A Survey on Event Relation Identification

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Abstract

Event relation identification aims to identify relations between events in texts, including causal relation, temporal relation, sub-class relation and so on. Most of the research focuses on temporal relation and causal relation. Extracting events and the relation between events is an essential step to build an event-centric knowledge graph, which plays an important role in story ending prediction and decision-making. The form of causal and temporal relation in natural language text is diverse, sparse and complex which brings challenges to relation identification. In recent years, the integration of deep learning and knowledge has promoted the relation identification progress. This paper describes in detail the characteristics of causal and temporal relations in natural language texts and their connections. What is more, this paper surveys existing approaches based on pattern matching, machine learning and deep learning. Besides, this paper analyzes corpus and points out the future development direction and contributes ideas to further improve relation identification between events. To our knowledge, this is the first paper to survey the event relation identification.

Corpus

Several well-known corpora are often used in relation recognition. Table 1 and Table 2 respectively, show the statistical analyses of causal and temporal relation datasets.

Table 1: corpora of causality.

Name	Doc	Event	Causal relation
Event-Causality (Do et al.2011)	25	1134	414
CausalTimeBank (Mirza et al.2014)	184	6813	318
Japanese dataset (Hashimoto et al.2014)			2,451,254 (event causality candidates)
EventStoryLine (Caselli et al.2017)	258	258	5000

Table 2: corpora of temporality.

Name	Doc	Event	T-Link	Words
TimeBank (Pustejovsky et al.2013)	183	6714	5121	61418
AQUAINT (David Graff 2002)	73	4431	5797	33973
Korean TimeBank (Lim et al.2020)	725	10519	4629	50674
TB Dense (Cassidy et al.2014)	36	1600	5700	

The State of the Art

Table 3, Table 4, Table 5, show the performance of each model on different datasets. And Pre., Rec. and F1 indicate precision (%), recall (%) and F1-score (%) respectively; Bold denotes best results;

Table 3: EventStoryLine

METHODS	PRE.	REC.	F1.
OP (Caselli et al.2017)	22.5	98.6	36.6
LSTM (Cheng et al.2017)	34.0	41.5	37.4
Seq (Choubey et al.2017)	32.7	44.9	37.8
LR+ (Gao et al.2019)	37.0	45.2	40.7
ILP (Gao et al.2019)	38.8	52.4	44.6
MFULL (Liu et al.2020)	41.9	62.5	50.1

Table 4: EventCausality

METHODS	PRE.	REC.	F1.
PMI (Do et al.2011)	26.6	20.8	23.3
ECD (Do et al.2011)	40.9	23.5	29.9
CEA (Do et al.2011)	62.2	28.0	38.6
MFULL (Liu et al.2020)	34.1	68.2	45.4

Table 5: Japanese

METHODS	PRE.	REC.	F1.	Avg.P
SVM (Hashimoto et al.2014)	-	-	-	45.96
MCNN (Kruengkrai et al.2017))	61.1	40.2	48.5	55.13
BERT (Kadowaki et al.2019)	52.0	64.0	57.4	57.4

For sentence-level causality identification, (Liu et al.2020)is the state of the art on EventStoryLine datasets and EventCausality datasets. In the context of low-resource environments, the knowledge-enhanced event causality identification proposed effectively utilized the extra knowledge in the knowledge graph, and the semantic representation based on BERT. (Kadowaki et al.2019)is the most advanced method on Japanese datasets.

Besides, existing methods mainly identify sentence-level causality, but they lack the document-level causality recognition. One reason is that different mentions of the same event are scattered in multiple sentences, and the effect of event extraction seriously affects the extraction of causality between events. The other reason is that event causality is sparse among all possible event pairs in the document. In addition, the explanation of causality is not clear. (Gao et al.2019)added global constraints to the document-level causality identification by adopting various measures such as extracting relationships around main events, sentence location, and event co-referencing. The combination of global structure and fine grained structure, segmented processing, event co-referencing, event fusion, and topic-based all help enrich the document-level causal structure.

For the extraction of temporal relation at the sentence level, (Lim et al.2020)designed the temporal information extraction model, it could not only predict backward relations in temporality (i.e., forward and backward), but also temporal information of specific events (i.e., including). Due to the limited data set, the representation of temporal relations is different in different languages. When some trigger words can not be found and hidden temporal relations between events cannot be identified, it is also worth exploring how to grasp the whole and improve the accuracy if we want to extract the temporal relation between multiple events,.

Conclusions

Despite recent advances in event relation identification, state-of-the-art identification results are still far from satisfactory. Most of the work is limited to sentence-level relation identification and regards relation identification between events as a classification task. Due to the complexity of the form of event relations, document level event relation extraction is still a difficult task. In a low-resource environment, there are not enough tool resources to learn effective features to detect events, parameters and corresponding relations between events, and there are not enough annotation samples to train the event and relation extraction. We can consider the following points.

(1) Joint extraction. We can consider the joint extraction and optimization of entities, events and event relations. Joint extraction can allow each task to correct each other's errors and make full use of the information and dependencies between entities and events.

(2) Integrating knowledge graph. Add external knowledge to enrich event expressions, which can be used to solve relation extraction that requires reasoning. The connections between entities not only explicitly exist in the knowledge graph, but also implicitly exist in the pre-training language model.

(3) Combination of global structure and local structure. We can learn from the idea of generating abstracts to extract the relation based on topic distribution and segmentation processing. Articles are composed of paragraphs, and different paragraphs focus on different topics and events. Modeling paragraphs to form the global structure of the article is beneficial to document-level event extraction.