

# A Survey on Deep Learning Event Extraction: Approaches and Applications

Qian Li, Jianxin Li<sup>1</sup>, *Member, IEEE*, Jiawei Sheng, Shiyao Cui, Jia Wu<sup>2</sup>, *Senior Member, IEEE*, Yiming Hei<sup>3</sup>, Hao Peng<sup>4</sup>, Shu Guo, Lihong Wang, Amin Beheshti<sup>5</sup>, and Philip S. Yu<sup>6</sup>, *Life Fellow, IEEE*

**Abstract**—Event extraction (EE) is a crucial research task for promptly apprehending event information from massive textual data. With the rapid development of deep learning, EE based on deep learning technology has become a research hotspot. Numerous methods, datasets, and evaluation metrics have been proposed in the literature, raising the need for a comprehensive and updated survey. This article fills the research gap by reviewing the state-of-the-art approaches, especially focusing on the general domain EE based on deep learning models. We introduce a new literature classification of current general domain EE research according to the task definition. Afterward, we summarize the paradigm and models of EE approaches, and then discuss each of them in detail. As an important aspect, we summarize the benchmarks that support tests of predictions and evaluation metrics. A comprehensive comparison among different approaches is also provided in this survey. Finally, we conclude by summarizing future research directions facing the research area.

**Index Terms**—Deep learning, evaluation metrics, event extraction (EE), research trends.

## I. INTRODUCTION

**E**VENT extraction (EE) is an important yet challenging task in information extraction research. As a particular form of information, an event refers to a specific occurrence

of something that happens in a certain time and a certain place involving one or more participants, which can usually be described as a change in state [1]. The EE task aims at extracting such event information from unstructured plain texts into a structured form, which mostly describes “who, when, where, what, why” and “how” of real-world events that happened. In terms of application, the task facilitates people to retrieve event information and analyze people’s behaviors, arousing information retrieval [2], [3], recommendation [4], [5], intelligent question answering (QA) [6], [7], knowledge graph construction [8], [9], and other event-related applications [10], [11], [12].

EE can be divided into two groups: close-domain EE [13], [14], [15] and open-domain EE [16], [17], [18]. Events are usually considered in a predefined event schema, where some specific people and objects are interacted at a specific time and place. The close-domain EE task aims to find words that belong to a specific event schema, which refers to an action or state change that occurs, and its extraction targets include time, place, person, and action, etc. In the open-domain EE task, events are considered as a set of related descriptions of a topic, which can be formulated into a classification or clustering task. Open-domain EE refers to acquiring a series of events related to a specific theme, usually composed of multiple events. Whether the close-domain or open-domain EE task, the purpose of EE is to capture the event types that we are interested in from numerous texts and show the essential arguments of events in a structured form.

Deep learning EE on general domain has a lot of work and has been a relatively mature research taxonomy. It discovers event mentions from texts and extracts events containing event triggers and event arguments, where event mentions are termed as sentences containing one or more triggers and arguments. EE requires to identify the event, classify event type, identify the argument, and judge the argument role. Specifically, trigger identification and trigger classification are usually formed as the event detection (ED) task [19], [20], [21], [22], while argument identification (AI) and argument role classification are usually defined as an argument extraction task. The trigger classification is a multiclassification classification [23], [24], [25] task to classify the type of each event. The role classification task is a multiclass classification task based on word pairs, determining the role relationship between any pair of triggers and entities in a sentence. From a technical perspective, EE can depend on some other foundational natural language processing (NLP) tasks such as named entity recognition (NER) [26], [27], [28], semantic parsing [29], [30], [31], and relationship extraction [32], [33], [34].

Manuscript received 29 November 2021; revised 1 May 2022 and 17 August 2022; accepted 4 October 2022. This work was supported in part by the NSFC under Grant U20B2053 and Grant 62106059 and in part by the Academic Excellence Foundation of Beihang University (BUAA) for PhD Students. The work of Philip S. Yu was supported by the NSF under Grant III-1763325, Grant III-1909323, Grant III-2106758, and Grant SaTC-1930941. (Corresponding author: Jianxin Li.)

Qian Li and Jianxin Li are with the School of Computer Science and Engineering, Beijing Advanced Innovation Center for Big Data and Brain Computing, Beihang University, Beijing 100083, China (e-mail: liqian@act.buaa.edu.cn; lijx@act.buaa.edu.cn).

Jiawei Sheng and Shiyao Cui are with the Institute of Information Engineering, Chinese Academy of Sciences, Beijing 100083, China, and also with the School of Cyber Security, University of Chinese Academy of Sciences, Beijing 100083, China (e-mail: shengjiawei@iie.ac.cn; cuishiyao@iie.ac.cn).

Jia Wu and Amin Beheshti are with the School of Computing, Macquarie University, Sydney, NSW 2109, Australia (e-mail: jia.wu@mq.edu.au; amin.beheshti@mq.edu.au).

Yiming Hei is with the School of Cyber Science and Technology, Beihang University, Beijing 100083, China (e-mail: black@buaa.edu.cn).

Hao Peng is with the School of Computer Science and Engineering, Beijing Advanced Innovation Center for Big Data and Brain Computing, Beihang University, Beijing 100083, China, and also with the Beijing Advanced Innovation Center for Big Data and Brain Computing, Beihang University, Beijing 100083, China (e-mail: penghao@act.buaa.edu.cn).

Shu Guo and Lihong Wang are with the National Computer Network Emergency Response Technical Team/Coordination Center of China, Beijing 100029, China (e-mail: guoshu@cert.org.cn; wlh@cert.org.cn).

Philip S. Yu is with the Department of Computer Science, University of Illinois at Chicago, Chicago, IL 60607 USA (e-mail: psyu@uic.edu).

Color versions of one or more figures in this article are available at <https://doi.org/10.1109/TNNLS.2022.3213168>.

Digital Object Identifier 10.1109/TNNLS.2022.3213168

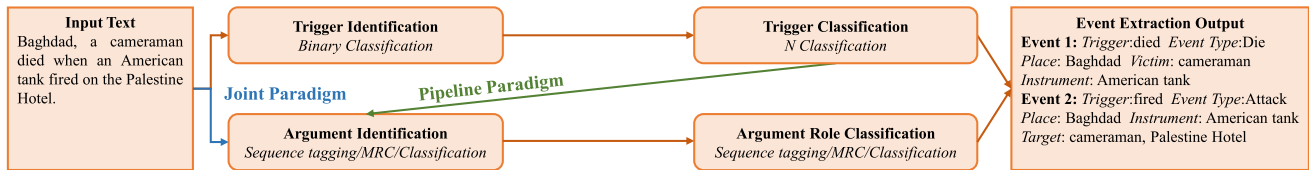


Fig. 1. Flowchart of deep learning EE on general domain.

We give the flowchart of deep learning EE on the general domain, as shown in Fig. 1. The EE is to find the focused event type and extract its arguments with its roles. For a pipeline paradigm EE, it is necessary to distinguish the event type in the text for a given text, called trigger classification. For different event types, different event schema is designed. Then, event arguments are extracted according to the schema, which includes AI and argument role classification subtasks. In the earliest stage, argument role classification is regarded as a word classification task, and each word in the text is classified. In addition, there are sequence labeling, machine reading comprehension (MRC), and sequence-to-structure generation methods. For a joint paradigm EE, the model classifies the event type and argument roles simultaneously to avoid error coming from the trigger classification subtask.

#### A. Contributions

For the traditional EE method, feature designing is necessary, while for the deep learning EE method on general domain, the features can be end-to-end extracted by the deep learning models. The existing reviews mainly introduce the extraction of subject events, where there are few EE methods based on the deep learning models [18], [35], [36]. In recent years, a large number of EE methods have been proposed, and the EE methods based on the Transformer have achieved significant improvement [37]. Furthermore, EE is no longer limited to classification and sequence annotation manner [38], [39], [40], but can also be formulated in MRC and generation [41], [42] manner. Therefore, we comprehensively analyze the existing deep-learning-based EE methods on general domain and outlook for future research work. The main contributions of this article are as follows.

- 1) We introduce the general domain EE technology, review the development history of EE methods, and point out that the EE methods with deep learning have become the mainstream. We summarize the necessary information of the deep learning models according to the year of publication in Table I.
- 2) We analyze various deep-learning-based extraction paradigm and models, including their advantages and disadvantages in detail. We introduce the currently available datasets and give the formulation of the main evaluation metrics. We summarize the necessary information of primary datasets in Table II.
- 3) We summarize EE accuracy scores on the automatic content extraction (ACE) 2005 dataset in Table IV and EE applications. We conclude the review by discussing the future research trends facing EE.

#### B. Organization of the Survey

The rest of the survey is organized as follows. Section II introduces the concepts and task definitions of EE. Section III summarizes the existing paradigm related to EE, including the pipeline-based methods and joint-based methods, constituting a summary table. Section IV introduces the traditional EE and deep learning-based EE with a comparison. Section V introduces the EE on different scenarios. Sections VI and VII describe primary EE corpus and metrics, respectively. We then give quantitative results of the leading models in classic EE datasets in Section VIII. Finally, we summarize EE applications and main challenges for EE in Sections IX and X, respectively, before concluding the article in Section XI.

## II. PRELIMINARY

This section introduces concepts, subtasks, and model manners in current EE researches.

#### A. Concepts

An event indicates an occurrence of an action or state change, often driven by verbs or gerunds. It contains the primary components involved in action, such as time, place, and character. The EE technology extracts events that users are interested in from unstructured texts and presents them to users in a structured form [39]. In short, EE detects event with its type and extracts the core arguments from the text, as shown in Fig. 2. Given a text, an EE technology can predict the events' mentions in the text, the triggers and arguments corresponding to each event, and classify the role of each argument. EE requires to recognize the two events (*Die* and *Attack*), triggered by the words "died" and "fired," respectively, as shown in Fig. 2. For *Die* event type, we recognize that "Baghdad," "cameraman," and "American tank" take on the event argument roles *Place*, *Victim*, and *Instrument*, respectively. For *Attack*, "Baghdad" and "American tank" take on the event argument roles *Place* and *Instrument*, respectively. And "cameraman" and "Palestine Hotel" take on the event argument roles *Target*.

EE involves many frontier disciplines, such as machine learning, pattern matching, and NLP. At the same time, EE in various fields can help relevant personnel quickly extract relevant content from massive information, improve work timeliness, and provide technical support for quantitative analysis. Therefore, EE has a broad application prospect in various fields. Typically, ACE describes an EE task holding the following terminologies.

- 1) **Entity**: The entity is an object or group of objects in a semantic category. Entity mainly includes people,

TABLE I  
BASIC INFORMATION OF DIFFERENT MODELS. ED, AE: ARGUMENT EXTRACTION, NER, AND MRC

Year	Model	Setting	Manner	Venue	Datasets	ED	AE	NER
2021	TEXT2EVENT [?]	supervised	generation	ACL	ACE05-EN, ERE-EN	✓	✓	-
	CasEE [15]	supervised	sequence labeling	ACL(Findings)	FewFC	✓	✓	-
	CLEVE [71]	supervised	classification	ACL	ACE, MAVEN	✓	✓	✓
	FEAE [72]	supervised	MRC	ACL	RAMS	✓	✓	✓
	GIT [73]	supervised	classification	ACL	ChFinAnn <sup>1</sup>	✓	✓	✓
	NoFPFN [74]	supervised	classification	ACL(Findings)	ChFinAnn	✓	✓	✓
	DualQA [75]	semi-supervised	MRC	AAAI	ACE, FewFC	-	✓	-
	GRIT [76]	supervised	generation	EACL	MUC-4	✓	✓	-
	Wen et al. [77]	supervised	classification	NAACL	ACE	✓	✓	-
	HPNet [78]	supervised	sequence labeling	COLING	ACE2005, TAC2015	✓	✓	-
	M2E2 [79]	weakly supervised	classification	ACL	M2E2	✓	✓	-
	MQAEE [42]	supervised	MRC	EMNLP	ACE	✓	✓	-
	Du et al. [41]	supervised	MRC	EMNLP	ACE	✓	✓	-
	Min et al. [80]	supervised	classification	LREC	ACE	-	✓	-
	Chen et al. [81]	supervised	MRC	EMNLP	ACE	-	✓	-
	EEGCN [82]	supervised	sequence labeling	EMNLP(Findings)	ACE	✓	-	-
2019	Doc2EDAG [83]	supervised	generation	EMNLP	ChFinAnn	✓	✓	✓
	Chen et al. [81]	supervised	MRC	arXiv	ACE	✓	✓	-
	GAIL-ELMo [84]	supervised	sequence labeling	Data Intell.	ACE	✓	✓	✓
	DYGE++ [85]	supervised	sequence labeling	EMNLP	ACE, SciERC, etc.	✓	✓	-
	HMEAE [86]	supervised	classification	EMNLP	ACE, TAC-KBP	-	✓	✓
	Han et al. [87]	supervised	classification	EMNLP	TB-Dense, MATRES	✓	✓	✓
	PLMEE [37]	supervised	sequence labeling	ACL	ACE	✓	✓	✓
	JointTransition [58]	supervised	classification	IJCAI	ACE	✓	✓	✓
	Joint3EE [88]	supervised	sequence labeling	AAAI	ACE	✓	✓	-
	Chan et al. [89]	supervised	classification	ACL	ACE	✓	✓	✓
	Li et al. [90]	supervised	MRC	ACL	ACE, CoNLL04	✓	✓	-
2018	DCFEE [91]	distance supervision	sequence labeling	ACL	NO.(ANN, POS, NEG)	✓	✓	-
	Zeng et al. [92]	distance supervision	sequence labeling	AAAI	FBWiki, ACE	✓	✓	✓
	Huang et al. [61]	supervised	classification	ACL	ACE	✓	✓	-
	DEEB-RNN [93]	supervised	classification	ACL	ACE	✓	-	-
	SELF [94]	supervised	classification	ACL	ACE, TAC-KBP	✓	-	-
	DBRNN [95]	supervised	classification	AAAI	ACE	✓	✓	✓
	JMEE [96]	supervised	sequence labeling	EMNLP	ACE	✓	✓	✓
	Ferguson et al. [14]	semi-supervised	classification	NAACL	ACE, TAC-KBP	✓	✓	-
2017	DMCNN-MIL [70]	distance supervision	classification	ACL	ACE	✓	✓	✓
	Liu et al. [97]	supervised	classification	ACL	ACE	✓	-	-
2016	RBPB [98]	supervised	classification	ACL	ACE	✓	✓	-
	Zeng et al. [99]	supervised	sequence labeling	NLPCC	ACE	✓	✓	-
	JRNN [40]	supervised	sequence labeling	NAACL	ACE	✓	✓	✓
	JOINTEVENTENTITY [13]	supervised	sequence labeling	NAACL	ACE	✓	✓	✓
	BDLSTM-TNNs [100]	supervised	classification	CCL	ACE	✓	✓	✓
	Liu et al. [69]	supervised	classification	ACL	ACE	✓	-	-
2015	DMCNN [39]	supervised	classification	ACL	ACE	✓	✓	✓

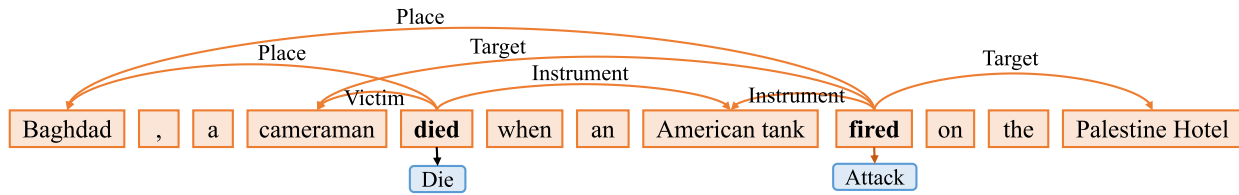


Fig. 2. Diagram of EE. The example can be divided into two types of event. The type of *Die* is triggered by “died” with three argument roles of *Place*, *Victim*, and *Instrument*, and the type of *Attack* is triggered by “fired” with three argument roles of *Place*, *Target*, and *Instrument*.

organizations, places, times, things, etc. In Fig. 2, the words “Baghdad,” “cameraman,” “American tank,” and “Palestine Hotel” are *Entity*.

- 2) **Event mentions:** The phrases or sentences that describe the event contain a trigger and the corresponding arguments.
- 3) **Event type:** The event type describes the nature of the event and refers to the category to which the event corresponds, usually represented by the type of the event trigger. For sentence in Fig. 2, it contains *Die* and *Attack* event types.

- 4) **Event trigger:** Event trigger refers to the core unit in EE, a verb, or a noun. Trigger identification is a key step in the pipeline-based EE. For event *Die* in Fig. 2, the event trigger is “died.”
- 5) **Event argument:** Event argument is the main attribute of events. It includes entities, nonentity participants, time, and so on. For event *Die* in Fig. 2, the event arguments are “Baghdad,” “cameraman,” and “American tank.”
- 6) **Argument role:** An argument role is a role played by an argument in an event, that is, the relationship

TABLE II  
SUMMARY STATISTICS FOR THE DATASETS. (DOC DENOTES THE NUMBER OF DOCUMENTS IN DATASET,  
SEN DENOTES THE NUMBER OF SENTENCES IN DATASET)

Datasets	Doc	Sen	Event Type	Language	Related Papers
MUC-4	1700	-	5	-	[114]
Google	11,909	-	30	English	[151]
Twitter	1,000	-	20	English	[151]
NO.ANN, NO.POS, NO.NEG (DCFEE)	2,976	-	4	Chinese	[91]
ChFinAnn (Doc2EDAG)	32,040	-	5	Chinese	[83]
ACE 2005	599	18,117	33	Multi-language	[33], [42], [75], [80], [84], [89], [95], [141], [152]
TAC KBP 2015	360	12,976	38	English	[14], [78]
TAC KBP 2016	500	9,042	18	Multi-language	[86]
Rich ERE	50	-	-	English	[153]
FSED	-	70,852	100	English	[133]
GNBusiness	12,985	1,450,336	-	English	[17]
FSD	-	2,453	20	English	[151]
FBI dataset	-	-	3	English	[154]
RAMS	3,993	-	139	English	[115]
WIKIEVENTS	246	6,132	-	English	[118]
MAVEN	4,480	49,873	168	English	[22] [71] [155]

representation between the event arguments and the event triggers. For argument “Baghdad” of *Die* event in Fig. 2, the argument role is *Place*.

### B. Subtasks

EE includes four subtasks: trigger classification, trigger identification, AI, and argument role classification.

- 1) **Trigger identification:** It is generally considered that the trigger is the core unit in EE that can clearly express an event’s occurrence. The trigger identification subtask is to find the trigger from the text. In Fig. 2, trigger identification is to identify the trigger “died” and “fired.”
- 2) **Trigger classification:** Trigger classification is to determine whether each sentence is an event according to the existing triggers. Furthermore, if the sentence is an event, we need to determine one or several events’ types the sentence belongs to. For example in Fig. 2, the subtask aims to classify the event type of trigger “died” and “fired,” which, respectively, correspond to *Die* and *Attack*. Therefore, the trigger classification subtask can be seen as a multilabel text classification task.
- 3) **Argument identification:** Argument identification is to identify all the arguments contained in an event type from the text. Argument identification usually depends on the result of trigger classification and trigger identification. For example in *Die* event in Fig. 2, AI is to extract the words “Baghdad,” “cameraman,” and “American tank.”
- 4) **Argument role classification:** Argument role classification is based on the arguments contained in the EE schema, and the category of each argument is classified according to the identified arguments. For the extracted words in Fig. 2, such as “cameraman,” this subtask is to classify the word to *Object* category. Thus, it can also be seen as a multilabel text classification task.

### C. EE Manner

EE is a very representative hot topic in information extraction, which studies how to extract a specific type of event information from unstructured text containing event information (news, blog, etc.). It can be simplified as multiple classification tasks, which determine the type of event and the argument role that each entity belongs to. For example, for the word “cameraman” in Fig. 2, the classification-based methods are to classify which argument role it belongs to in a given role set. The classification method depends on NER, leading to the propagation of error information. Based on this, an EE method based on sequence labeling is proposed, which labels the start and end positions of each argument. The sequence labeling-based methods give a label in *BIO* of the word “cameraman.” The task of EE is complex, and arguments are closely related to each other. MRC is adopted to learn association, and each argument is found through question and answering pairs. The MRC-based methods generate a question for argument role, such as *Object*, and the model is to find the word play the argument role *Object*. Therefore, EE task can be regarded as the classification task, sequence labeling task, and MRC task. Recently, some works focus on using a generative way [43], [44]. The definitions of these four tasks in more detail are as follows.

1) **Classification-Based Task:** For the classification task [45], [46], the authors usually predefine  $n$  event types and their corresponding argument roles, e.g., the event  $e_i$  ( $i \in [1, n]$ ) contains a set of argument roles  $[r_{i,1}, r_{i,2}, \dots, r_{i,l}]$ . Given an input event mention  $m$ , the model needs to output a result vector  $T$ , where the  $i$ th argument  $T_i$  represents the probability that  $m$  belongs to the event  $e_i$ . In the classification-based task, the trigger identification is to classify whether a word is a trigger. After obtaining the final event (or a set)  $e_k$  of  $m$ , the model outputs a matrix  $R$  where the argument  $R_{i,j}$  means the probability that the extracted argument  $a_i$  belongs to argument roles  $r_{k,j}$ . As shown in Fig. 3(a), it classifies each entity to a predefined argument role.



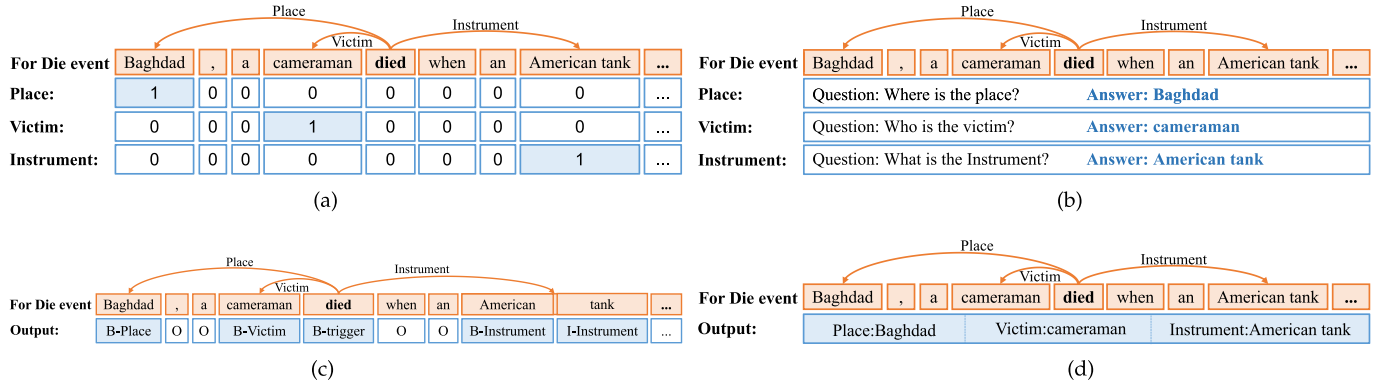


Fig. 3. How to implement argument extraction for Die event on the classification-based, sequence labeling-based, QA-based, and sequence-to-structure generation-based tasks. (a) Classification-based task. (b) QA-based task. (c) Sequence labeling-based task. (d) Sequence-to-structure generation-based task.

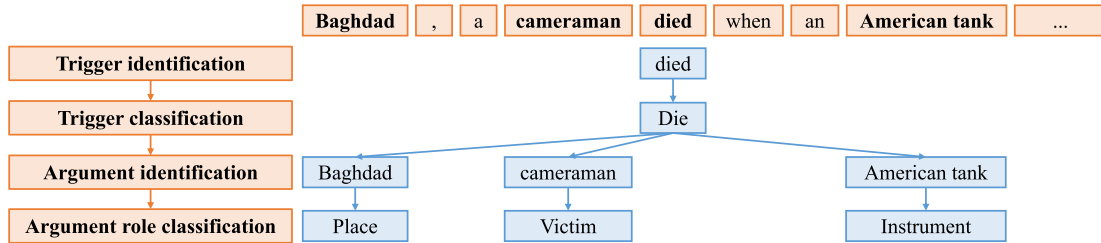


Fig. 4. Example of the pipeline-based EE.

2) *MRC-Based Task*: The MRC model [47], [48], [49] can understand a piece of text in natural language and answer questions about it [50]. In the MRC-based task, the trigger identification is also to classify whether a word is a trigger. First, a question schema is designed for each argument role  $r$ , called  $Q_r$ . Since different event types have different arguments, the model needs to first identify the event type to which the text belongs. Then, the argument roles to be extracted are determined according to the event types. Finally, the EE method based on MRC is to input the text  $T$  and apply the designed questions  $Q_r$  one by one to the extraction model, as shown in Fig. 3(b). The model extracts the answer  $A_r$ , which is the corresponding argument for each argument role  $r$ .

3) *Sequence Labeling-Based Task*: The sequence labeling task [51], [52], [53] is a multiclassification task [54], [55], [56] based on word level, which can directly match event arguments based on word-level event-type extraction. The EE mainly includes two core tasks: identifying and classifying event categories and extracting event arguments. EE based on sequence labeling can simply and quickly realize the matching of event type and event argument without additional features. In the sequence labeling-based task, the trigger identification is to label a word as a trigger. The sequence labeling method marks out the target from the text, which is suitable for the EE task. As shown in Fig. 3(c), for a given text  $T = x_1, x_2, \dots, x_N$  and event schema, the argument role  $r$  corresponding to the argument is labeled with the sequence labeling model. The output  $y = y_1, y_2, \dots, y_N$  of the sequence labeling model is to tag all the words in the text.

4) *Sequence-to-Structure Generation-Based Task*: The sequence-to-structure generation-based EE extracts events from the text in an end-to-end manner [43]. In the sequence-to-structure generation-based task, the trigger identification is to

generate a trigger. It uniformly models all the tasks in a single model and universally predicts different labels. As shown in Fig. 3(d), the sequence-to-structure generation-based methods directly generate all the arguments and their roles. It usually adopts the encoder-decoder models [43], which is an easy way to convert text into a structured form.

### III. EE PARADIGM

EE includes four subtasks: trigger identification, event-type classification, AI, and argument role classification. According to the procedure to settle these four subtasks, the EE task is divided into pipeline-based EE and joint-based EE. The pipeline-based method is first adopted [39], [57]. It first detects the triggers and judges the event type according to the triggers. The argument extraction model then extracts arguments and classifies argument roles according to the prediction results of event type and the triggers. To overcome the propagation of error information caused by ED, researchers propose a joint-based EE paradigm [58], [59], [60]. It reduces the propagation of error information by combining the ED and argument extraction tasks.

#### A. Pipeline-Based Paradigm

The pipeline-based method treats all the subtasks as independent classification problems [61], [62], [63]. The pipeline approach is widely used since it simplifies the entire EE task. The pipeline-based EE method, as shown in Fig. 4, converts the EE tasks into a multistage classification problem. The required classifiers include. 1) A trigger classifier is used to determine whether the term is the event trigger and the type of event.

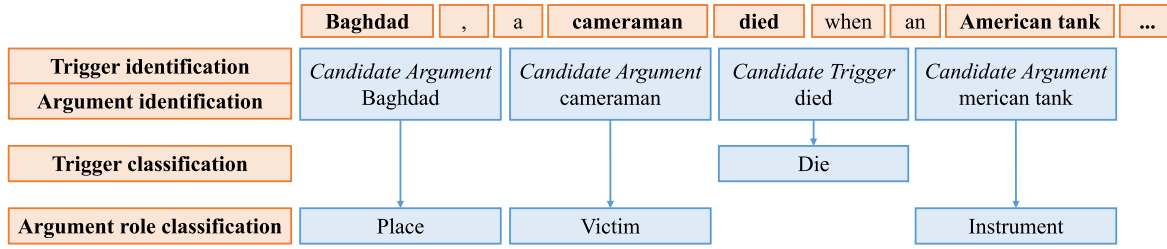


Fig. 5. Simplified architecture of the joint-based EE paradigm.

2) An argument classifier is used to determine whether the word is the argument of the event.

3) An argument role classifier is used to determine the category of arguments.

The classical deep-learning-based EE model dynamic multipooling convolutional neural network (DMCNN) [39] uses two dynamic multipooling convolutional neural networks (CNNs) for trigger classification and argument classification. The trigger classification model identifies the trigger. If there is a trigger, the argument classification model is used to identify arguments and their roles. Pretrained language model-based event extractor (PLMEE) [37] also uses two models using trigger extraction and argument extraction. Argument extractor uses the result of trigger extraction to reason. It performs well through introducing bidirectional encoder representation from transformer (BERT) [64].

The pipeline-based EE methods provide additional information for subsequent subtasks through previous subtasks and take advantage of dependencies between subtasks. Du and Cardie [41] adopt a QA method to implement EE. First, the model identifies the trigger in the input sentence through the designed question template of the trigger. The input of the model includes the input sentence and question. Then, it classifies the event type according to the identified trigger. The trigger can provide additional information for trigger classification, but the result of wrong trigger identification can also affect trigger classification. Finally, the model identifies the event argument and classifies argument roles according to the schema corresponding to the event type. In argument extraction, the model uses the answers of the previous round of history content.

The most significant defect of this method is error propagation. Intuitively, if there is an error in trigger identification in the first step, then the accuracy of AI will be lowered. Therefore, when using pipelines to extract events, there will be error cascading and task splitting problems. The pipeline EE method can extract event arguments using the information of triggers. However, this requires high accuracy of trigger identification. A wrong trigger will seriously affect the accuracy rate of argument extraction. Therefore, the pipeline EE method considers the trigger as the core of an event.

*Summary:* The pipeline-based method transforms the EE task into a multistage classification problem. The pipeline-based EE method first identifies the triggers, and AI is based on the result of trigger identification. It considers the trigger as the core of an event. Yet, this staged strategy will lead to error propagation. The recognition error of the

trigger will be passed to the argument classification stage, which will lead to the degradation of the overall performance. Moreover, because the trigger detection always precedes the argument detection, the argument will not be considered while detecting triggers. Therefore, each link is independent and lacks interaction, ignoring the impact between them. Thus, the overall dependency relationship cannot be handled. The classic case is DMCNN [39].

### B. Joint-Based Paradigm

EE is of great practical value in NLP. Before using deep learning to model the EE tasks, the joint learning method has been studied in EE. As shown in Fig. 5, this method identifies the triggers and arguments according to candidate triggers and entities in the first stage. In the second stage, to avoid the error information propagation from event type, trigger classification and argument role classification are realized simultaneously. It classifies trigger “died” to *Die* event type and argument “Baghdad” to *Place* argument role, etc.

The deep learning EE method based on the joint model mainly uses deep learning and joint learning to interact with feature learning, which can avoid the extended learning time and complex feature engineering [65], [66], [67]. Li et al. [38] study the joint learning of trigger extraction and argument extraction tasks based on the traditional feature extraction method and obtain the optimal result through the structured perceptron model. Zhu et al. [68] design efficient discrete features, including local features of all the information contained in feature words and global features that can connect trigger with argument information. Nguyen et al. [40] successfully construct local features and global features through deep learning and joint learning. It uses a recurrent neural network (RNN) to combine event recognition and argument role classification. The local features constructed are text sequence features and local window features. The input text consists of word vectors, entity vectors, and event arguments. Then the text is transferred to the RNN model to obtain the sequence characteristics of the deep learning. A deep learning model with memory is also proposed to model it. It mainly aimed at the global characteristics between event triggers, between event arguments, and between event triggers and event arguments to improve the performance of tasks simultaneously.

EE involves related tasks such as entity recognition, which helps improve EE. Liu et al. [69] use the local characteristics of arguments to assist role classification. They adopted a joint learning task for entities for the first time, aiming to reduce

the complexity of the task. The previous methods input the dataset with characteristics which are marked and output the event. Chen et al. [70] simplify the process, namely, plain text input and output. In the middle of the process, it is the joint learning on event arguments. This joint learning factor mainly provides the relationship and entity information of different events within each input event.

The above joint learning method can achieve joint modeling EE of triggers and arguments. However, in the actual work process, the extraction of triggers and arguments is carried out successively rather than concurrently, which is an urgent problem to be discussed later. Besides, if an end-to-end mode is added to deep learning, the feature selection workload will be significantly reduced, which will also be discussed later. The joint EE method avoids the influence of trigger identification error on event argument extraction, considering trigger and argument are equally important, but it cannot use the information of triggers.

*Summary:* To overcome the shortcomings of the pipeline method, researchers proposed a joint method. The joint method constructs a joint learning model to trigger recognition and argument recognition, where the trigger and argument can mutually promote each other's extraction effect. The experiment proves that the effect of the joint learning method is better than the pipeline learning method. The classic case is joint event extraction via recurrent neural network (JRNN) [40]. The joint EE method avoids trigger identification on event argument extraction, but it cannot use the information of trigger. The joint EE method considers that the trigger and argument in an event are equally important. However, neither pipeline-based EE nor joint-based EE can avoid the impact of event-type prediction errors on the performance of argument extraction. Moreover, these methods cannot share information among different event types and learn each type independently, which is disadvantageous to EE with only a small amount of labeled data.

#### IV. DEEP LEARNING EE MODELS

The traditional EE methods are challenging to learn in-depth features, making it difficult to improve the task of EE that depends on complex semantic relationships. Most recent EE works are based on a deep learning architecture such as CNNs [39], [101], RNN [95], [102], graph neural network (GNN) [82], [96], [103], [104], [105], Transformer [37], [106], [107], or other networks [58], [78]. As shown in Table I, we show the basic information of the existing models according to the publish year. It includes the domain which is the model exploring, venue the model published, and datasets the model used. Furthermore, we conclude whether each model contains ED, argument extraction, and NER. The deep learning method can capture complex semantic relationships and significantly improve multiple EE datasets. We introduce several typical EE models.

##### A. CNN-Based Models

To automatically extract lexical and sentence-level features without using complex NLP tools, Chen et al. [39] introduce

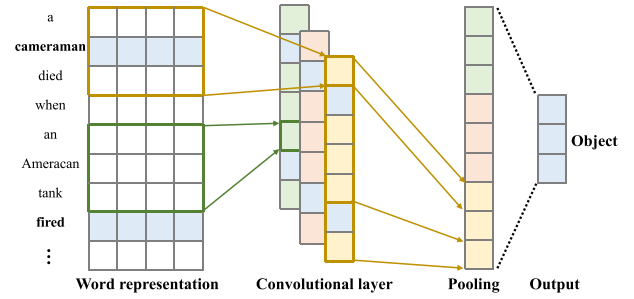


Fig. 6. Architecture of CNN-based argument extraction. It illustrates processing of one instance with predicted trigger “fired” and candidate argument “cameraman.”

a word representation model, called DMCNN. It captures the meaningful semantic rules of words and adopts a framework based on a CNN to capture sentence-level clues. However, CNN can only capture the essential information in a sentence, and it uses a dynamic multipool layer to store more critical information based on event triggers and arguments. EE is a two-stage multiclass classification realized by a dynamic multipool CNN with automatic learning features. The first stage is trigger classification. DMCNN classifies each word in the sentence to identify triggers. For a sentence having a trigger, this phase applies a similar DMCNN to assign arguments to the trigger and align the arguments' roles. Fig. 6 depicts the architecture of argument classification. Lexical-level feature representation and sentence-level features' extraction are used to capture lexical clues and learn the sentences' compositional semantic features.

CNN induces the underlying structures of the k-grams in the sentences. Thus, some researchers also study the EE techniques based on CNNs. Nguyen and Grishman [108] use CNN to investigate the ED task, which overcomes complex feature engineering and error propagation limitations compared with the traditional feature-based approaches. But it relies extensively on other supervised modules and manual resources to obtain features. It is significantly superior to the feature-based method in terms of cross-domain generalization performance. Furthermore, to consider nonconsecutive k-grams, Nguyen and Grishman [102] introduce nonconsecutive CNN. The CNN models apply the in pipeline-based and joint-based paradigm through structured predictions with rich local and global characteristics to automatically learn hidden feature representations. The joint-based paradigm can mitigate error propagation problems compared with the pipeline-based approach and exploit the interdependencies between event triggers and argument roles.

##### B. RNN-Based Models

In addition to the CNN-based EE method, some other researches are carried out on RNN. The RNN is used for modeling sequence information to extract arguments in the event, as shown in Fig. 7. JRNN [40] is proposed with a bidirectional RNN for EE in a joint-based paradigm. It has an encoding stage and a prediction stage. In the encoding stage, it uses RNN to summarize the context information.

<sup>1</sup><http://www.cninfo.com.cn/new/index>

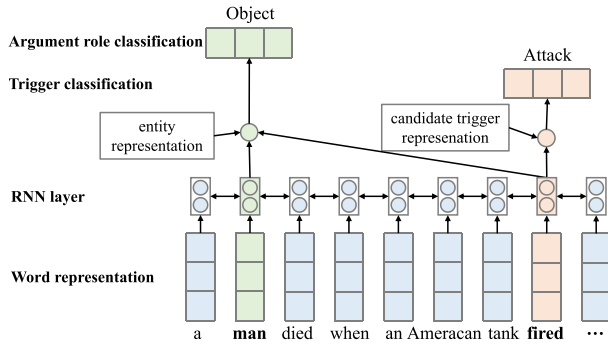


Fig. 7. Simplified architecture of RNN-based argument extraction for the input sentence “a man died when a tank fired in Baghdad” for candidate trigger “fired.”

Furthermore, it predicts both the trigger and argument roles in the prediction stage.

Previous approaches relied heavily on language-specific knowledge and existing NLP tools. A more promising method from data automatically learning useful features, Feng et al. [109] develop a hybrid neural network to capture in the context of a specific sequence and pieces of information and use them for training a multilingual event detector. The model uses a bidirectional long short-term memory (LSTM) to obtain the document’s sequence information that needs to be recognized. Then it uses the CNN to get the phrase chunk information in the document, combine the two kinds of information, and finally identify the trigger. The method are robust, efficient, and accurate detection for multiple languages (English, Chinese, and Spanish). The composite model is superior to the traditional feature-based approach in terms of cross-language generalization performance. The tree structure and sequence structure in a deep learning have better performance than a sequential structure. To avoid over-reliance on lexical and syntactic features, the dependence bridge recursive neural network (DBRNN) [95] is based on bidirectional RNNs for EE. The DBRNN is enhanced by relying on bridging grammar-related words. DBRNN is an RNN-based framework that leverages the dependency graph information to extract event triggers and argument roles.

### C. Attention-Based Models

The automatic extraction of event features by the deep learning model and the enhancement of event features by external resources mainly focus on the information of event triggers, and less on the information of event arguments and interword dependencies. Sentence-level sequential modeling suffers a lot from low efficiency in capturing very long-range dependencies. Furthermore, the RNN-based and CNN-based models do not fully model the associations between events. The modeling of structural information in the attention mechanism has gradually attracted the attention of researchers. As research methods are constantly proposed, models that add the attention mechanisms appear gradually, as shown in Fig. 8. The attention mechanism’s feature determines that it can use global information to model local context without considering location information. It has a good application effect when updating the semantic representation of words.

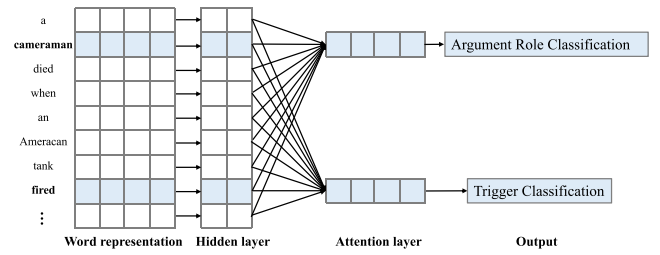


Fig. 8. Architecture of attention-based EE.

By controlling the different weight information of each part of the sentence, the attention mechanism makes the model pay attention to the important feature information of the sentence while ignoring other unimportant feature information and rationally allocate resources to extract more accurate results. At the same time, the attention mechanism itself can be used as a kind of alignment, explaining the alignment between the input and the output in the end-to-end model, to make the model more interpretable.

Some researchers also use a hierarchical attention mechanism to conduct the global aggregation of information. The jointly multiple EE (JMEE) [96] composes of four modules: word representation, syntactic graph convolution network, self-attention trigger classification, and argument classification modules. The information flow is enhanced by introducing a syntax shortcut arc. The graph convolution network based on attention is used to jointly model the graph information to extract multiple event triggers and arguments. Furthermore, it optimizes a biased loss function when jointly extracting event triggers and arguments to settle the dataset imbalances.

### D. GCN-Based Models

Syntactic representations present an efficient method for straight linking words to their informative context for ED in sentences [33], [82], [110], [111]. Nguyen and Grishman [110] investigate a CNN based on dependency trees to perform ED which is the first to integrate the dependency tree relationship information into neural ED. The model uses the proposed model with graph convolutional networks (GCNs) [111] and entity mention-based pooling. They propose a novel pooling method that relies on entity mentions to aggregate convolution vectors. The model operates a pooling over the graph-based convolution vectors of the current word and the entity mentions in the sentences. The model aggregates convolution vectors to generate a single-vector representation for event-type prediction. The model is to explicitly model the information from entity mentions to improve the performance for ED.

In [77], the text analysis conference 2015 (TAC)-knowledge base population (KBP) time slot is used to fill the quaternary time representation proposed in the task, and the model predicts the earliest and latest start and end times of the event, thus representing the ambiguous time span of the event. The model constructs a document-level event graph for each input document based on shared arguments and time relationships and uses a graph-based attention network method to propagate time information on the graph, as shown in Fig. 9, where entities are underlined and events are in bold face. Wen et al. [77] construct a document-level event diagram method based on



The enemy have now been flown out and we're treating them including a man who is almost dead with a gunshot wound to the chest after we (Royal Marines) sent in one of our companies of about 100 men in here (Umm Kiou) this morning.

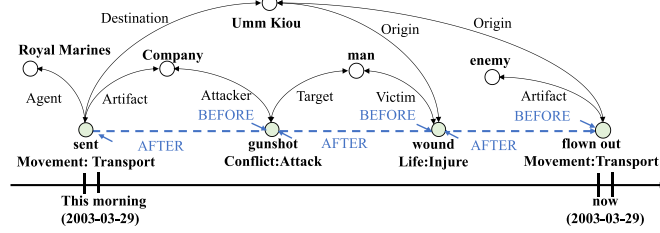


Fig. 9. Example event graph. The solid line consists of event arguments, while the dashed line graph is constructed based on time relationships [77].

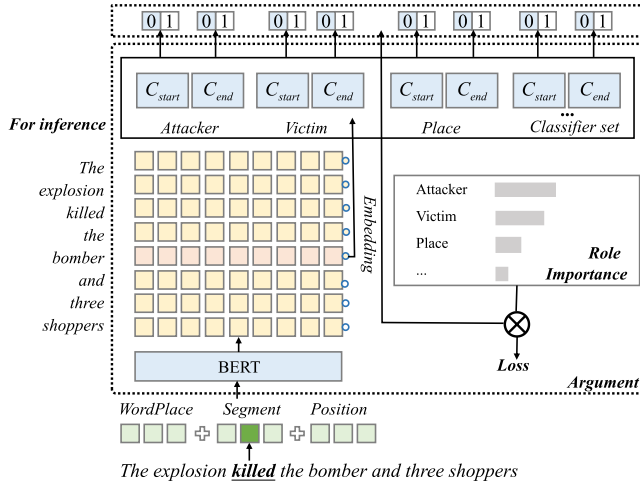


Fig. 10. Architecture of PLMEE [37] for extraction.

event–event relationships for input documents. The event arguments in the document are extracted. The events then are arranged in the order of time according to keywords such as *Before* and *After* and the time logic of the occurrence of the events. Entity arguments are shared among different events. The model implementation incorporates events into a more accurate timeline.

### E. Transformer-Based Models

It is challenging to exploit one argument that plays different roles in various events to improve EE. Yang et al. [37] use a method to separate the argument prediction in terms of argument roles for overcoming the roles' overlap problem. Moreover, this method automatically generates labeled data by editing prototypes and screening developed samples through ranking the quality due to inadequate training data. They present a framework, PLMEE [37], as shown in Fig. 10. The PLMEE promotes EE using a combination of an extraction model and a generation method based on the pretrained language models. It is a two-stage task, including trigger extraction and argument extraction, and consists of a trigger extractor and an argument extractor, both of which rely on BERT's feature representation. Then it exploits the importance of roles to reweight the loss function.

GAIL [84] is an embeddings from language model (ELMo)-based [112] model using a generative adversarial network

(GAN) to help the model focus on harder-to-detect events. They propose an entity and EE framework based on generative adversarial imitation learning. It is an inverse reinforcement learning (IRL) method using GAN. The model directly evaluates the correct and incorrect labeling of instances in entity and EE through a dynamic mechanism using IRL.

Dynamic graph information extraction (DYGIE)++ [85] is a BERT-based framework that models text spans and captures the within-sentence and cross-sentence context. Much information extraction tasks, such as NER, relationship extraction, EE, and coreference resolution, can benefit from the global context across sentences or from phrases that are not locally dependent. They carry out EE as additional task and span update in the relationship graph of event trigger and its argument. The span representation is constructed on the basis of multisentence BERT coding.

**Summary:** Most of the traditional EE methods adopt the artificial construction method for feature representation and use the classification model to classify triggers and identify the role of the argument. In recent years, deep learning has shown outstanding effects in image processing, speech recognition, NLP, etc. To settle drawbacks of the traditional methods, deep-learning-based EE is systematically discussed. Before the emergence of the BERT model, the mainstream method is to find the trigger from the text and judge the event type of the text according to the trigger. Recently, with the introduction of the EE model by BERT, the method of identifying event types based on the full text has become mainstream. It is because BERT has outstanding contextual representation ability and performs well in the text classification tasks, especially when there is only a small amount of data.

## V. EE SCENARIOS

There are some works focusing on document-level, low-resource, multilingual, and Chinese EE, and their goal is to improve the ability of EE in different scenarios.

### A. Document-Level EE Scenario

Document-level EE (DEE) aims to extract events across an article. Compared with sentence-level EE (SEE), two challenges are proposed.

1) **Arguments-Scattering:** Arguments of one event may be scattered in multiple sentences in the document, which means that one event record cannot be extracted from a single sentence.

2) **Multievents:** One document may simultaneously contain multiple events, which demands a holistic modeling about interdependency among the events.

By far, the existing DEE researches could be generally grouped into two lines.

The first line mainly focuses on extracting the scattering event arguments in the document, namely, the first challenge. Early works [76], [113] cast document-level argument extraction as a slot-filling paradigm following the task setting of Message Understanding Conference-4 (MUC-4) [114]. Furthermore, researchers [115], [116] cast document-level event arguments as an *Argument-linking* problem in roles across

multiple sentences (RAMS) [115] dataset, which seeks to identify event arguments throughout the document of given event triggers. Still, the works above are conducted under the assumption that the event type or triggers are given in advance, which may be unrealistic in real-world scenarios.

Instead of directly identifying event arguments, the second line of works follows the detect-then-extraction paradigm similar to SEE to extract events from the document. Specifically, Yang et al. [91], Huang and Peng [117], and Li et al. [118] first identify the specific event triggers to decide the event type, and then extract the event arguments beyond the sentence boundaries. Furthermore, researchers [83], [119], [120] also attempt to conduct DEE in a trigger-free manner in the ChFinAnn dataset [83], where event types are directly judged based on the document semantics. Du et al. [121] propose to simultaneously identify the event type and arguments in a generative template manner. These methods attempt to simultaneously tackle the two challenges of DEE and have drawn much research attention.

### B. Open-Domain EE Scenario

In the absence of a predefined event pattern, open-domain EE is designed to detect events from text and, in most cases, to cluster similar events through extracted event keywords. Event keywords are those words/phrases that primarily describe events, sometimes further divided into triggers and parameters. Open-domain EE [16], [17], [18] does not have a fixed argument role template. Therefore, arguments are often obtained by extracting keywords. Chau et al. [16] propose a method to filter irrelevant headlines and perform preliminary EE, relying on public news headlines. Both price and text are fed back into a 3D CNN to learn correlations between events and market movements. Liu et al. [17] design a novel latent variable neural model using an unsupervised generative method to explore latent event-type vectors and entity mention redundancy. The experimental results show that it is scalable to very large corpus.

### C. Low-Resource EE Scenario

Due to the arduously expensive annotation in data emerging, there usually only exist insufficient data to train an accurate EE model with fully supervised methods. In this survey, we term such a situation as the low-resource scenario. To alleviate data sparsity, the existing researches have explored distant supervision (DS) [91] methods to boost annotation data. Besides, several promising methods also investigate semisupervised methods [14], [75], [122] or multilingual methods (See Section V-D) to enrich supervision information. Recently, several researches have explored EE in three typical low-resource settings, including few-shot learning setting (FSED), zero-shot learning (ZSL) setting, and incremental learning setting. In this section, we will briefly introduce the recent EE methods in the above settings as a quick reference.

1) *Few-Shot Learning Setting*: Recently, the few-shot learning methods [123], [124] have been widely researched in several NLP tasks [125], [126], which aims to conduct task predictions with extremely limited (few-shot, like one-shot, three-shot, ...) observed training samples. In EE area, most existing studies focus on the ED subtask applied in the FSED.

The first line of works [127], [128], [129], [130], [131], [132] aims to conduct trigger classification given the candidate triggers with the meta-learning methods. To approach real applications, the second line of works [133], [134], [135] jointly conducts trigger identification and trigger classification with only plain textual data. Among them, Cong et al. [134] further learn robust sequence label transition scores with a prototypical amortized conditional random field (CRF), achieving significant improvements.

2) *ZSL Setting*: Most of the previous supervised EE methods rely on features derived from manual annotations, which cannot handle new event types without additional annotations. An extremely challenging low-resource scenario is to achieve EE without any available labeled data. To investigate the possibility of this scenario, recent researches [61], [136] explore ZSL for EE. Huang et al. [61] first address this problem, which exploits the structural ontology of event mentions and types for representations and conducts predictions with a semantic similarity measurement. Lyu et al. [136] further investigate the transfer learning methods for new events, which formulate EE into textual entailment (TE) and QA queries (e.g., “A city was attacked” entails “There is an attack”) and exploit pretrained TE/QA models for direct transfer. Though these methods still have a large gap from supervised approaches, they reveal an insightful vision and provide possible improvement directions for the extremely low-resource EE.

3) *Incremental Learning Setting*: The existing ED methods usually require a fixed number of event types and perform once-and-for-all training on a fixed dataset. Such a paradigm usually encounters challenges when there continually occur new event types along with new emerging data. For realistic consideration, a practical ED system ought to incrementally learn new event types and simultaneously remain predictive on the existing types, instead of requiring a fixed dataset to retrain all the event types again. Recent researches [137], [138] on incremental learning (also called continual learning or lifelong learning) focus on catastrophic forgetting, where the learned system usually suffers from significant performance drop on old types when it adapts to new types. Cao et al. [139] is the first work to tackle the incremental ED, which solves the catastrophic forgetting and semantic ambiguity issues by a proposed knowledge consolidation network, achieving effective performance on incremental ED.

### D. Multilingual EE Scenario

Monolingual training for EE is also an effective method in low-resource environments [33], [140], [141]. Liu et al. [141] propose a new multilingual approach called the gated multilingual attention (GMLATT) framework to address both the problems simultaneously and develop consistent information in multilingual data through the contextual attention mechanisms. It uses consistent evidence in multilingual data, models the credibility of cues provided by other languages, and controls information integration in various languages. Ahmad et al. [33] propose a graph attention transformer encoder (GATE) framework, which uses GCNs to learn language-independent sentences. The model embeds the dependency structure into contextual representation. It introduces a self-attention mechanism to learn the dependencies

between words with different syntactic distances. The method can capture the long-distance dependencies and then calculate the syntactic distance matrix between words through the mask algorithm. It performs well in cross-language sentence-level relationships and EE.

#### E. Chinese EE Scenario

Compared with EE in English corpus, Chinese EE can be regarded as a special case of EE, having particular properties and challenges. Early methods [142], [143], [144], [145] conduct Chinese EE using elaborately designed linguistic features. In the following, the neural-network-based approaches [99], [146] are proposed to reduce the heavy rely on feature engineering. Note that compared with English EE, Chinese EE suffers from the absence of natural word delimiters and is thus conducted tokenwise instead of wordwise. To alleviate the semantic limitation tokenwise in Chinese, the exquisite methods are designed to incorporate the word-level information to enrich the token semantics. Specifically, Lin et al. [147] propose nugget proposal networks (NPNs), which derive hybrid character representations for event trigger tagging, by capturing both the structural and semantic information from characters and words. Still, the scope of event triggers in NPN is restricted within a fix-sized window, making it inflexible and suffering from the overlapping between event triggers. Consequently, Ding et al. [148] propose trigger-aware lattice neural network (TLNN), which makes advantage of the Lattice structure [149] to incorporate the word and character semantics. Since NPN and TLNN limit that each character could interact with only one matched word, Cui et al. [150] propose a heterogeneous graph equipped with two types of nodes (words/characters) and three kinds of edges to maximally preserve word–character interactions.

### VI. EE CORPUS

The availability of labeled datasets for EE has become the main driving force behind the fast advancement. In this section, we summarize these datasets.

#### A. Document Level

- 1) *MUC-4*: MUC-4 is proposed in the fourth MUC [114]. The dataset consists of 1700 documents, where five types of event are annotated with the associated role filler templates.
- 2) *Google*: The Google dataset<sup>1</sup> is a subset of global database of events, language and tone (GDELT) Event Database1; event-related words retrieve documents with 30 event types containing 11909 news articles.
- 3) *Twitter*: The Twitter dataset is collected from tweets published in December 2010 applying Twitter streaming application programming interface (API), including 20 event types with 1000 tweets.
- 4) *NO.ANN, NO.POS, NO.NEG [document-level Chinese financial event extraction (DCFEE)]*: In article [91], researchers carry out experiments on four types of financial events: Equity Freeze event, Equity Pledge event, Equity Repurchase event, and Equity Overweight

event. A total of 2976 announcements (ANN) have been labeled by automatically generating data. NO.ANN represents the number of announcements that can be labeled automatically for each event type. NO.POS represents the total number of positive (POS) case mentions. On the contrary, NO. represents the number of negative (NEG) mentions.

- 5) *ChFinAnn [Doc2 entity-based directed acyclic graph (EDAG)]*: In [83], a DS-based event labeling is conducted based on the ten-year ChFinAnn4 documents<sup>2</sup> and human-summarized event knowledge bases. The new Chinese event dataset includes 32040 documents and five event types: Equity Freeze, Equity Repurchase, Equity Underweight, Equity Overweight, and Equity Pledge.
- 6) *RAMS*: RAMS is released by Eber et al. [115] for Argument-Linking task, which aims to identify event arguments of given event triggers from a five-sentence window. The dataset contains 3194 documents, where 9124 events are annotated from news based on an ontology of 139 event types and 65 roles.
- 7) *WIKIEVENTS*: It is released by Li et al. [118] as a document-level benchmark dataset. The dataset is collected from English Wikipedia articles which describe real-world events.

#### B. Sentence-Level

- 1) *ACE [1]*: The ACE 2005 is the most widely used dataset in EE. It contains a complete set of training data in English, Arabic, and Chinese for the ACE 2005 technology evaluation. The corpus consists of various types of data annotated for entities, relationships, and events by the Language Data Alliance (LDC). It includes 599 documents with EIGHT event types, 33 event subtypes, and 35 argument roles.<sup>3</sup>
- 2) *Text Analysis Conference Knowledge base Filling (TAC KBP)*: As a standalone component task in KBP, the goal of TAC KBP event tracking (from 2015 to 2017) is to extract information about the event so that it is suitable for input into the knowledge base. TAC KBP 2015<sup>4</sup> defines nine different event types and 38 event subtypes in English. TAC KBP 2016<sup>5</sup> and TAC KBP 2017<sup>6</sup> have corpora in three languages: English, Chinese, and Spanish, where they own eight event types and 18 event subtypes.
- 3) *Rich ERE*: It extends entities, relationships, and event ontologies, and extends the concept of what is Taggable. Rich event relation extraction (ERE) also introduces the concept of event jumping to address the pervasive challenge of event coreferencing, particularly with regard to event references within and between documents and granularity changes in event arguments, paving the

<sup>2</sup><http://www.cninfo.com.cn/new/index>

<sup>3</sup><https://catalog.ldc.upenn.edu/LDC2006T06>

<sup>4</sup><https://tac.nist.gov/2015/KBP/data.html>

<sup>5</sup><https://tac.nist.gov/2016/KBP/data.html>

<sup>6</sup><https://tac.nist.gov/2017/KBP/data.html>

<sup>1</sup><http://data.gdeltproject.org/events/index.html>



TABLE III  
NOTATIONS USED IN EVALUATION METRICS

Notations	Descriptions
$T$	The reference trigger
$TD$	The detected trigger
$N_T$	The actual number of triggers
$N_{TD}$	The number of detected triggers
$T_t$	The true event type
$TD_t$	The detected event type
$A$	The reference argument
$AD$	The detected argument
$N_A$	The actual number of arguments
$N_{AD}$	The number of detected arguments
$A_r$	The detected argument role
$AD_r$	The number of detected arguments

way for the creation of (hierarchical or nested) cross-document representations of events.

- 4) *FSED*: Based on ACE 2005 and TAC KBP 2017, the FSED dataset [133] is a generated dataset tailored particularly for the few-shot scenario. In detail, it contains 70852 mentions with 19 event types and 100 event subtypes.
- 5) *GNBusiness*: GNBUSINESS [17] collects news reports from Google Business News to describe each event from different sources. It obtains 55 618 business articles with 13 047 news clusters in 288 batches from October 17, 2018, to January 22, 2019. The full text corpus is released as GNBUSINESSFull-Text<sup>7</sup>.
- 6) *FSD*: The first story detection (FSD) dataset [151] is a story detection dataset including 2499 tweets. Researchers filter out events mentioned in fewer than 15 samples considering events mentioned in several samples are usually not important. It includes 2453 tweets with 20 event types.
- 7) *FBI Dataset*: The FBI dataset [154] is built by scraping about 370k unlabeled news articles in the “Fire and Crime” category of Patch. It contains two classes for classifying if there is a specific hate crime in the text. Furthermore, it labels the attributes of hate crime articles.

## VII. METRICS

For the four subtasks [15], [37], [100], [160] defined in EE, three metrics including precision (P), recall (R), and F1 are used to measure the performance.

Here, we denote an indicator function  $I(\text{boolean})$ :  $I(\text{True}) = 1$  and  $I(\text{False}) = 0$ .

1) **Trigger Identification**: A trigger is correctly identified if its span offsets exactly match a reference trigger. The corresponding metrics include

$$P_{TI} = \frac{\sum I(TD = T \wedge TD_L = T_L \wedge TD_R = T_R)}{N_{TD}} \quad (1)$$

$$R_{TI} = \frac{\sum I(TD = T \wedge TD_L = T_L \wedge TD_R = T_R)}{N_T} \quad (2)$$

$$F1_{TI} = \frac{2 * P_{TI} * R_{TI}}{(P_{TI} + R_{TI})} \quad (3)$$

where  $TD$  is the detected trigger,  $TD_L$  and  $TD_R$  are the left and right boundaries of  $TD$ , respectively,  $T$  is the reference

trigger,  $T_L$  and  $T_R$  are the left and right boundaries of  $T$ , respectively, and  $N_{TD}$  and  $N_T$  denote the number of detected triggers and the actual number of triggers, respectively.

2) **Trigger Classification**: A trigger is correctly classified if its span offsets and event subtype exactly match a reference trigger. The corresponding metrics include

$$P_{TC} = \frac{\sum I(TD = T \wedge TD_t = T_t \wedge TD_L = T_L \wedge TD_R = T_R)}{N_{TD}} \quad (4)$$

$$R_{TC} = \frac{\sum I(TD = T \wedge TD_t = T_t \wedge TD_L = T_L \wedge TD_R = T_R)}{N_T} \quad (5)$$

$$F1_{TC} = \frac{2 * P_{TC} * R_{TC}}{(P_{TC} + R_{TC})} \quad (6)$$

where  $TD_{\text{type}}$  and  $T_{\text{type}}$  denote the detected event type and the true event type, respectively.

3) **Argument Identification**: An argument is correctly identified if its span offsets and the corresponding event subtype exactly match a reference argument. The corresponding metrics include

$$P_{AI} = \frac{\sum I(AD = A \wedge AD_t = T_t \wedge AD_L = A_L \wedge AD_R = A_R)}{N_{AD}} \quad (7)$$

$$R_{AI} = \frac{\sum I(AD = A \wedge AD_t = T_t \wedge AD_L = A_L \wedge AD_R = A_R)}{N_A} \quad (8)$$

$$F1_{AI} = \frac{2 * P_{AI} * R_{AI}}{(P_{AI} + R_{AI})} \quad (9)$$

where  $AD$  is the detected argument,  $AD_L$  and  $AD_R$  are the left and right boundaries of  $AD$ , respectively,  $A$  is the reference argument,  $A_L$  and  $A_R$  are the left and right boundaries of  $A$ , and  $N_{AD}$  and  $N_A$  denote the number of detected arguments and the actual number of arguments, respectively.

4) **Argument Classification**: An argument is correctly classified if its span offsets, corresponding event subtype, and argument role exactly match a reference argument. Its corresponding metrics include

$$P_{AC} = \frac{\sum I(AD = A \wedge AD_t = T_t \wedge AD_r = A_r \wedge AD_L = A_L \wedge AD_R = A_R)}{N_{AD}} \quad (10)$$

$$R_{AC} = \frac{\sum I(AD = A \wedge AD_t = T_t \wedge AD_r = A_r \wedge AD_L = A_L \wedge AD_R = A_R)}{N_A} \quad (11)$$

$$F1_{ac} = \frac{2 * P_{ac} * R_{ac}}{(P_{ac} + R_{ac})} \quad (12)$$

where  $AD_r$  and  $A_r$  denote the detected argument role and the true argument role, respectively.

## VIII. QUANTITATIVE RESULTS

This section mainly summarizes the existing EE work and compares the performance on the ACE 2005 dataset, as shown

<sup>7</sup><https://github.com/lx865712528/ACL2019-ODEE>



TABLE IV  
COMPARISON OF THE EE METHODS ON ACE 2005 USING ENTITY ANNOTATIONS. WE SHOW THE PERFORMANCE OF TRIGGER CLASSIFICATION AND ARGUMENT ROLE CLASSIFICATION SUBTASKS

Year-Method	Neural Network	External Resource	Paradigm	Trigger Classification			Role Classification		
				P	R	F1	P	R	F1
2008 - Ji et al. [156]	-	-	-	60.2	76.4	67.3	51.3	36.4	42.6
2010 - Liao et al. [157]	-	-	-	68.7	68.9	68.8	45.1	44.1	44.6
2011 - Hong et al. [158]	-	-	-	72.9	64.3	68.3	51.6	45.5	48.4
2013 - Li et al. [38]	-	-	-	73.7	62.3	67.5	64.7	44.4	52.7
2015 - Nguyen et al. [108]	✓	-	-	71.8	66.4	69.0	-	-	-
2015 - DMCNN [39]	✓	-	Pipeline	75.6	63.6	69.1	62.2	46.9	53.5
2016 - JRNN [40]	✓	-	Joint	66.0	73.0	69.3	54.2	56.7	55.4
2016 - JOINTEVENTENTIT [13]	-	-	Joint	75.1	63.3	68.7	70.6	36.9	48.4
2016 - NC-CNN [102]	✓	-	-	-	-	71.3	-	-	-
2016 - HNN [109]	✓	-	-	84.6	64.9	73.4	-	-	-
2016 - BDLSTM-TNNs [100]	✓	-	Joint	75.3	63.4	68.9	62.9	47.5	54.1
2017 - DMCNN-MIL [70]	✓	✓	Joint	75.5	66.0	70.5	62.8	50.1	55.7
- 2018 - DEEB-RNN [93]	✓	-	Pipeline	72.3	75.8	74	-	-	-
2018 - SELF [94]	✓	-	Pipeline	71.3	74.7	73.0	-	-	-
2018 - GMLATT [141]	✓	-	Joint	78.9	66.9	72.4	-	-	-
2018 - Zeng et al. [92]	✓	✓	Pipeline	<b>85.3</b>	79.9	<b>82.5</b>	41.9	34.6	37.9
2019 - Liu et al. [159]	✓	-	Joint	62.5	35.7	45.4	-	-	-
2019 - GAIL-ELMo [84]	✓	-	Joint	74.8	69.4	72.0	61.6	45.7	52.4
2019 - HMEAE [86]	✓	-	Joint	-	-	-	62.2	56.6	59.3
2019 - JointTransition [58]	✓	-	Joint	74.4	73.2	73.8	55.7	51.1	53.3
2019 - PLMEE [37]	✓	-	Joint	81.0	<b>80.4</b>	80.7	62.3	54.2	58.0
2021-Li et al. [118]	✓	-	-	-	-	71.1	-	-	53.7
2021-GATE (En2ZH) [33]	✓	-	Joint	-	-	-	-	-	63.2
2021-CasEE [15]	✓	-	Joint	77.9	78.5	78.2	<b>71.3</b>	<b>71.5</b>	<b>71.4</b>

TABLE V  
COMPARISON OF THE EE METHODS ON ACE 2005 WITHOUT USING ENTITY ANNOTATIONS. EVEN THE TEXT2EVENT MODEL DOES NOT USE TOKEN ANNOTATIONS. WE SHOW THE PERFORMANCE OF TRIGGER CLASSIFICATION AND ARGUMENT ROLE CLASSIFICATION SUBTASKS

Year-Method	Neural Network	External Resource	Paradigm	Trigger Classification			Role Classification		
				P	R	F1	P	R	F1
2016 - Liu et al. [69]	✓	✓	Joint	77.6	65.2	70.7	-	-	-
2016 - Huang et al. [153]	✓	✓	Joint	<b>80.7</b>	50.1	61.8	51.9	39.4	44.8
2016 - RBPB [98]	✓	-	Pipeline	70.3	67.5	68.9	54.1	53.5	53.8
2017 - Liu et al. [97]	✓	-	Pipeline	78.0	66.3	71.7	-	-	-
2018 - DEEB-RNN [93]	✓	-	Pipeline	72.3	75.8	74	-	-	-
2018 - SELF [94]	✓	-	Pipeline	71.3	<b>74.7</b>	73.0	-	-	-
2018 - GMLATT [141]	✓	-	Joint	78.9	66.9	72.4	-	-	-
2019 - Joint3EE [88]	✓	-	Joint	68.0	71.8	69.8	52.1	52.1	52.1
2019 - Chen et al. [81]	✓	-	Joint	66.7	74.7	70.5	44.3	40.7	42.4
2019 - DYIE++ [85]	✓	-	Joint	-	-	69.7	-	-	48.8
2020 - Chen et al. [81]	✓	-	Pipeline	66.7	74.7	70.5	44.3	40.7	42.4
2020 - MQAEE [42]	✓	-	Pipeline	-	-	<b>73.8</b>	-	-	<b>55.0</b>
2020 - Du et al. [41]	✓	-	Pipeline	71.1	73.7	72.3	<b>56.7</b>	50.2	53.3
2021-Text2Event [43]	✓	-	Joint	69.6	74.4	71.9	52.5	<b>55.2</b>	53.8

in Tables IV and V. The evaluation metrics include precision, recall, and F1.

In recent years, the EE methods are primarily based on the deep learning models. As shown in Table IV, in terms of the value of F1, the deep-learning-based method is superior to the machine-learning-based method and pattern matching method in both ED and argument extraction. GATE (En2ZH) [33] is under single-source transfer from English to Chinese, which performs well on the argument role classification task. Li et al. [118] propose a document-level neural event argument

extraction model. It is applied for ACE 2005 for zero-shot EE seen in all event types. We can get the validity of the EE method based on the deep learning models. It may indicate that the deep-learning-based method can better learn the dependencies among arguments in the EE task. In the deep-learning-based model, the BERT-based approach performs the best, both in Tables IV and V. It shows that BERT can better learn the context information of the sentence and learn word representation according to the current text. It better learns the semantic association of words in

the current context and helps learn the association between arguments.

Comparing the pipeline-based methods (regularization-based pattern balancing method for event extraction (RBPB) [98] and document embedding enhanced Bi-RNN (DEEB-RNN) [93]) with the join-based methods (JRNN [40] and DBRNN [95]) without the Transformer [161], it can be seen that the EE method of the joint model is better than the pipeline model, especially for the argument role classification task. From DMCNN [39] and DMCNN-multi-instance learning (MIL) [70], it can be concluded that when external resources are used on the deep-learning-based methods, the effect is significantly improved and slightly higher than the joint model. Zeng et al. [92] introduce external resources, improving the performance of trigger classification on precision and F1. Thus, it may show that increasing external knowledge is an effective method, but it still needs to be explored to introduce external knowledge into argument extraction.

## IX. EE APPLICATIONS

In this section, we introduce several event-related applications, which can be regarded as direct downstream tasks of EE. Generally, the identified events can be used for event graph construction [162], event evolution analysis [163], and other event-based NLP applications [164], such as QA [165], [166] and reading comprehension [167]. Among the tasks, we focus on three widely researched tasks associated with events, namely, script event prediction (SEP), event factuality identification (EFI), and ERE.

### A. Event Factuality Identification

EFI aims to identify the degree of certainty about whether events actually occur or not in the real world, which can be seen as a downstream task of EE in event knowledge graph construction [168]. Generally, event factuality can be classified into five categories [169]: certain POS (certainly (CT) happening, CT+), certain NEG (CT not happening, CT−), possible POS (possibly (PS) happening, PS+), possible NEG (PS not happening, PS−), and underspecified (events' factuality cannot be identified, Uu). Therefore, an EFI model ought to be able to predict the factuality of the event that is PS+.

Most existing EFI studies focus on the sentence-level task [170], [171], [172], [173]. The early works on this task mainly use the rule-based methods [169], [174], [175] or machine learning methods with manually designed features [170], [171], [176], [177], [178], [179]. In recent years, neural networks have been introduced into the EFI task, and achieve state-of-the-art performance [172], [173], [180], [181], [182], which usually adopt GANs [183] or GNNs [184] to capture enriched textual information. Despite these successful efforts, sentence-level event factuality can easily encounter expression conflicts in texts. To this end, Qian et al. [185] propose the document-level EFI task with adversarial neural network. Besides, Cao et al. [168] further exploit the uncertainty of local information and the global structure within documents

and achieve significant improvements on the document-level EFI task.

### B. Event Relation Extraction

Extracting event relationships is an important yet challenging task for constructing event knowledge graph [162], which aims to detect the relationships between the identified events, and thus can also be seen as the downstream tasks of EE. Generally, the existing ERE studies mainly focus on three event relationship types, including coreferential relationship, causal relationship, and temporal relationship. Since the three relationship types are usually investigated separately and have no consistent task formulation so far, this section will briefly introduce the above three ERE problems separately as different tasks. For more detailed ERE reviews, we recommend the readers to Liu et al. [162].

1) *Event Coreference Resolution*: Event coreference resolution (ECR) aims to identify whether the candidate events refer to the same event in the real-world, where those events may appear across several sentences. The existing methods [186], [187] usually formulate ECR as a classification or ranking problem and mainly focus on the contextual features around the two events, such as syntactic features, event topic information, and linguistic features [188]. To enrich the clues for resolution, the existing works also exploit document-level or topical structures [189], event argument information [190], [190], [191], [192], [193], and other event-related task information [194], [195], [196], such as ED [197] and entity recognition [198].

2) *Event Causal Relation Extraction*: Event causal relation extraction (ECE) aims to identify the event causal relationship [199] and distinguish the cause and effect between two events, which benefits the real-world event evolution understanding and thereby promotes ED and event prediction. According to the used evidence, the ECE methods can be manifested in two groups.

1) The methods exploiting internal information, which assume that the textual contexts contain sufficient clues for causal relationship extraction, where the contextual features include syntactic features, lexical features, explicit causal patterns [200], [201], [202], statistic causal association [203], [204], [205], and document-level structures [206]. 2) The methods exploiting external information, which enhances the textual representation with external knowledge, such as pre-trained language model [207], and causal-related common-sense or knowledge base [208], [209], [210], [211]. There are also studies [212], [213] using DS from knowledge base to alleviate the data sparsity issue in ECE.

3) *Event Temporal Relation Extraction*: Event temporal relation extraction (ETE) aims to understand the temporal order among events in the texts. Most existing studies on ETE follow the TimeML format [214], which is widely used to markup events, time expressions, and temporal relations. Generally, the existing ETE studies can be roughly divided into three groups: 1) rule-based methods, which infer the temporal relationship for events relying on temporal rules, such as syntactic analyzers [215], regular expression patterns over tokens [216], and other linguistic rules [217];

2) machine-learning-based methods, which leverage statistical temporal contextual features and achieve the task with statistical classifiers [218], [219]; and 3) neural models, which capture temporal relationship with neural networks, such as CNNs and LSTMs [220], [221]. More external features are also considered in neural models, including dependency paths [222], domain knowledge [223], contextualized language models [224], and so on.

### C. Script Event Prediction

Script [225] is a chain of ordered events describing activities about a protagonist, and SEP aims to predict the subsequent event of a given chain from a candidate event list. As an important task to understand the evolutionary patterns among events, SEP has supported various downstream applications, including anaphora resolution [226], story generation [227], and financial analysis [228]. In SEP, each event is represented in the form of a tuple  $e = v(s, o, p)$ , where  $v, s, o$ , and  $p$  are the event arguments, respectively, denoting the verb, subject, object, and indirect object of the event. For example,  $e = \text{give}(\text{waiter}, \text{bob}, \text{water})$  means that “A waiter gives bob water.” By far, the most widely used benchmark for SEP is New York Times (NYT) dataset [229], where the event chains are extracted from the NYT portion of the Gigaword corpus [230]. The dataset consists of 140331/10000/10000 event chains for training/validation/test. Each event chain contains eight events and has five candidate events where only one is the correct subsequent event. Next, we introduce the details about the existing SEP works.

The existing SEP works could be categorized into two groups. The **first** line of works mainly focuses on the event cooccurrence relationship to predict the subsequent from three aspects. Specifically, early works [229], [231], [232], [233], [234] model the *event-pair-level* semantic relationship to predict the subsequent event of the given event chain. Furthermore, to alleviate semantics limitation to event chain, Lv et al. [235] regard the given event chain as a combination of several *event segments* and capture clues from diverse event segments to facilitate event prediction. In the following, researchers encode the full *event chain* [236], [237], [238] to grasp semantic signals to predict subsequent event. Wang et al. [238] and Zheng et al. [239] also use the graph structure to model the event chain. The **second** line of works integrates external knowledge to help understand the scripts, since the absence of text contexts makes the semantics in scripts more sparse than normal texts. Specifically, Ding et al. [240] use knowledge bases, Event2Mind [241], and Atlas Of MachIne Commonsens (ATOMIC) [242], to refine sentiment and intention information to enrich the semantics of the script. Furthermore, Lv et al. [243] incorporate event knowledge base activities, states, events, and their relations (ASERs) [244] to provide causal and temporal relationships between events to predict the subsequent event, achieving great success in this task.

## X. FUTURE RESEARCH TRENDS

EE is an essential and challenging task in text mining, which mainly learns the structured representation of events from the

relevant text describing the events. EE is mainly divided into two subtasks: ED and argument extraction. The core of EE is identifying the event-related words in the text and classifying them into appropriate categories. The EE method based on the deep learning model automatically extracts features and avoids the tedious work of designing features manually. The EE tasks are constructed as an end-to-end system, using word vectors with rich language features as input, to reduce the errors caused by the underlying NLP tools. Previous methods focus on studying effective features to capture the lexical, syntactic, and semantic information of candidate triggers and candidate arguments. Furthermore, they explore the dependence between triggers and multiple entities related to the same trigger, and the relationship between multiple triggers associated with the same entity. According to the characteristics of EE and the current research status, we summarize the following technical challenges.

### A. Challenges From EE Corpus

1) *EE Dataset Construction*: The EE task is complex, and the existing pretraining model lacks the learning of the EE task. The existing EE datasets have a few labeled data, and manual annotation of EE dataset has a high time cost. Therefore, the construction of large-scale EE dataset or the design of automatic construction EE dataset is also a future research trend.

2) *External Resources*: The dataset of EE is small. Deep learning combining external resources and constructing a large-scale dataset has achieved good results. Due to the difficulties in constructing labeled datasets and the small size of datasets, it is also an urgent research direction that how to make better use of deep learning to extract events effectively with the help of external resources.

3) *EE Schema*: The EE methods can be divided into close-domain EE methods and open-domain EE methods. The effect of EE methods without schema is challenging to evaluate, and the template-based EE methods need to design different event schema according to different event types. Therefore, how to design a general EE schema based on event characteristics is an essential means to overcome the difficulty in constructing EE dataset and sharing knowledge among classes.

### B. Challenges From EE Models

1) *Dependency Learning*: The EE method using BERT has become mainstream at present. However, EE is different from the task learned by the BERT model in pretraining. Argument extraction needs to consider the relationship between the event argument roles to extract different roles under the same event type. It requires the EE model to learn the syntactic dependencies of the text. Therefore, making the dependency relationship between the event arguments is an urgent problem to solve to comprehensively and accurately extract the arguments of each event type.

2) *End-to-End Learning Model*: The advantage of the deep learning method based on the joint model over the traditional approach is the joint representation form. The EE depends on the label of entities. So this article believes that establishing an



end-to-end autonomous learning model based on deep learning is a direction worthy of research and exploration, and how to design multitask and multifederation is a major challenge.

3) *Multievent Extraction*: According to the different granularity of EE, EE can be divided into SEE and DEE. There have been a lot of researches on SEE. However, DEE is still in the exploratory stage, and DEE is closer to practical application. Therefore, how to design the multievent extraction method for the text is of great research significance.

4) *Domain EE*: The domain text often contains numerous technical terms, which increases the difficulty of domain EE [245]. For example, biomedical EE (BEE) aims to extract events capturing an interplay between biomedical entities [217], [246], [247], [248]. Extracting and harnessing them is beneficial for medical research and disease prevention [249], [250]. Therefore, how to design effective methods to understand the deep semantic information and context correspondence in the domain text has become an urgent problem to solve.

5) *Interpretability for EE*: EE includes four subtasks, and the existing EE often considers how to improve the accuracy of extraction, but there is little research on the interpretability of EE [251]. Due to the fact that the task of EE is complex, it is difficult to understand directly why the model divides a word into a certain argument role for a complex text. This requires the EE model to be interpretable to facilitate the manual discrimination of the predicted results, which is very important in the biological and medical fields [252].

## XI. CONCLUSION

This article principally introduces the existing deep learning models for EE tasks. First, we introduce concepts and definitions from three aspects of EE. Then we divide the deep-learning-based EE paradigm into the pipeline and joint parts and introduce them, respectively. The deep-learning-based models enhance the performance by improving the presentation learning method, model structure, and additional data and knowledge. Then, we introduce the datasets with a summary table and evaluation metrics. Furthermore, we give the quantitative results of the leading models in a summary table on the ACE 2005 datasets. Finally, we summarize the possible future research trends of EE.

## REFERENCES

- [1] G. R. Doddington, A. Mitchell, M. A. Przybocki, L. A. Ramshaw, S. M. Strassel, and R. M. Weischedel, "The automatic content extraction (ace) program-tasks, data, and evaluation," in *Proc. LREC*, 2004, pp. 1–4.
- [2] W. Zhang, X. Zhao, L. Zhao, D. Yin, and G. H. Yang, "DRL4IR: 2nd workshop on deep reinforcement learning for information retrieval," in *Proc. 44th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Jul. 2021, pp. 2681–2684.
- [3] A. Kuhnle, M. Aroca-Ouellette, A. Basu, M. Sensoy, J. Reid, and D. Zhang, "Reinforcement learning for information retrieval," in *Proc. 44th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Jul. 2021, pp. 2669–2672.
- [4] C.-Y. Liu, C. Zhou, J. Wu, H. Xie, Y. Hu, and L. Guo, "CPMF: A collective pairwise matrix factorization model for upcoming event recommendation," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, May 2017, pp. 1532–1539.
- [5] L. Gao, J. Wu, Z. Qiao, C. Zhou, H. Yang, and Y. Hu, "Collaborative social group influence for event recommendation," in *Proc. 25th ACM Int. Conf. Inf. Knowl. Manage.*, Oct. 2016, pp. 1941–1944.
- [6] J. Boyd-Graber and B. Börschinger, "What question answering can learn from trivia nerds," in *Proc. 58th Annu. Meeting Assoc. Comput. Linguistics*, 2020, pp. 1–15.
- [7] Q. Cao, H. Trivedi, A. Balasubramanian, and N. Balasubramanian, "DeFormer: Decomposing pre-trained transformers for faster question answering," in *Proc. ACL*, 2020, pp. 1–11.
- [8] X. Wu, J. Wu, X. Fu, J. Li, P. Zhou, and X. Jiang, "Automatic knowledge graph construction: A report on the 2019 ICDM/ICBK contest," in *Proc. IEEE Int. Conf. Data Mining (ICDM)*, Nov. 2019, pp. 1540–1545.
- [9] A. Bosselut, R. L. Bras, and Y. Choi, "Dynamic neuro-symbolic knowledge graph construction for zero-shot commonsense question answering," in *Proc. AAAI*, 2021, pp. 1–9.
- [10] X. Su et al., "A comprehensive survey on community detection with deep learning," *IEEE Trans. Neural Netw. Learn. Syst.*, 2022.
- [11] F. Liu et al., "Deep learning for community detection: Progress, challenges and opportunities," in *Proc. IJCAI*, 2020, pp. 1–7.
- [12] X. Ma et al., "A comprehensive survey on graph anomaly detection with deep learning," *IEEE Trans. Knowl. Data Eng.*, early access, 2021.
- [13] B. Yang and T. M. Mitchell, "Joint extraction of events and entities within a document context," in *Proc. NAACL HLT*, 2016, pp. 1–11.
- [14] J. Ferguson, C. Lockard, D. S. Weld, and H. Hajishirzi, "Semi-supervised event extraction with paraphrase clusters," in *Proc. NAACL-HLT*, 2018, pp. 1–6.
- [15] J. Sheng et al., "CasEE: A joint learning framework with cascade decoding for overlapping event extraction," in *Proc. ACL/IJCNLP*, 2021, pp. 1–11.
- [16] M. T. Chau, D. Esteves, and J. Lehmann, "Open-domain event extraction and embedding for natural gas market prediction," *CoRR*, to be published.
- [17] X. Liu, H. Huang, and Y. Zhang, "Open domain event extraction using neural latent variable models," in *Proc. ACL*, 2019, pp. 1–12.
- [18] M. Mejri and J. Akaichi, "A survey of textual event extraction from social networks," in *Proc. LPKM*, 2017, pp. 1–13.
- [19] Z. Li, X. Chang, L. Yao, S. Pan, Z. Ge, and H. Zhang, "Grounding visual concepts for zero-shot event detection and event captioning," in *Proc. ACM SIGKDD*, 2020, pp. 297–305.
- [20] J. Liao, X. Zhao, X. Li, L. Zhang, and J. Tang, "Learning discriminative neural representations for event detection," in *Proc. 44th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Jul. 2021, pp. 644–653.
- [21] H. Lin, Y. Lu, X. Han, and L. Sun, "Cost-sensitive regularization for label confusion-aware event detection," in *Proc. ACL*, 2019, pp. 1–6.
- [22] Y. Cao, H. Peng, J. Wu, Y. Dou, J. Li, and P. S. Yu, "Knowledge-preserving incremental social event detection via heterogeneous GNNs," in *Proc. Web Conf.*, Apr. 2021, pp. 3383–3395.
- [23] R. Aly, S. Remus, and C. Biemann, "Hierarchical multi-label classification of text with capsule networks," in *Proc. ACL*, 2019, pp. 323–330.
- [24] I. Chalkidis, M. Fergadiotis, P. Malakasiotis, and I. Androustopoulos, "Large-scale multi-label text classification on EU legislation," in *Proc. ACL*, 2019, pp. 1–9.
- [25] W. Chang, H. Yu, K. Zhong, Y. Yang, and I. S. Dhillon, "Taming pretrained transformers for extreme multi-label text classification," in *Proc. ACM SIGKDD*, 2020, pp. 3163–3171.
- [26] X. Li, J. Feng, Y. Meng, Q. Han, F. Wu, and J. Li, "A unified MRC framework for named entity recognition," in *Proc. ACL*, 2020, pp. 1–11.
- [27] J. Yu, B. Bohnet, and M. Poesio, "Named entity recognition as dependency parsing," in *Proc. ACL*, 2020, pp. 1–7.
- [28] B. Y. Lin et al., "TriggerNER: Learning with entity triggers as explanations for named entity recognition," in *Proc. ACL*, 2020, pp. 1–10.
- [29] R. Cao et al., "Unsupervised dual paraphrasing for two-stage semantic parsing," in *Proc. ACL*, 2020, pp. 1–12.
- [30] E. Stengel-Esklin, A. S. White, S. Zhang, and B. V. Durme, "Universal compositional semantic parsing," in *Proc. ACL*, 2020, pp. 1–13.
- [31] I. Abdelaziz, S. Ravishankar, P. Kapanipathi, S. Roukos, and A. G. Gray, "A semantic parsing and reasoning-based approach to knowledge base question answering," in *Proc. AAAI*, 2021, pp. 15985–15987.
- [32] T. Chen et al., "Empower distantly supervised relation extraction with collaborative adversarial training," in *Proc. AAAI*, 2021, pp. 12675–12682.
- [33] W. U. Ahmad, N. Peng, and K. Chang, "GATE: Graph attention transformer encoder for cross-lingual relation and event extraction," in *Proc. AAAI*, 2021, pp. 12462–12470.



- [34] K. Sun, R. Zhang, S. Mensah, Y. Mao, and X. Liu, "Progressive multi-task learning with controlled information flow for joint entity and relation extraction," in *Proc. AAAI*, 2021, pp. 13851–13859.
- [35] F. Hogenboom, F. Frasincar, U. Kaymak, F. de Jong, and E. Caron, "A survey of event extraction methods from text for decision support systems," *Decis. Support Syst.*, vol. 85, pp. 12–22, May 2016.
- [36] W. Xiang and B. Wang, "A survey of event extraction from text," *IEEE Access*, vol. 7, pp. 173111–173137, 2019.
- [37] S. Yang, D. Feng, L. Qiao, Z. Kan, and D. Li, "Exploring pre-trained language models for event extraction and generation," in *Proc. ACL*, 2019, pp. 5284–5294.
- [38] Q. Li, H. Ji, and L. Huang, "Joint event extraction via structured prediction with global features," in *Proc. ACL*, 2013, pp. 73–82.
- [39] Y. Chen, L. Xu, K. Liu, D. Zeng, and J. Zhao, "Event extraction via dynamic multi-pooling convolutional neural networks," in *Proc. ACL*, 2015, pp. 167–176.
- [40] T. H. Nguyen, K. Cho, and R. Grishman, "Joint event extraction via recurrent neural networks," in *Proc. NAACL HLT*, 2016, pp. 300–309.
- [41] X. Du and C. Cardie, "Event extraction by answering (almost) natural questions," in *Proc. EMNLP*, 2020, pp. 1–13.
- [42] F. Li et al., "Event extraction as multi-turn question answering," in *Proc. EMNLP*, 2020, pp. 829–838.
- [43] Y. Lu et al., "Text2Event: Controllable sequence-to-structure generation for end-to-end event extraction," in *Proc. ACL/IJCNLP*, 2021, pp. 1–12.
- [44] I. Hsu et al., "Degree: A data-efficient generative event extraction model," 2021, *arXiv:2108.12724*.
- [45] D. Mekala and J. Shang, "Contextualized weak supervision for text classification," in *Proc. ACL*, 2020, pp. 323–333.
- [46] B. Guo, S. Han, X. Han, H. Huang, and T. Lu, "Label confusion learning to enhance text classification models," in *Proc. AAAI*, 2021, pp. 12929–12936.
- [47] S. Guo et al., "A frame-based sentence representation for machine reading comprehension," in *Proc. ACL*, 2020, pp. 891–896.
- [48] B. Zheng et al., "Document modeling with graph attention networks for multi-grained machine reading comprehension," in *Proc. ACL*, 2020, pp. 1–11.
- [49] S. Chen, Y. Wang, J. Liu, and Y. Wang, "Bidirectional machine reading comprehension for aspect sentiment triplet extraction," in *Proc. AAAI*, 2021, pp. 12666–12674.
- [50] W. Yuan, T. He, and X. Dai, "Improving neural question generation using deep linguistic representation," in *Proc. Web Conf.*, Apr. 2021, pp. 3489–3500.
- [51] L. Chen, W. Ruan, X. Liu, and J. Lu, "SeqVAT: Virtual adversarial training for semi-supervised sequence labeling," in *Proc. ACL*, 2020, pp. 8801–8811.
- [52] T. Gui et al., "Uncertainty-aware label refinement for sequence labeling," in *Proc. EMNLP*, 2020, pp. 1–11.
- [53] A. Ramponi, R. van der Goot, R. Lombardo, and B. Plank, "Biomedical event extraction as sequence labeling," in *Proc. EMNLP*, 2020, pp. 5357–5367.
- [54] T. Jiang, D. Wang, L. Sun, H. Yang, Z. Zhao, and F. Zhuang, "LightXML: Transformer with dynamic negative sampling for high-performance extreme multi-label text classification," in *Proc. AAAI*, 2021, pp. 7987–7994.
- [55] L. Xiao, X. Zhang, L. Jing, C. Huang, and M. Song, "Does head label help for long-tailed multi-label text classification," in *Proc. AAAI*, 2021, pp. 1–9.
- [56] X. Liang, D. Cheng, F. Yang, Y. Luo, W. Qian, and A. Zhou, "F-HMTC: Detecting financial events for investment decisions based on neural hierarchical multi-label text classification," in *Proc. IJCAI*, 2020, pp. 4490–4496.
- [57] A. Subburathinam et al., "Cross-lingual structure transfer for relation and event extraction," in *Proc. EMNLP-IJCNLP*, 2019, pp. 313–325.
- [58] J. Zhang, Y. Qin, Y. Zhang, M. Liu, and D. Ji, "Extracting entities and events as a single task using a transition-based neural model," in *Proc. 28th Int. Joint Conf. Artif. Intell.*, Aug. 2019, pp. 5422–5428.
- [59] D. Li, L. Huang, H. Ji, and J. Han, "Biomedical event extraction based on knowledge-driven tree-LSTM," in *Proc. NAACL-HLT*, 2019, pp. 1421–1430.
- [60] J. Sheng et al., "A joint learning framework for the CCKS-2020 financial event extraction task," *Data Intell.*, vol. 3, no. 3, pp. 444–459, 2021.
- [61] L. Huang, H. Ji, K. Cho, I. Dagan, S. Riedel, and C. R. Voss, "Zero-shot transfer learning for event extraction," in *Proc. ACL*, 2018, pp. 1–10.
- [62] H. Funke, S. Breß, S. Noll, V. Markl, and J. Teubner, "Pipelined query processing in coprocessor environments," in *Proc. SIGMOD Conf.*, 2018, pp. 1603–1618.
- [63] M. Gasmí, O. Mosbahi, M. Khalgui, L. Gomes, and Z. Li, "R-node: New pipelined approach for an effective reconfigurable wireless sensor node," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 6, pp. 892–905, Jun. 2018.
- [64] J. Devlin, M. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proc. NAACL-HLT*, 2019, pp. 1–16.
- [65] Y. Lin, H. Ji, F. Huang, and L. Wu, "A joint neural model for information extraction with global features," in *Proc. ACL*, 2020, pp. 7999–8009.
- [66] M. V. Nguyen, V. D. Lai, and T. H. Nguyen, "Cross-task instance representation interactions and label dependencies for joint information extraction with graph convolutional networks," in *Proc. NAACL-HLT*, 2021, pp. 1–12.
- [67] Z. Zhang and H. Ji, "Abstract meaning representation guided graph encoding and decoding for joint information extraction," in *Proc. NAACL-HLT*, 2021, pp. 39–49.
- [68] Z. Zhu, S. Li, G. Zhou, and R. Xia, "Bilingual event extraction: A case study on trigger type determination," in *Proc. ACL*, 2014, pp. 842–847.
- [69] S. Liu, Y. Chen, S. He, K. Liu, and J. Zhao, "Leveraging framelet to improve automatic event detection," in *Proc. ACL*, 2016, pp. 2134–2143.
- [70] Y. Chen, S. Liu, X. Zhang, K. Liu, and J. Zhao, "Automatically labeled data generation for large scale event extraction," in *Proc. ACL*, 2017, pp. 409–419.
- [71] Z. Wang et al., "CLEVE: Contrastive pre-training for event extraction," in *Proc. ACL-IJCNLP*, 2021, pp. 6283–6297.
- [72] K. Wei, X. Sun, Z. Zhang, J. Zhang, G. Zhi, and L. Jin, "Trigger is not sufficient: Exploiting frame-aware knowledge for implicit event argument extraction," in *Proc. ACL-IJCNLP*, 2021, pp. 4672–4682.
- [73] R. Xu, T. Liu, L. Li, and B. Chang, "Document-level event extraction via heterogeneous graph-based interaction model with a tracker," in *Proc. ACL-IJCNLP*, 2021, pp. 3533–3546.
- [74] S. Zheng, W. Cao, W. Xu, and J. Bian, "Revisiting the evaluation of end-to-end event extraction," in *Proc. ACL-IJCNLP*, 2021, pp. 4609–4617.
- [75] Y. Zhou, Y. Chen, J. Zhao, Y. Wu, J. Xu, and J. Li, "What the role is vs. what plays the role: Semi-supervised event argument extraction via dual question answering," in *Proc. AAAI*, 2021, pp. 14638–14646.
- [76] X. Du, A. M. Rush, and C. Cardie, "GRIT: Generative role-filler transformers for document-level event entity extraction," in *Proc. ACL*, 2021, pp. 1–13.
- [77] H. Wen et al., "Event time extraction and propagation via graph attention networks," in *Proc. NAACL-HLT*, 2021, pp. 62–73.
- [78] P. Huang, X. Zhao, R. Takanobu, Z. Tan, and W. Xiao, "Joint event extraction with hierarchical policy network," in *Proc. COLING*, 2020, pp. 2653–2664.
- [79] M. Li et al., "Cross-media structured common space for multimedia event extraction," in *Proc. ACL*, 2020, pp. 1–12.
- [80] B. Min, Y. S. Chan, and L. Zhao, "Towards few-shot event mention retrieval: An evaluation framework and a Siamese network approach," in *Proc. LREC*, 2020, pp. 1747–1752.
- [81] Y. Chen, T. Chen, S. Ebner, A. S. White, and B. V. Durme, "Reading the manual: Event extraction as definition comprehension," in *Proc. NLP@EMNLP*, 2020, pp. 1–10.
- [82] S. Cui, B. Yu, T. Liu, Z. Zhang, X. Wang, and J. Shi, "Edge-enhanced graph convolution networks for event detection with syntactic relation," in *Proc. EMNLP (Findings)*, 2020, pp. 1–11.
- [83] S. Zheng, W. Cao, W. Xu, and J. Bian, "Doc2EDAG: An end-to-end document-level framework for Chinese financial event extraction," in *Proc. EMNLP-IJCNLP*, 2019, pp. 1–16.
- [84] T. Zhang, H. Ji, and A. Sil, "Joint entity and event extraction with generative adversarial imitation learning," *Data Intell.*, vol. 1, no. 2, pp. 99–120, May 2019.
- [85] D. Wadden, U. Wennberg, Y. Luan, and H. Hajishirzi, "Entity, relation, and event extraction with contextualized span representations," in *Proc. EMNLP-IJCNLP*, 2019, pp. 1–9.
- [86] X. Wang et al., "HMEAE: Hierarchical modular event argument extraction," in *Proc. EMNLP-IJCNLP*, 2019, pp. 5777–5783.
- [87] R. Han, Q. Ning, and N. Peng, "Joint event and temporal relation extraction with shared representations and structured prediction," in *Proc. EMNLP-IJCNLP*, 2019, pp. 1–11.

- [88] T. M. Nguyen and T. H. Nguyen, "One for all: Neural joint modeling of entities and events," in *Proc. AAAI*, 2019, pp. 6851–6858.
- [89] Y. S. Chan, J. Fasching, H. Qiu, and B. Min, "Rapid customization for event extraction," in *Proc. ACL*, 2019, pp. 1–7.
- [90] X. Li et al., "Entity-relation extraction as multi-turn question answering," in *Proc. ACL*, 2019, pp. 1–11.
- [91] H. Yang, Y. Chen, K. Liu, Y. Xiao, and J. Zhao, "DCFEE: A document-level Chinese financial event extraction system based on automatically labeled training data," in *Proc. ACL*, 2018, pp. 50–55.
- [92] Y. Zeng et al., "Scale up event extraction learning via automatic training data generation," in *Proc. AAAI*, 2018, pp. 1–8.
- [93] Y. Zhao, X. Jin, Y. Wang, and X. Cheng, "Document embedding enhanced event detection with hierarchical and supervised attention," in *Proc. ACL*, 2018, pp. 414–419.
- [94] J. Hong, W. Zhou, J. Zhang, Q. Zhu, and G. Zhou, "Self-regulation: Employing a generative adversarial network to improve event detection," in *Proc. ACL*, 2018, pp. 515–526.
- [95] L. Sha, F. Qian, B. Chang, and Z. Sui, "Jointly extracting event triggers and arguments by dependency-bridge RNN and tensor-based argument interaction," in *Proc. AAAI*, 2018, pp. 1–8.
- [96] X. Liu, Z. Luo, and H. Huang, "Jointly multiple events extraction via attention-based graph information aggregation," in *Proc. EMNLP*, 2018, pp. 1–10.
- [97] S. Liu, Y. Chen, K. Liu, and J. Zhao, "Exploiting argument information to improve event detection via supervised attention mechanisms," in *Proc. ACL*, 2017, pp. 1789–1798.
- [98] L. Sha, J. Liu, C. Lin, S. Li, B. Chang, and Z. Sui, "RBPB: Regularization-based pattern balancing method for event extraction," in *Proc. ACL*, 2016, pp. 1224–1234.
- [99] Y. Zeng, H. Yang, Y. Feng, Z. Wang, and D. Zhao, "A convolution BiLSTM neural network model for Chinese event extraction," in *Proc. NLPCC*, 2016, pp. 275–287.
- [100] Y. Chen, S. Liu, S. He, K. Liu, and J. Zhao, "Event extraction via bidirectional long short-term memory tensor neural networks," in *Proc. CCL*, 2016, pp. 190–203.
- [101] Z. Zhang, W. Xu, and Q. Chen, "Joint event extraction based on skip-window convolutional neural networks," in *Proc. NLPCC*, 2016, pp. 324–334.
- [102] T. H. Nguyen and R. Grishman, "Modeling skip-grams for event detection with convolutional neural networks," in *Proc. EMNLP*, 2016, pp. 886–891.
- [103] Y. Hei et al., "HAWK: Rapid Android malware detection through heterogeneous graph attention networks," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Aug. 2021.
- [104] Q. Sun et al., "SUGAR: Subgraph neural network with reinforcement pooling and self-supervised mutual information mechanism," in *Proc. WWW*, 2021, pp. 2081–2091.
- [105] Q. Sun et al., "Graph structure learning with variational information bottleneck," in *Proc. AAAI*, 2022, pp. 4165–4174.
- [106] J. Liu, Y. Chen, K. Liu, W. Bi, and X. Liu, "Event extraction as machine reading comprehension," in *Proc. EMNLP*, 2020, pp. 1641–1651.
- [107] Q. Li et al., "Event extraction by associating event types and argument roles," 2021, *arXiv:2108.10038*.
- [108] T. H. Nguyen and R. Grishman, "Event detection and domain adaptation with convolutional neural networks," in *Proc. ACL*, 2015, pp. 365–371.
- [109] X. Feng, L. Huang, D. Tang, H. Ji, B. Qin, and T. Liu, "A language-independent neural network for event detection," in *Proc. ACL*, 2016, pp. 66–71.
- [110] T. H. Nguyen and R. Grishman, "Graph convolutional networks with argument-aware pooling for event detection," in *Proc. AAAI*, 2018, pp. 1–8.
- [111] L. Yao, C. Mao, and Y. Luo, "Graph convolutional networks for text classification," in *Proc. AAAI*, 2019, pp. 1–8.
- [112] M. E. Peters et al., "Deep contextualized word representations," in *Proc. NAACL-HLT*, 2018, pp. 2227–2237.
- [113] X. Du and C. Cardie, "Document-level event role filler extraction using multi-granularity contextualized encoding," in *Proc. ACL*, 2020, pp. 1–12.
- [114] B. Sundheim, "Overview of the fourth message understanding evaluation and conference," in *Proc. MUC*, 1992, pp. 3–21.
- [115] S. Ebner, P. Xia, R. Culkin, K. Rawlins, and B. Van Durme, "Multi-sentence argument linking," in *Proc. ACL*, 2020, pp. 1–21.
- [116] Z. Zhang, X. Kong, Z. Liu, X. Ma, and E. Hovy, "A two-step approach for implicit event argument detection," in *Proc. ACL*, 2020, pp. 7479–7485.
- [117] K.-H. Huang and N. Peng, "Document-level event extraction with efficient end-to-end learning of cross-event dependencies," in *Proc. 3rd Workshop Narrative Understand.*, 2021, pp. 1–12.
- [118] S. Li, H. Ji, and J. Han, "Document-level event argument extraction by conditional generation," in *Proc. ACL*, 2021, pp. 1–11.
- [119] H. Yang, D. Sui, Y. Chen, K. Liu, J. Zhao, and T. Wang, "Document-level event extraction via parallel prediction networks," in *Proc. ACL-IJCNLP*, 2021, pp. 6298–6308.
- [120] Y. Huang and W. Jia, "Exploring sentence community for document-level event extraction," in *Proc. EMNLP*, 2021, pp. 340–351.
- [121] X. Du, A. Rush, and C. Cardie, "Template filling with generative transformers," in *Proc. ACL*, 2021, pp. 909–914.
- [122] L. Huang and H. Ji, "Semi-supervised new event type induction and event detection," in *Proc. EMNLP*, 2020, pp. 718–724.
- [123] O. Vinyals et al., "Matching networks for one shot learning," in *Proc. Adv. Neural Inf. Process. Syst.*, 2016, pp. 1–9.
- [124] C. Finn, P. Abbeel, and S. Levine, "Model-agnostic meta-learning for fast adaptation of deep networks," in *Proc. Int. Conf. Mach. Learn.*, 2017, pp. 1126–1135.
- [125] J. Sheng et al., "Adaptive attentional network for few-shot knowledge graph completion," in *Proc. EMNLP*, 2020, pp. 1–11.
- [126] Z. Ye and Z. Ling, "Multi-level matching and aggregation network for few-shot relation classification," in *Proc. ACL*, 2019, pp. 1–10.
- [127] V. D. Lai, F. Deroncourt, and T. H. Nguyen, "Exploiting the matching information in the support set for few shot event classification," in *Proc. Pacific-Asia Conf. Knowl. Discovery Data Mining*. Cham, Switzerland: Springer, 2020.
- [128] V. D. Lai, F. Deroncourt, and T. H. Nguyen, "Extensively matching for few-shot learning event detection," in *Proc. Workshop NUSE*, 2020, pp. 38–45.
- [129] S. Shen, T. Wu, G. Qi, Y. Li, G. Haffari, and S. Bi, "Adaptive knowledge-enhanced Bayesian meta-learning for few-shot event detection," in *Proc. ACL/IJCNLP*, 2021, pp. 1–13.
- [130] V. Lai, F. Deroncourt, and T. H. Nguyen, "Learning prototype representations across few-shot tasks for event detection," in *Proc. EMNLP*, 2021, pp. 5270–5277.
- [131] J. Zheng, F. Cai, W. Chen, W. Lei, and H. Chen, "Taxonomy-aware learning for few-shot event detection," in *Proc. Web Conf.*, Apr. 2021, pp. 3546–3557.
- [132] V. D. Lai, M. V. Nguyen, T. H. Nguyen, and F. Deroncourt, "Graph learning regularization and transfer learning for few-shot event detection," in *Proc. 44th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Jul. 2021, pp. 2172–2176.
- [133] S. Deng, N. Zhang, J. Kang, Y. Zhang, W. Zhang, and H. Chen, "Meta-learning with dynamic-memory-based prototypical network for few-shot event detection," in *Proc. 13th Int. Conf. Web Search Data Mining*, Jan. 2020, pp. 151–159.
- [134] X. Cong, S. Cui, B. Yu, T. Liu, Y. Wang, and B. Wang, "Few-shot event detection with prototypical amortized conditional random field," in *Proc. Findings ACL-IJCNLP*, 2021, pp. 3533–3546.
- [135] J. Chen, H. Lin, X. Han, and L. Sun, "Honey or poison? Solving the trigger curse in few-shot event detection via causal intervention," in *Proc. EMNLP*, 2021, pp. 1–11.
- [136] Q. Lyu, H. Zhang, E. Sulem, and D. Roth, "Zero-shot event extraction via transfer learning: Challenges and insights," in *Proc. ACL/IJCNLP*, 2021, pp. 322–332.
- [137] M. B. Ring, "Continual learning in reinforcement environments," GMD-Bericht, Oldenbourg, Univ. Texas Austin, TX, USA, 1995, pp. 1–127, vol. 255.
- [138] S. Thrun, "Lifelong learning algorithms," in *Learning to Learn*. Boston, MA, USA: Springer, 1998, pp. 181–209.
- [139] P. Cao, Y. Chen, J. Zhao, and T. Wang, "Incremental event detection via knowledge consolidation networks," in *Proc. EMNLP*, 2020, pp. 707–717.
- [140] A. Hsi, Y. Yang, J. G. Carbonell, and R. Xu, "Leveraging multilingual training for limited resource event extraction," in *Proc. COLING*, 2016, pp. 1201–1210.
- [141] J. Liu, Y. Chen, K. Liu, and J. Zhao, "Event detection via gated multilingual attention mechanism," in *Proc. AAAI*, 2018, pp. 1–8.
- [142] Z. Chen and H. Ji, "Language specific issue and feature exploration in Chinese event extraction," in *Proc. HLT-NAACL (Short Papers)*, 2009, pp. 1–4.
- [143] P. Li, G. Zhou, Q. Zhu, and L. Hou, "Employing compositional semantics and discourse consistency in Chinese event extraction," in *Proc. EMNLP-CoNLL*, 2012, pp. 1–11.
- [144] B. Qin, Y. Zhao, X. Ding, T. Liu, and G. Zhai, "Event type recognition based on trigger expansion," *Tsinghua Sci. Technol.*, vol. 15, no. 3, pp. 251–258, Jun. 2010.

- [145] P. Li and G. Zhou, "Employing morphological structures and sememes for Chinese event extraction," in *Proc. COLING*, 2012, pp. 1–16.
- [146] N. Xu, H. Xie, and D. Zhao, "A novel joint framework for multiple Chinese events extraction," in *Proc. CNCL*, 2020, pp. 174–183.
- [147] H. Lin, Y. Lu, X. Han, and L. Sun, "Nugget proposal networks for Chinese event detection," in *Proc. ACL*, 2018, pp. 1–10.
- [148] N. Ding, Z. Li, Z. Liu, H. Zheng, and Z. Lin, "Event detection with trigger-aware lattice neural network," in *Proc. EMNLP-IJCNLP*, 2019, pp. 347–356.
- [149] Y. Zhang and J. Yang, "Chinese NER using lattice LSTM," in *Proc. ACL*, Melbourne, VIC, Australia, 2018, pp. 1–11.
- [150] S. Cui, B. Yu, X. Cong, T. Liu, Q. Li, and J. Shi, "Label enhanced event detection with heterogeneous graph attention networks," 2020, *arXiv:2012.01878*.
- [151] S. Petrovic, M. Osborne, R. McCreadie, C. Macdonald, I. Ounis, and L. Shrimpton, "Can Twitter replace newswire for breaking news?" in *Proc. ICWSM*, 2013, pp. 713–716.
- [152] V. Lai, M. Van Nguyen, H. Kaufman, and T. H. Nguyen, "Event extraction from historical texts: A new dataset for black rebellions," in *Proc. ACL-IJCNLP*, 2021, pp. 2390–2400.
- [153] L. Huang et al., "Liberal event extraction and event schema induction," in *Proc. ACL*, 2016, pp. 258–268.
- [154] A. M. Davani et al., "Reporting the unreported: Event extraction for analyzing the local representation of hate crimes," in *Proc. EMNLP-IJCNLP*, 2019, pp. 1–5.
- [155] X. Wang et al., "MAVEN: A massive general domain event detection dataset," in *Proc. EMNLP*, 2020, pp. 1652–1671.
- [156] H. Ji and R. Grishman, "Refining event extraction through cross-document inference," in *Proc. ACL*, 2008, pp. 254–262.
- [157] S. Liao and R. Grishman, "Using document level cross-event inference to improve event extraction," in *Proc. ACL*, 2010, pp. 789–797.
- [158] Y. Hong, J. Zhang, B. Ma, J. Yao, G. Zhou, and Q. Zhu, "Using cross-entity inference to improve event extraction," in *Proc. ACL*, 2011, pp. 1127–1136.
- [159] J. Liu, Y. Chen, K. Liu, and J. Zhao, "Neural cross-lingual event detection with minimal parallel resources," in *Proc. EMNLP-IJCNLP*, 2019, pp. 738–748.
- [160] W. Li, D. Cheng, L. He, Y. Wang, and X. Jin, "Joint event extraction based on hierarchical event schemas from FrameNet," *IEEE Access*, vol. 7, pp. 25001–25015, 2019.
- [161] A. Vaswani et al., "Attention is all you need," in *Proc. NeurIPS*, 2017, pp. 1–11.
- [162] K. Liu, Y. Chen, J. Liu, X. Zuo, and J. Zhao, "Extracting events and their relations from texts: A survey on recent research progress and challenges," *AI Open*, vol. 1, pp. 22–39, Jan. 2020.
- [163] X. Ding, Z. Li, T. Liu, and K. Liao, "ELG: An event logic graph," 2019, *arXiv:1907.08015*.
- [164] J. Liu, L. Min, and X. Huang, "An overview of event extraction and its applications," 2021, *arXiv:2111.03212*.
- [165] T. S. Costa, S. Gottschalk, and E. Demidova, "Event-QA: A dataset for event-centric question answering over knowledge graphs," in *Proc. CIKM*, 2020, pp. 3157–3164.
- [166] J. Wang, A. Jatowt, M. Färber, and M. Yoshikawa, "Answering event-related questions over long-term news article archives," in *Proc. ECIR* (Lecture Notes in Computer Science), 2020, pp. 774–789.
- [167] R. Han et al., "ESTER: A machine reading comprehension dataset for reasoning about event semantic relations," in *Proc. EMNLP*, 2021, pp. 7543–7559.
- [168] P. Cao, Y. Chen, Y. Yang, K. Liu, and J. Zhao, "Uncertain local-to-global networks for document-level event factuality identification," in *Proc. EMNLP*, 2021, pp. 2636–2645.
- [169] R. Saurí, "A factuality profiler for eventualities in text," Brandeis Univ., Waltham, MA, USA, 2008.
- [170] R. Saurí and J. Pustejovsky, "Are you sure that this happened? Assessing the factuality degree of events in text," *Comput. Linguistics*, vol. 38, no. 2, pp. 261–299, 2012.
- [171] M.-C. de Marneffe, C. D. Manning, and C. Potts, "Did it happen? The pragmatic complexity of veridicality assessment," *Comput. Linguistics*, vol. 38, no. 2, pp. 301–333, Jun. 2012.
- [172] R. Rudinger, A. S. White, and B. V. Durme, "Neural models of factuality," in *Proc. NAACL-HLT*, 2018, pp. 1–14.
- [173] A. P. B. Veyseh, T. H. Nguyen, and D. Dou, "Graph based neural networks for event factuality prediction using syntactic and semantic structures," in *Proc. ACL*, 2019, pp. 1–7.
- [174] R. Nairn, C. Condoravdi, and L. Karttunen, "Computing relative polarity for textual inference," in *Proc. 5th Int. Workshop Inference Comput. Semantics (ICoS-5)*, 2006, pp. 1–10.
- [175] A. Lotan, A. Stern, and I. Dagan, "Truth-teller: Annotating predicate truth," in *Proc. NAACL-HLT*, 2013, pp. 1–6.
- [176] M. T. Diab, L. S. Levin, T. Mitamura, O. Rambow, V. Prabhakaran, and W. Guo, "Committed belief annotation and tagging," in *Proc. LAW*, 2009, pp. 1–6.
- [177] V. Prabhakaran, O. Rambow, and M. T. Diab, "Automatic committed belief tagging," in *Proc. COLING*, 2010, pp. 1–9.
- [178] K. Lee, Y. Artzi, Y. Choi, and L. Zettlemoyer, "Event detection and factuality assessment with non-expert supervision," in *Proc. EMNLP*, 2015, pp. 1643–1648.
- [179] Z. Qian, P. Li, and Q. Zhu, "A two-step approach for event factuality identification," in *Proc. Int. Conf. Asian Lang. Process. (IALP)*, Oct. 2015, pp. 103–106.
- [180] Z. Qian, P. Li, Y. Zhang, G. Zhou, and Q. Zhu, "Event factuality identification via generative adversarial networks with auxiliary classification," in *Proc. 27th Int. Joint Conf. Artif. Intell.*, Jul. 2018, pp. 4293–4300.
- [181] J. Sheng, B. Zou, Z. Gong, Y. Hong, and G. Zhou, "Chinese event factuality detection," in *Proc. NLPCC* (Lecture Notes in Computer Science), 2019, pp. 486–496.
- [182] R. Huang, B. Zou, H. Wang, P. Li, and G. Zhou, "Event factuality detection in discourse," in *Proc. NLPCC* (Lecture Notes in Computer Science), 2019, pp. 404–414.
- [183] I. J. Goodfellow et al., "Generative adversarial nets," in *Proc. NeurIPS*, 2014, pp. 2672–2680.
- [184] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," in *Proc. ICLR*, 2017, pp. 1–14.
- [185] Z. Qian, P. Li, Q. Zhu, and G. Zhou, "Document-level event factuality identification via adversarial neural network," in *Proc. NAACL-HLT*, 2019, pp. 2799–2809.
- [186] A. Cybulska and P. Vossen, "Translating granularity of event slots into features for event coreference resolution," in *Proc. EVENTS@HLP-NAACL*, 2015, pp. 1–10.
- [187] J. Lu and V. Ng, "Learning antecedent structures for event coreference resolution," in *Proc. 16th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2017, pp. 113–118.
- [188] C. A. Bejan and S. M. Harabagiu, "Unsupervised event coreference resolution with rich linguistic features," in *Proc. ACL*, 2010, pp. 1412–1422.
- [189] P. K. Choubey and R. Huang, "Improving event coreference resolution by modeling correlations between event coreference chains and document topic structures," in *Proc. ACL*, 2018, pp. 485–495.
- [190] Y. J. Huang, J. Lu, S. Kurohashi, and V. Ng, "Improving event coreference resolution by learning argument compatibility from unlabeled data," in *Proc. ACL*, 2019, pp. 785–795.
- [191] Z. Chen, H. Ji, and R. M. Haralick, "A pairwise event coreference model, feature impact and evaluation for event coreference resolution," in *Proc. Workshop Events Emerg. Text Types*, 2009, pp. 17–22.
- [192] Z. Chen and H. Ji, "Graph-based event coreference resolution," in *Proc. Graph-Based Methods Natural Lang. Process. (TextGraphs-4)*, 2009, pp. 54–57.
- [193] P. K. Choubey and R. Huang, "Event coreference resolution by iteratively unfolding inter-dependencies among events," in *Proc. EMNLP*, 2017, pp. 2124–2133.
- [194] C. Chen and V. Ng, "Joint inference over a lightly supervised information extraction pipeline: Towards event coreference resolution for resource-scarce languages," in *Proc. AAAI*, 2016, pp. 2913–2920.
- [195] J. Lu, D. Venugopal, V. Gogate, and V. Ng, "Joint inference for event coreference resolution," in *Proc. COLING*, 2016, pp. 3264–3275.
- [196] J. Lu and V. Ng, "Joint learning for event coreference resolution," in *Proc. ACL*, 2017, pp. 1–12.
- [197] J. Araki and T. Mitamura, "Joint event trigger identification and event coreference resolution with structured perceptron," in *Proc. EMNLP*, 2015, pp. 1–7.
- [198] S. Barhom, V. Schwartz, A. Eirew, M. Bugert, N. Reimers, and I. Dagan, "Revisiting joint modeling of cross-document entity and event coreference resolution," in *Proc. ACL*, 2019, pp. 4179–4189.
- [199] P. Mirza, "Extracting temporal and causal relations between events," in *Proc. ACL Student Res. Workshop*, 2014, pp. 10–17.
- [200] M. Riaz and R. Girju, "Another look at causality: Discovering scenario-specific contingency relationships with no supervision," in *Proc. IEEE 4th Int. Conf. Semantic Comput.*, Sep. 2010, pp. 361–368.
- [201] M. Riaz and R. Girju, "Toward a better understanding of causality between verbal events: Extraction and analysis of the causal power of verb-verb associations," in *Proc. SIGDIAL Conf.*, 2013, pp. 21–30.



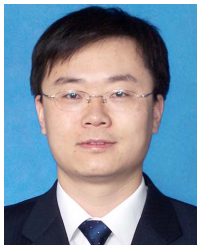
- [202] C. Hashimoto et al., "Toward future scenario generation: Extracting event causality exploiting semantic relation, context, and association features," in *Proc. ACL*, 2014, pp. 1–11.
- [203] P. Mirza and S. Tonelli, "An analysis of causality between events and its relation to temporal information," in *Proc. COLING*, 2014, pp. 1–10.
- [204] P. Mirza and S. Tonelli, "CATENA: Causal and temporal relation extraction from natural language texts," in *Proc. COLING*, 2016, pp. 1–12.
- [205] Z. Hu and M. Walker, "Inferring narrative causality between event pairs in films," in *Proc. SIGDIAL Conf.*, 2017, pp. 1–10.
- [206] L. Gao, P. K. Choubey, and R. Huang, "Modeling document-level causal structures for event causal relation identification," in *Proc. ACL*, 2019, pp. 1–10.
- [207] K. Kadowaki, R. Iida, K. Torisawa, J.-H. Oh, and J. Kloetzer, "Event causality recognition exploiting multiple annotators' judgments and background knowledge," in *Proc. EMNLP-IJCNLP*, 2019, pp. 5816–5822.
- [208] H. Rashkin, M. Sap, E. Allaway, N. A. Smith, and Y. Choi, "Event2Mind: Commonsense inference on events, intents, and reactions," in *Proc. ACL*, 2018, pp. 463–473.
- [209] N. Mostafazadeh et al., "GLUCOSE: Generalized and contextualized story explanations," in *Proc. EMNLP*, 2020, pp. 4569–4586.
- [210] J. Liu, Y. Chen, and J. Zhao, "Knowledge enhanced event causality identification with mention masking generalizations," in *Proc. IJCAI*, 2020, pp. 3608–3614.
- [211] P. Cao et al., "Knowledge-enriched event causality identification via latent structure induction networks," in *Proc. ACL/IJCNLP*, 2021, pp. 4862–4872.
- [212] M. Riaz and R. Girju, "Recognizing causality in verb-noun pairs via noun and verb semantics," in *Proc. EACL*, 2014, pp. 1–10.
- [213] X. Zuo, Y. Chen, K. Liu, and J. Zhao, "KnowDis: Knowledge enhanced data augmentation for event causality detection via distant supervision," in *Proc. COLING*, 2020, pp. 1–7.
- [214] J. Pustejovsky et al., "TimeML: Robust specification of event and temporal expressions in text," in *New Directions in Question Answering*, vol. 3. 2003, pp. 28–34.
- [215] C. Hagège and X. Tannier, "XRCE-T: XIP temporal module for TempEval campaign," in *Proc. SemEval*, 2007, pp. 1–4.
- [216] A. Chang and C. D. Manning, "Sutime: Evaluation in tempeval-3," in *Proc. SemEval*, 2013, pp. 1–5.
- [217] N. Chambers, T. Cassidy, B. McDowell, and S. Bethard, "Dense event ordering with a multi-pass architecture," *Trans. Assoc. Comput. Linguistics*, vol. 2, pp. 273–284, Dec. 2014.
- [218] I. Mani, M. Verhagen, B. Wellner, C. M. Lee, and J. Pustejovsky, "Machine learning of temporal relations," in *Proc. ACL*, 2006, pp. 1–8.
- [219] Q. Ning, Z. Feng, and D. Roth, "A structured learning approach to temporal relation extraction," in *Proc. EMNLP*, 2017, pp. 1027–1037.
- [220] D. Dligach, T. Miller, C. Lin, S. Bethard, and G. Savova, "Neural temporal relation extraction," in *Proc. ACL (Short Papers)*, 2017, pp. 746–751.
- [221] J. Tourville, O. Ferret, A. Neveol, and X. Tannier, "Neural architecture for temporal relation extraction: A Bi-LSTM approach for detecting narrative containers," in *Proc. ACL*, 2017, pp. 224–230.
- [222] F. Cheng and Y. Miyao, "Classifying temporal relations by bidirectional lstm over dependency paths," in *Proc. ACL (Short Papers)*, 2017, pp. 1–6.
- [223] R. Han, Y. Zhou, and N. Peng, "Domain knowledge empowered structured neural net for end-to-end event temporal relation extraction," in *Proc. EMNLP*, 2020, pp. 5717–5729.
- [224] H. Ross, J. Cai, and B. Min, "Exploring contextualized neural language models for temporal dependency parsing," in *Proc. EMNLP*, 2020, pp. 8548–8553.
- [225] R. C. Schank and R. P. Abelson, "Scripts, plans, goals, and understanding," in *Readings in Cognitive Science: A Perspective From Psychology and Artificial Intelligence*, A. M. Collins and E. E. Smith, Eds. Hillsdale, NJ, USA: Erlbaum, 1977, ch. 1-3–1-68, pp. 190–223.
- [226] D. Bean and E. Riloff, "Unsupervised learning of contextual role knowledge for coreference resolution," in *Proc. HLT-NAACL*, 2004, pp. 297–304.
- [227] S. Chaturvedi, H. Peng, and D. Roth, "Story comprehension for predicting what happens next," in *Proc. EMNLP*, 2017, pp. 1603–1614.
- [228] Y. Yang, Z. Wei, Q. Chen, and L. Wu, "Using external knowledge for financial event prediction based on graph neural networks," in *Proc. 28th ACM Int. Conf. Inf. Knowl. Manage.*, Nov. 2019, pp. 2161–2164.
- [229] M. Granroth-Wilding and S. Clark, "What happens next? Event prediction using a compositional neural network model," in *Proc. AAAI*, 2016, pp. 1–7.
- [230] D. Graff and C. Cieri, "English gigaword corpus," in *Linguistic Data Consortium*, 2003.
- [231] N. Chambers and D. Jurafsky, "Unsupervised learning of narrative event chains," in *Proc. ACL*, 2008, pp. 1–9.
- [232] B. Jans, S. Bethard, I. Vulić, and M. F. Moens, "Skip n-grams and ranking functions for predicting script events," in *Proc. ACL*, 2012, pp. 1–9.
- [233] K. Pichotta and R. Mooney, "Statistical script learning with multi-argument events," in *Proc. ACL*, 2014, pp. 1–10.
- [234] R. Rudinger, P. Rastogi, F. Ferraro, and B. Van Durme, "Script induction as language modeling," in *Proc. EMNLP*, 2015, pp. 1–6.
- [235] S. Lv, W. Qian, L. Huang, J. Han, and S. Hu, "SAM-Net: Integrating event-level and chain-level attentions to predict what happens next," in *Proc. AAAI*, 2019, pp. 1–8.
- [236] K. Pichotta and R. Mooney, "Learning statistical scripts with LSTM recurrent neural networks," in *Proc. AAAI*, 2016, pp. 1–7.
- [237] Z. Wang, Y. Zhang, and C.-Y. Chang, "Integrating order information and event relation for script event prediction," in *Proc. EMNLP*, 2017, pp. 57–67.
- [238] L. Wang et al., "Multi-level connection enhanced representation learning for script event prediction," in *Proc. WWW*, 2021, pp. 3524–3533.
- [239] J. Zheng, F. Cai, Y. Ling, and H. Chen, "Heterogeneous graph neural networks to predict what happen next," in *Proc. COLING*, 2020, pp. 328–338.
- [240] X. Ding, K. Liao, T. Liu, Z. Li, and J. Duan, "Event representation learning enhanced with external commonsense knowledge," in *Proc. EMNLP-IJCNLP*, 2019, pp. 1–10.
- [241] H. Rashkin, M. Sap, E. Allaway, N. A. Smith, and Y. Choi, "Event2Mind: Commonsense inference on events, intents, and reactions," in *Proc. ACL*, 2018, pp. 1–13.
- [242] M. Sap et al., "ATOMIC: An atlas of machine commonsense for if-then reasoning," 2019, *arXiv:1811.00146*.
- [243] S. Lv, F. Zhu, and S. Hu, "Integrating external event knowledge for script learning," in *Proc. COLING*, 2020, pp. 306–315.
- [244] H. Zhang, X. Liu, H. Pan, Y. Song, and C. Leung, "ASER: A large-scale eventuality knowledge graph," in *Proc. WWW*, 2020, pp. 201–211.
- [245] K. Huang, M. Yang, and N. Peng, "Biomedical event extraction on graph edge-conditioned attention networks with hierarchical knowledge graphs," in *Proc. EMNLP*, 2020, pp. 1277–1285.
- [246] J. A. Vanegas, S. Matos, F. A. González, and J. L. Oliveira, "An overview of biomolecular event extraction from scientific documents," *Comput. Math. Methods Med.*, vol. 2015, Oct. 2015, Art. no. 571381.
- [247] J. Björne and T. Salakoski, "Generalizing biomedical event extraction," in *BioNLP@ACL (Shared Task)*, 2011, pp. 1–9.
- [248] J. Björne and T. Salakoski, "Biomedical event extraction using convolutional neural networks and dependency parsing," in *Proc. BioNLP Workshop*, 2018, pp. 98–108.
- [249] L. Li, Y. Liu, and M. Qin, "Extracting biomedical events with parallel multi-pooling convolutional neural networks," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, vol. 17, no. 2, pp. 599–607, Mar./Apr. 2020.
- [250] H.-L. Trieu, T. T. Tran, K. N. A. Duong, A. Nguyen, M. Miwa, and S. Ananiadou, "DeepEventMine: End-to-end neural nested event extraction from biomedical texts," *Bioinformatics*, vol. 36, no. 19, pp. 4910–4917, Dec. 2020.
- [251] Z. Tang, G. Hahn-Powell, and M. Surdeanu, "Exploring interpretability in event extraction: Multitask learning of a neural event classifier and an explanation decoder," in *Proc. ACL*, 2020, pp. 169–175.
- [252] G. Frisoni, G. Moro, and A. Carbonaro, "A survey on event extraction for natural language understanding: Riding the biomedical literature wave," *IEEE Access*, vol. 9, pp. 160721–160757, 2021.



**Qian Li** is currently pursuing the Ph.D. degree with the School of Computer Science and Engineering, Beijing Advanced Innovation Center for Big Data and Brain Computing, Beihang University, Beijing, China.

Her research interests include knowledge graph and information extraction.





**Jianxin Li** (Member, IEEE) is currently a Professor with the School of Computer Science and Engineering, Beijing Advanced Innovation Center for Big Data and Brain Computing, Beihang University, Beijing, China.

His current research interests include social networks, machine learning, big data, and trustworthy computing. He has published research articles in top-tier journals and conferences, including the IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING (TKDE), the IEEE TRANSACTIONS ON DEPENDABLE AND SECURE COMPUTING (TDSC), *Journal of Artificial Intelligence Research* (JAIR), *ACM Transactions on Information Systems* (TOIS), the *ACM Transactions on Knowledge Discovery from Data* (TKDD), *Knowledge Discovery and Data Mining* (KDD), Association for the Advancement of Artificial Intelligence (AAAI), and The International Conference of World Wide Web (WWW).



**Jiawei Sheng** is currently pursuing the Ph.D. degree with the Institute of Information Engineering, Chinese Academy of Sciences, Beijing, China.

His current research interests include information extraction, knowledge graph embedding, and knowledge acquisition.



**Shiyao Cui** is currently pursuing the Ph.D. degree with the Institute of Information Engineering, Chinese Academy of Sciences, Beijing, China.

Her current research interests include event extraction, event relation identification, and script event prediction.



**Jia Wu** (Senior Member, IEEE) received the Ph.D. degree in computer science from the University of Technology Sydney, Sydney, NSW, Australia, in 2015.

He is currently an Australian Research Council (ARC) Discovery Early Career Researcher Award (DECRA) Fellow with the School of Computing, Macquarie University, Sydney. His current research interests include data mining and machine learning. Since 2009, he has published more than 100 refereed journal and conference papers, including the IEEE

TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE (TPAMI), the IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING (TKDE), the IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS (TNNLS), the IEEE TRANSACTIONS ON MULTIMEDIA (TMM), *ACM Transactions on Knowledge Discovery from Data* (TKDD), *Neural Information Processing Systems* (NIPS), The International Conference of World Wide Web (WWW), and ACM's Special Interest Group on Knowledge Discovery and Data Mining (SIGKDD).



**Yiming Hei** is currently pursuing the Ph.D. degree with the School of Cyber Science and Technology, Beihang University, Beijing, China.

His research interests include graph embedding, information extraction, and application security.



**Hao Peng** is currently an Assistant Professor with the School of Cyber Science and Technology, Beijing Advanced Innovation Center for BigData and Brain Computing, Beihang University, Beijing, China. His research interests include representation learning, machine learning, and graph mining.



**Shu Guo** received the Ph.D. degree from the Institute of Information Engineering, Chinese Academy of Sciences, Beijing, China, in 2018.

She is currently working with the National Computer Network Emergency Response Technical Team/Coordination Center of China, Beijing. Her research interests include knowledge graph embedding, knowledge acquisition, and web mining.



**Lihong Wang** is currently a Professor with the National Computer Network Emergency Response Technical Team/Coordination Center of China, Beijing, China. Her current research interests include information security, cloud computing, big data mining and analytics, information retrieval, and data mining.



**Amin Beheshti** received the bachelor's and master's degrees (Hons.) in computer science and the Ph.D. degree in computer science and engineering from UNSW Sydney, Sydney, NSW, Australia, in 2013.

He is a Postdoc with UNSW Sydney. He is the Director of AI-enabled Processes (AIP) Research Centre and the Head of the Data Analytics Research Laboratory, Department of Computing, Macquarie University, Sydney. He is also a Senior Lecturer in data science with Macquarie University and an Adjunct Academic in computer science with UNSW Sydney.



**Philip S. Yu** (Life Fellow, IEEE) is a Distinguished Professor and the Wexler Chair in Information Technology with the Department of Computer Science, University of Illinois at Chicago, Chicago, IL, USA, and also holds the Wexler Chair in Information Technology. Before joining UIC, he was with the IBM Watson Research Center, Ossining, NY, USA.

Dr. Yu is a Fellow of Association for Computing Machinery (ACM). He was the Editor-in-Chief of the *ACM Transactions on Knowledge Discovery from Data* (TKDD) from 2011 to 2017 and

the IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING from 2001 to 2004.