share time and participant parameters(italics). In E2, although the trigger chunk(bold) only appears once, we can judge that it's actually two "Be-born" events according to the following text *the eldest son Ping A* and *the second son Ping B*. Existing event technologies which focus on this problem are not useful in our data, for example [9], which will be compared with our method in Section 4.

Against the background of these challenges, we propose an approach for extracting the core events to accelerate the clearness of dispute issues.

3 APPROACH

In this section, we will take divorce cases as an example and introduce our approach to extract core events from case materials. Section 3.1 gives an overview of the architecture and its components. Section 3.2 through 3.5 introduces each component in detail.

Overview

Figure 4 shows the architecture of our approach. The apprach comprises three components:

- Definition of core event types. We propose a method to define the core event types.

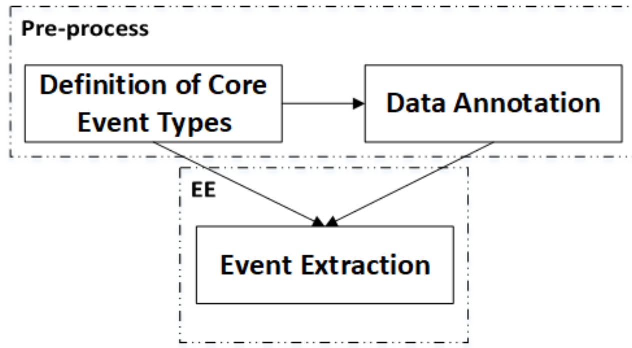

Figure 4: Overview of the Approach

- Data annotation. The existing methods(DS)[7],[8],[9] to generate training data automatically can't be implemented, because of the lack of event knowledge database. So we manually annotated the training data.
- Event extraction. Extract the defined core events from case materials.

Definition of core event types

Collect Focus Set. In the process of trial, the focus of cases with different casuses is different, so it's the same for the target events. But all kinds of focus can be found in the existing laws. Therefore, the focus can be obtained by combining the law and some interpretation documents[4] [5].

Filter Set of Focus. In all concerns, we need to filter them by two rules: (1) Is it a description of a procedural event. For example, a focus-*whether there is a event of domestic violence* that can be mapped to the Attack event type, which can be retained. And the focus-*whether the divorce is voluntary or not* that is not an event and needs to be deleted. (2) Is it available in the case materials

Convert Focus to Event Types. After obtaining the final set of focus, we also need to convert the focus into extractable target event structures. There are two ways to convert: (1) Direct conversion. For example, a focus-*whether there is domestic violence* that can be directly converted into domestic violence events (including violent people, violence objects, and three parameters of violence time). (2) Indirect conversion. For example, a focus-*when someone file a divorce lawsuit, whether the distance limit for the most recent divorce proceedings is more than six months* that can be indirectly converted into divorce proceedings (including prosecution time, prosecutor, court acceptance, judgment time, judgment, and judgment results).

[4] *Marriage Law of the Perple's Republic of China(2001)*
[5] *Interpretations of the Supreme People's Court about Several Issues Concerning the Application of the Marriage Law of the People's Republic of China (I),(II),(III)*

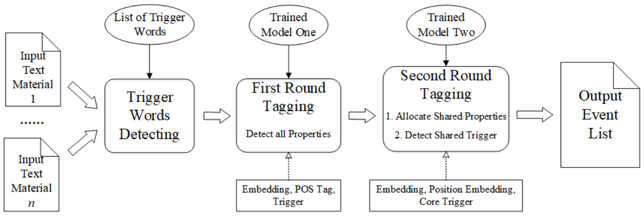

Figure 5: The Process of Event Extraction

Finally, we have 13 types of focus events for divorce cases, as shown below.

- Know(KnowTime,Participant1,Participant2)
- BeInLove(BeInLoveTime,Participant1,Participant2)
- Marry(MarryTime,Participant1,Participant2)
- Remarry(Participant)
- Bear(Time,Gender,Name,Age)
- FamilyConflict(Participant1,Participant2)
- DomesticViolence(Time,Perpetrators,Victim)
- BadHabit(Participant)
- Derailed(Time,Derailer,DerailedTarget)
- Separation(BeginTime,EndTime,Duration)
- DivorceLawsuit(SueTime,Initiator,Court,JudgeTime, JudgeDocument,Result)
- Wealth(Value,IsCommon,IsPersonal,Whose)
- Debt(Value,Debtor,Creditor)

Data Annotation

For the pre-defined 13 types of divorce events, we manually mark 3100 case materials using the standard begininside-outside (BIO) scheme.The steps are as follows.

- Pre-labeling: Select a small amount of material to mark, and check the results.
- Setting up the annotation environment: we use the open-source annotation tool[6].
- Labeling.

Event Extraction

Figure 5 shows the process of event extraction, which is described in detail in the following subsections.

Trigger Words Dictionary. For a specific cause of cases, we can collect as many trigger words as we can and form a dictionary, which contains most of the event triggers

Filter and Classify Trigger Words. Enter the text material, first use LTP(a kind of NLP tool[7]) to split sentences. For every single sentence, the trigger words dictionary is retrieved to determine whether it contains the target event. And the event trigger word is determined.

[6]http://brat.nlplab.org/about.html
[7]http://www.ltp-cloud.com/

Table 1: Transition Labels and Meanings

Transition label	Meaning
Time	Time
Person	Participant
Gender	Gender of the child
Age	Age of the child
Duration	Separation duration
IsPersonal	Whether it is personal property
IsCommon	Whether it belongs to common property
Money	Property value
Court	Court that accepts divorce proceedings
Document	Litigation judgment
Result	Judgment result of divorce proceedings
Negated	Negative words

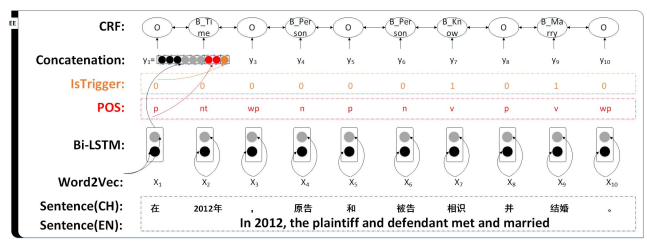

Figure 6: The Architecture of First Labelling

First Labeling. The neural network was confirmed to be able to automatically obtain the feature information in the text. Bi-LSTM can obtain the context feature, and CRF can supplement the transfer information between the result labels to obtain the best label sequence. Both [8] and [9] use them to extract events from a single sentence.

As shown in 3.2 subsection, the divorce dispute target events contain a total of 13 types of trigger words and 40 (39+1, an additional tag that identifies a negative meaning) event parameters. We define 12 transition labels (Table 1) in conjunction with named entity categories and event-specific parameters. The original 40 parameter labels are mapped to 12 transition labels, reducing the label category and increasing the frequency of individual labels.

And the predicted structure of the transition label is shown in Figure 6.

- Pretreatment: split into tokens and pad.
- Input: Word embedding can automatically retrieve information contains word semantic vector said [5].The word2vec model is then used to transform each word into a tensor.
- Bi-LSTM: we use BI-LSTM to combine the semantic information of the words before and after.
- Concatenation:

  - Word Encoding.Semantic features of Word encoding obtained by BI-LSTM encoding
  - POS Embedding.
  - whether each word is a trigger word: In section 3.3, we have determined the trigger word in each input sentence, and 0,1 is used to indicate[8].
- CRF: Add a layer of CRF to get transfer information between labels.
- Output: The output is a predefined intermediate label type IDs.

Second Labelling. To solve the problem of sharing, there are several ideas. The first thought is to set a new label type for each sharing situation, but the sharing situations are complex and diverse, which will produce a lot of label types, and little number of some labels. The second thought is that we make multiple predictions for a sentence, one of which only takes a trigger word and the corresponding event into considertion, but this will lead to the number of the meaningless label (O) far more than the number of meaningful labels. Finally, we adopt the two-level label method. Through first labeling, we obtaine the transition label for each word, which identifies all meaningful labels, including trigger words, event-specific label, and event-shareable label. We then just need to assign parameters for different events. We use different allocation strategies for shared parameters and shared trigger words.

For multi-events shared parameters in single sentence, the parameters are allocated multiple times to different events. But other unique parameters are assigned once. For each sentence, we use a CRF model to mark the transition label to the final destination label only considering one trigger chunk once time. If there are several trigger words in a single sentence, it is necessary to mark them several times and obtain a complete event each time.

- Input:
  - Embedding of transition labels and trigger labels.
  - Whether the trigger word of current concern. (0 or 1)
  - Embedding of the position relative to the center triggered word.
- CRF: same as the previous stage.
- Output: The output is the tag type of the final labels for all kinds of trigger types and argument types.

For multi-events shared trigger words in single sentence, statistics show that the phenomenon of sharing trigger words occurs in "Be-Born" and "DivorceLawsuit" events. For "Be-Born" events, only time parameter can be shared, and the rest parameters are unique type parameters, such as child name, gender and age. So, we can define:

[8]Figure 6 shows that the dimension of the result vector after the connection is not the real dimension set in the experiment

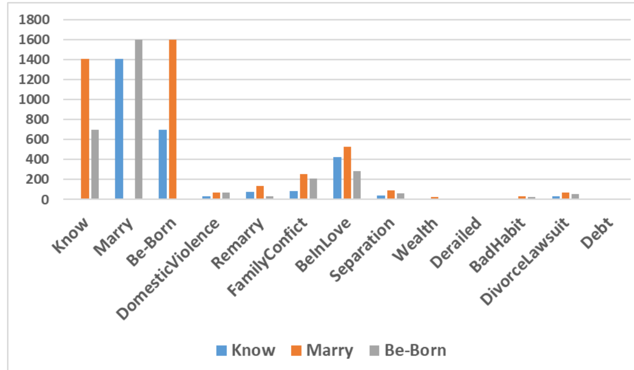

Figure 7: The Frequency Distribution of Know,Marry,Be-Born and Other Event Types in a Single Sentence

If in a transition labele sequence, the unique parameter of "Be-Born" event contains multiple values, then several parameter values contain several "Bear" events, and other single parameter types are shared by multiple "Be-Born" events.

Similarly, we can define for "DivorceLawsuit" :

In a transition labele sequence, (a)for roles unique to "DivorceLawsuit", if a single role has multiple parameter values, several parameter values contain several divorce proceedings, and other single parameter types are shared.(b)for the time parameter in divorce proceedings, if there are time parameters that are not the parameter value of other types of events, On the same side of the trigger word, there are as many "DivorceLawsuit" events as there are time parameters. Other single parameter types are shared.

The problem of sharing trigger words can be solved by using the above rules.

4 EXPERIMENTS

Data Preparation

We tagged 3,100 litigation text case materials. In these materials, the frequency distribution of Know, Marry, Be-Born, and other event types in the single sentence is shown in Figure 7

The types of events contained in each litigation text are indeterminate and random. The rules for constructing training set, validation set and test set are as follows. We firstly divided the entire data set into three intervals according to document size, namely [1,3)KB, [3,6)KB and [6,9]KB. Next, each interval are randomly divided into ten pieces. Then, to make a 10-fold data set for cross validation, we randomly select and remove one piece from each of the three intervals to combin one fold. This was repeated for ten times. Eventually, each fold consists of the same size distribution of texts. However, we do not restrict the same distribution of event

Table 2: Our Method Compared with Two Baseline Approaches

Experiment	P	R	F1
Hang et al. (2018)	0.86	0.81	0.82
Ying et al. (2018)	0.86	0.82	0.83
Two-labeling	0.87	0.83	0.84

types over all folds. In cross validation, each fold was used as test set and validation set once. The average result of 10-folds is viewed as a single result of the proposed approach.

Evaluation Indicators

We define precision P, recall R, and F1 as follows:

$$P = \frac{S}{S_t}$$

$$R = \frac{S}{S_p}$$

$$F1 = \frac{2PR}{P + R}$$

S_t is the sum of all triggers word chunks and arguments chunks, S the completely correct trigger word chunks and arguments chunks in the extraction results. S_p is the sum of predicted triggers word chunks and arguments chunks.

We compared our approach with Hang et al. (2018)[8] and Ying et al. (2018)[9]. Hang et al uses BI-LSTM-CRF to extract events from a single sentence without considering the case of sharing. Ying et al. uses BI-LSTM-CRF to obtain the probability distribution of possible labels of each word, and then a ILP solver is used to output multiple optimal sequences, corresponding to multiple events. We conducted the 10-fold cross validation of our method for 12 times, as well as the baseline approaches. Paired T-test results show that our approach is significantly outperforming the baselines. Table 2 shows the average results of three approaches.

5 CONCLUSION

In view of the current situation that judges need to manually find the key to the case, this paper proposes a framework to automatically extracting target events containing the key. Taking cases of the divorce dispute as an example, experimental results show it's superior to existing methods. The implementation process of the framework is not limited to divorce disputes and can be transplanted to other cases. But the approach still has some problems. Firstly, the system implementation needs to manually annotate data to train the model. Labeling errors cannot be completely avoided. Secondly, the approach can't get the disputed issues directly. Our next steps are to explore how to automate the generation of training data and to try to get disputed issues directly.

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REFERENCES

[1] Yubo Chen, Liheng Xu, Kang Liu, Daojian Zeng, and Jun Zhao. 2015. Event Extraction via Dynamic Multi-Pooling Convolutional Neural Networks. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, ACL 2015, July 26-31, 2015, Beijing, China, Volume 1: Long Papers*. 167–176. http://aclweb.org/anthology/P/P15/P15-1017.pdf

[2] Goran Glavas and Jan Snajder. 2014. Event graphs for information retrieval and multi-document summarization. *Expert Syst. Appl.* 41, 15 (2014), 6904–6916. https://doi.org/10.1016/j.eswa.2014.04.004

[3] Lifu Huang, Heng Ji, Kyunghyun Cho, Ido Dagan, Sebastian Riedel, and Clare R. Voss. 2018. Zero-Shot Transfer Learning for Event Extraction. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 1: Long Papers*. 2160–2170. https://aclanthology.info/papers/P18-1201/p18-1201

[4] Xiao Liu, Zhunchen Luo, and Heyan Huang. 2018. Jointly Multiple Events Extraction via Attention-based Graph Information Aggregation. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018*. 1247–1256. https://aclanthology.info/papers/D18-1156/d18-1156

[5] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient Estimation of Word Representations in Vector Space. In *1st International Conference on Learning Representations, ICLR 2013, Scottsdale, Arizona, USA, May 2-4, 2013, Workshop Track Proceedings*. http://arxiv.org/abs/1301.3781

[6] Thien Huu Nguyen and Ralph Grishman. 2018. Graph Convolutional Networks With Argument-Aware Pooling for Event Detection. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18), the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18), New Orleans, Louisiana, USA, February 2-7, 2018*. 5900–5907. https://www.aaai.org/ocs/index.php/AAAI/AAAI18/paper/view/16329

[7] Julia Wiedmann. 2017. Joint Learning of Structural and Textual Features for Web Scale Event Extraction. In *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, February 4-9, 2017, San Francisco, California, USA*. 5056–5057. http://aaai.org/ocs/index.php/AAAI/AAAI17/paper/view/14520

[8] Hang Yang, Yubo Chen, Kang Liu, Yang Xiao, and Jun Zhao. 2018. DCFEE: A Document-level Chinese Financial Event Extraction System based on Automatically Labeled Training Data. In *Proceedings of ACL 2018, Melbourne, Australia, July 15-20, 2018, System Demonstrations*. 50–55. https://aclanthology.info/papers/P18-4009/p18-4009

[9] Ying Zeng, Yansong Feng, Rong Ma, Zheng Wang, Rui Yan, Chongde Shi, and Dongyan Zhao. 2018. Scale Up Event Extraction Learning via Automatic Training Data Generation. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18), the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18), New Orleans, Louisiana, USA, February 2-7, 2018*. 6045–6052. https://www.aaai.org/ocs/index.php/AAAI/AAAI18/paper/view/16119