

Event Extraction without Human-annotated Text

Anonymous EMNLP submission

Abstract

Existing event extraction systems are typically investigated in the supervised learning paradigm. The effectiveness of these systems heavily relies on the quality of expert-annotated datasets which still require a costly and time-consuming construction process. As a result, the built datasets often only cover a limited variety of event types, making the learned event extractor hard to generalize. In this paper, we address the problem of automatically building event extractors for rich event types with little expert involvement. We achieve this by employing distant supervision to automatically create event annotations from unlabelled data using structured knowledge bases. We then propose a novel neural network model with ILP-based inference, committing to detecting events of various types and extracting their corresponding arguments involved. We evaluate our approach by automatically collecting training data for many event types from Freebase, where our proposed extraction model is designed to identify both typed event mentions and typed arguments. Both automatic and manual evaluations demonstrate that it is possible to learn to effectively extract various events without human-annotated training data.

1 Introduction

Event extraction, as represented by the Automatic Content Extraction (ACE) task, is a key enabling technique for many natural language processing (NLP) applications. Current event extractors are typically built through applying supervised learning to learn over labelled datasets. This means

that the performance of event extraction systems highly dependent on the quality of the training datasets.

Constructing high-quality training data for event extraction is, however, an expensive and error-prone process. This requires the involvement of linguists to design annotation templates and rules, and the employment of annotators to manually label data. To scale up the event extraction systems, we would like to reduce expert involvement. Furthermore, existing event extraction systems have two major drawback: (1) they can only handle single-token triggers¹ and (2) they only support scenarios where each event is merely associated with a single type. To make event extractors more practical, we need to support scenarios where the trigger annotations are unavailable or events with more than one type.

This paper presents a novel approach for automatic training data generation, specifically targeting event extraction. Our approach has two advantages over prior work~~FIX:()~~. Firstly, it significantly reduces the expert involvement as it does not rely on expert-annotated texts. Secondly, it supports multi-typed events. The automatic event extraction is achieved by employing distant supervision to automatically annotate event structures from plain text, using information extracted from existing structured knowledge bases such as Freebase. To support multi-typed event extraction, we propose a novel neural network model with ILP-based inference to extract multiple event types without explicit trigger annotations.

Our key insights are described as follows. First, we observe that structured knowledge bases (KB) often organize complex structured information in tables, which share similar structures with ACE event definitions. A particular entry of such tables

¹In the ACE task, a trigger is the word that most clearly expresses the occurrence of an event.

usually implies the occurrence of certain events. On the other hand, recent studies (Mintz et al., 2009; Zeng et al., 2015) have demonstrated the effectiveness of KB as distant supervision (DS) for binary relation extraction. However, there are two major challenges when leveraging KB to event extraction: first, event structures are more complex than binary relations. They can be represented as $\langle event_type, argument_1, \dots, argument_n \rangle$, which are n-ary relations with various numbers of arguments. Second, there is no explicit trigger information in any existing knowledge base. However, we find that for a particular event type, there is a group of **key arguments** which together can imply an event instead of explicit triggers. For example, “*spouse*” is the key argument of “*marriage*” events, while “*location of ceremony*” is too generic to become a key argument. Therefore, we put forward a distant supervision approach to event extraction: a sentence that contains all key arguments of an event is likely to express that event in some way. To explore the sets of key arguments, we investigate different hypotheses for better data quality and quantity. We utilize Freebase as our knowledge base and Wikipedia articles as text for data generation as a major source of Freebase is the tabular data from Wikipedia (Mintz et al., 2009). Figure 1 illustrates examples of sentences annotated by our algorithm.

Second, unlike previous studies that focus on tasks defined by ACE evaluation framework (Ahn, 2006; Li et al., 2013; Chen et al., 2015; Nguyen et al., 2016), we propose a novel event extraction paradigm with key arguments to characterize an event type. We consider event extraction as two sequence labeling subtasks, namely event detection and argument detection. Inspired by neural network models in sequence labeling tasks (Huang et al., 2015; Lample et al., 2016), we utilize LSTM-CRF models to label key arguments and non-key arguments in the each sentence separately. However, event structures are not simple sequences and there are strong dependencies among key arguments. We therefore reformulate the hypotheses as constraints, and apply linear integer programming to output multiple optimal label sequences to capture multi-type events.

In this paper, we exploit existing structured knowledge bases, e.g., Freebase, as distant supervision to automatically annotate event structures

from plain text without human annotations. We further propose a novel event extraction paradigm that harnesses key arguments to imply certain event types without explicit trigger annotations. We present an LSTM-CRF model with post inference to extract both Freebase-style events as well as multi-type event mentions on the generated dataset, which is demonstrated effective by both manual and automatic evaluations.

2 Dataset Preparation

Here, we will employ the event-related entries in Freebase (Bollacker et al., 2008) to automatically annotate event descriptions in Wikipedia’s pages, with the essence of DS. We regard a sentence as positive when it mentions the occurrence of an event, or otherwise negative. For example, S1 and S2 are positive examples with their arguments in italics and underlined (also shown in Figure 1), while S3 and S4 are negative.

S1: *Remedy Corp* was sold to *BMC Software* as the *Service Management Business Unit* in *2004*.

S2: *Microsoft* spent \$6.3 billion buying online display advertising company *aQuantive* in *2007*.

S3: Microsoft hopes aQuantive’s Brian McAndrews can outfox Google.

S4: On April 29th, Elizabeth II and Prince Philip witnessed the marriage of Prince William.

2.1 Freebase

Freebase is a structured knowledge base, and there are three basic concepts: *instance*, *type* and *property*. *Instances* are entries in Freebase, and related to real-world entities and their relationships. *Types* are different perspectives of *instances*. **Compound Value Type** (CVT) is a special type in Freebase to represent complex structured data where instances are described with multiple *properties*, usually organized in a table. Some of the CVT schemas indeed imply certain events, e.g., *people.marriage*, *military.military_service* and *business.acquisition*, and closely resemble to event structures, where CVT properties can be treated as event arguments. As shown in Figure 1, the properties of CVT *business.acquisition* actually can be used to label the

participants and attributes of the events mentioned in S1 and S2.

We use the Freebase copy of 2013-06, containing 1010 CVTs. After filtering out those describing the Freebase structures or irrelevant to events (e.g., *food.recipe_ingredient*), we obtain 24 CVTs with around 280 million instances.

Instances of <i>business.acquisition</i> in Freebase				
id	property	company_acquired	acquiring_company	date
m.07bh4j7		Remedy Corp	BMC Software	2004
m.05nb3y7		aQuantive	Microsoft	2007
				divisions_formed
				Service Management Business Unit
				NONE

Event structures in our dataset				
Wiki text	S1: Remedy Corp was sold to BMC Software as the Service Management Business Unit in 2004.			
Event type	<i>business.acquisition</i>			
Arguments	company_acquired	acquiring_company	date	divisions_formed
	Remedy Corp	BMC Software	2004	Service Management Business Unit
Wiki text	S2: Microsoft spent \$6.3 billion buying online display advertising company aQuantive in 2007.			
Event type	<i>business.acquisition</i>			
Arguments	acquiring_company	company_acquired	date	divisions_formed
	Microsoft	aQuantive	2007	—

Figure 1: Examples of CVT instances in Freebase, and labeled sentences in our dataset. *Company_acquired*, *acquiring_company* and *date* are key arguments in *business.acquisition*.

2.2 Data Generation

Now we will describe how to automatically collect training data with quality event annotations, by pushing forward the DS framework.

H1: Positive sentences should contain all properties Our first hypothesis is that *if a sentence contains all properties of an entry in a CVT, this sentence will be considered as a positive sample to indicate an event of such type characterized by this CVT*. We will then label the sentence as a mention of this CVT event, and the words or phrases that match this entry’s properties as the involved arguments, with the roles specified by their corresponding property names. For example, S1 contains all the properties of instance *m.07bh4j7* with a CVT type *business.acquisition*, we thus consider S1 as a positive sample implying an event about *business.acquisition*, and *BMC Software*, *Remedy Corp*, *Service Management Business Unit* and *2004* will be labeled as the arguments that play the role of *acquiring_company*, *company_acquired*, *divisions_formed*, and *date* in this event, respectively.

H2: Positive sentences should contain all key properties In practice, we find that *H1* is too strict to include many positive sentences like S2. We thus relax *H1* by replacing **all properties** with

CVT	Key properties
award.award_honor	award_winner, award, ..., year
film.performance	actor, film, character
education.education	institution, student, end_date
business.employment_tenure	company, title, person, from

Table 1: Examples of key properties of four CVTs.

all key properties. We define the CVT property that plays an important part in its CVT structure and helps to distinguish with other CVTs as a **key property**. A **key argument** is the word/phrase that matches a key property of a CVT instance. For example, *company_acquired* and *acquiring_company* are the key properties of CVT *business.acquisition*, therefore, S2 should be a positive sentence for a *business.acquisition* event, since it contains all key properties. Table 1 lists the key properties of four CVTs.

The importance of a property *prop* (e.g., *date*) to its CVT *cvt* (e.g., *business.acquisition*) can be defined as:

$$degree_{cvt,prop} = \log \frac{count(cvt, prop)}{count(cvt) \times count(prop)} \quad (1)$$

where *count(cvt)* is the number of all instances of type *cvt*, *count(prop)* is the number of times *prop* appearing in all CVTs, and *count(cvt, prop)* is the number of *cvt* instances that contain the property *prop*.

H3: Key properties should include time properties Although time-related arguments are often missing in the currently imperfect KBs, time-related properties are indeed crucial to indicate an actual event mention, e.g., S3, containing *Microsoft* as *acquiring_company* and *aQuantive* as *company_acquired* but without time-related arguments, will be considered as a positive sample for event *business.acquisition* by mistake. We thus include time-related properties with highest importance scores as supplementary key properties.

H4: Key properties should be close on dependency path Intuitively, two arguments participating in the same event are likely to be closer to each other in syntactic structures, which will help to eliminate negative samples. In Figure 2, both *Prince Philip* and *marriage* can be matched as key properties in a *people.marriage* entry, but are far from each other on the dependency path, thus S4 should be labeled as negative. In our experiments, we set the maximum distance between two key arguments as 2.

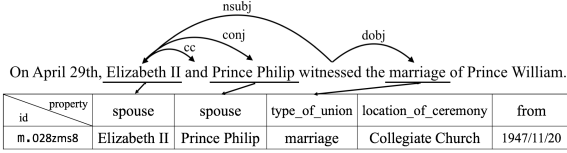


Figure 2: An illustration of dependency tree of S4, which partially matches an entry of *people.marriage*.

We conduct a series of manual evaluations on the quantity and quality of the datasets produced by different hypotheses (see Sec 4.2), and the combination of *H3* and *H4* produces the best dataset, thus serves as our final strategy.

3 Our Approach

Existing works in event extraction rely on explicit trigger identification to detect the occurrence of an event, which is crucial to later decide its event type and label its arguments. In our automatically collected dataset, where human-labeled event triggers are unavailable, we argue that **key arguments** can play the same role as explicit event triggers. We thus treat the event extraction as a pipeline of two subtasks, namely, event detection and argument detection.

Event detection aims to identify key arguments in a sentence. If a sentence contains **all** key arguments of a specific event type, it will be considered to imply an event of the corresponding type. Take S1 as an example, *Remedy Corp, BMC Software, and 2004* could be identified as *company_acquired*, *acquiring_company*, and *date*, respectively, indicating that S1 may mention a *business.acquisition* event.

Argument detection aims to identify other non-key arguments for each event in the sentence. For the *business.acquisition* event in S1, *Service Management Business Unit* should be identified as *divisions_formed*.

3.1 Event Detection

Next, we first present our solution for multi-words arguments, and then introduce each component in our model.

Tagging scheme There 68% of arguments in our dataset consisting of more than one word. To address this issue, we model each subtask in a sequence labeling paradigm rather than word-level classifications. Each word in the given sentence

is tagged with the BIO scheme, where each token is labeled as B-role if it is the beginning of an event argument with its corresponding role *role*, or I-role if it is inside an argument, or O otherwise.

LSTM Long Short-Term Memory Network (LSTM) (Hochreiter and Schmidhuber, 1997) is a natural fit for sequence labeling, which maintains a memory based on historical contextual information. Formally, given a sentence $w = \{w_1, w_2, \dots, w_n\}$ of length n , we use \mathbf{x}_t to represent feature vector, e.g., word embeddings, corresponding to the t -th word w_t . At each time step t , an LSTM unit takes \mathbf{x}_t as input and computes the output vector \mathbf{h}_t through several multiplicative gates. The output vector is fed into a softmax layer to estimate a probability distribution over all possible labels.

CRF A straightforward way to find the label sequence for given sentence is to choose the best label for each word individually according to LSTM output. However, this greedy strategy ignores the dependencies between labels, thus can not guarantee the best sequence. Therefore, we introduce a CRF layer over the LSTM output, which is admittedly effective in various sequence labeling tasks (Collobert et al., 2011; Huang et al., 2015).

We consider \mathbf{P} to be a matrix of confidence scores output by LSTM, and the element $\mathbf{P}_{i,j}$ of the matrix denotes the probability of the label j for the i -th word in a sentence. The CRF layer takes a transition matrix \mathbf{A} as parameter, where $\mathbf{A}_{i,j}$ represents the score of a transition from label i to label j . The score of a sentence w along with a path of labels $\mathbf{y} = \{y_1, y_2, \dots, y_n\}$ is measured by the sum of LSTM outputs and transition scores:

$$\text{score}(w, \mathbf{y}) = \sum_{i=0}^n \mathbf{P}_{i,y_i} + \sum_{i=1}^n \mathbf{A}_{y_i,y_{i+1}}, \quad (2)$$

During test, given a sentence w , we adopt the Viterbi algorithm (Rabiner, 1989) to find the optimal label sequence with the maximum score among all possible label sequences.

ILP-based Post Inference Basically, event detection is a structure prediction problem, while the output sequences of LSTM-CRF do not necessarily satisfy the structural constraints. For instance, regardless of how many key arguments are correctly identified by LSTM-CRF, if there is one key

argument missing, this detection should be considered as failed.

We thus propose to apply Integer Linear Programming (ILP) to further globally optimize the LSTM-CRF output to produce the best label sequence. Formally, let \mathcal{L} be the set of possible argument labels. For each word w_i in the sentence w and a pair of labels $\langle l, l' \rangle \in \mathcal{L} \times \mathcal{L}$, we create a binary variable $v_{i,l,l'} \in \{0, 1\}$, denoting whether or not the i -th word w_i is tagged as label l and its following word w_{i+1} is tagged as label l' at the same time. The objective of ILP is to maximize the overall score of the variables as:

$$\sum_{i,l,l'} v_{i,l,l'} * (\mathbf{P}_{i,l} + \mathbf{A}_{l,l'}).$$

where we consider the following four constraints:

C1: Each word should be and only be annotated with one label, i.e.:

$$\sum_{l,l'} v_{i,l,l'} = 1 \quad (3)$$

C2: If the value of $v_{i,l,l'}$ is 1, then there has to be a label l^* that will make v_{i+1,l',l^*} equal to 1, i.e.:

$$v_{i,l,l'} = \sum_{l^*} v_{i+1,l',l^*} \quad (4)$$

C3: If the current label is I-arg, then its previous label must be B-arg or I-arg, i.e.:

$$v_{i,\text{I-arg},l'} = v_{i-1,\text{B-arg},\text{I-arg}} + v_{i-1,\text{I-arg},\text{I-arg}} \quad (5)$$

C4: For a specific event type, all its key arguments should co-occur in the sentence, or none of them appears in the resulting sequence. For any pair of key arguments arg_1 and arg_2 with respect to the same event type, the variables related to them are subject to:

$$\sum_{i,l'} v_{i,\text{B-arg}_1,l'} \leq n * \sum_{j,l^*} v_{j,\text{B-arg}_2,l^*} \quad (6)$$

where n is the length of the sentence.

In order to address the multi-type event mention issue, we allow our ILP solver to output multiple optimal sequences. Specifically, after our model outputs the best sequence s^t at time t , we remove the previously best solutions $\{s^1, \dots, s^t\}$ from the solution space, and re-run our solver to obtain the next optimal sequences s^{t+1} . We repeat the optimization procedure until the difference between the scores of s^1 and s^T is greater than a threshold λ , and consider all solutions $\{s^1, s^2, \dots, s^{T-1}\}$ as the optimal label sequences. We use Gurobi (Gurobi Optimization,

	Train	Dev	Test
#Sent.	4800	1200	1180
#Eve.	4918	1247	1229
#Arg.	17274	4318	4248
%Multi_Eve.	3.0	3.2	3.1
%Multi_Arg.	67.4	67.0	67.9

Table 2: Statistics for the generated dataset. #Sent. is the number of sentences, #Eve. is the number of event mentions, and #Arg. is the number of event arguments. %Multi_Eve. is the ratio of multi-type events, and %Multi_Arg. is the ratio of multi-word arguments.

2016) as our ILP solver and set $\lambda = 0.05 \times n$, which averagely produce 1.04 optimal sequences for each sentence.

3.2 Argument Detection

After event detection, a sentence will be classified into different event types, and labeled with its corresponding key arguments. The next step is argument detection, which aims to identify the remaining non-key arguments in the sentence.

We adopt the same LSTM-CRF architecture (in Sec 3.1) for argument detection, where we encode the event label (output of event detection) of each word into a key-argument feature vector through a look-up table, and concatenate it with the original word embedding as the input to the new LSTM-CRF. Note that we do not need post inference here.

4 Experiments

4.1 Experimental Setup

We use Freebase and the English Wikipedia dump of 2016-11-20, to construct our dataset. Statistics for the generated dataset is shown in Table 2. Note that all sentences in the dataset are positive. We conduct both automatic evaluation and manual evaluation in our experiments. We first manually evaluate the quality of our test set. And then, we regard the automatically generated data as gold standard and evaluate our model accordingly. Finally, we manually evaluate a subset of events detected by our model and analyze the differences with regards to the automatic evaluation.

Evaluation Measures We evaluate our models in terms of precision (P), recall (R), and F-measure (F) for each subtask. These performance metrics are computed according to the following standards of correctness:

- For event type classification, an event is correctly classified if its reference sentence contains all key arguments of this event type.
- For argument detection, an argument is correctly detected if its offsets, role, and related event type exactly match the reference argument within the same sentence.
- For event detection, an event is correctly detected if its type and all its key arguments match a reference event within the same sentence.

Training All hyper-parameters are tuned on the development set. In event detection, we set the size of word embeddings to 200, the size of LSTM layer to 100. In argument detection, we use the same size of word embedding, while the size of LSTM layer is 150, and the size of key argument embedding is 50. Word embeddings are pre-trained using skip-gram word2vec (Mikolov et al., 2013) on English Wikipedia pages and fine tuned during training. To mitigate overfitting, we apply a dropout rate of 0.5 on both the input and output layers.

4.2 Dataset Evaluation

To investigate the possibility of automatically constructing training data for event extraction, we evaluate five datasets that utilize different hypotheses to collect positive sentences from Wikipedia pages. We randomly select 100 sentences in each dataset, and annotators are asked to determine whether a sentence implies a given event.

Hypothesis	H1	H2	H2+H4	H3	H3+H4
Instances	0.3M	3.6M	3.6M	1.3M	1.3M
Dataset	203	108K	12K	9241	7180
Event type	9	24	24	24	24
Correct (%)	98	22	37	81	89

Table 3: Statistic of the datasets built with different hypotheses. *Instances* denotes the number of CVT instances that can be used for each hypothesis. *Dataset* is the number of sentences found. *Event type* indicates the number of different CVT types in each dataset. *Correct* is the percentage of sentences mentioning the given events explicitly.

As shown in Table 3, it is not surprising that the most strict hypothesis, *H1*, guarantees the quality of the generated data, while we can merely obtain 203 sentences covering 9 types of events,

which is insufficient for further applications. *H2* relaxes *H1* by allowing the absence of non-key arguments, which expands the resulting dataset, but introduces more noise into the dataset. This side effect indicates that *H2* is inappropriate to be used as a soft constraint. Compared with *H2*, the significant improvement in the quality of sentences collected by *H3* proves that time-related properties within CVT schemas are critical to imply an event occurrence. Among all hypotheses, data obtained by a combination of *H3* and *H4* achieves the highest precision, while still accounting for 7,180 sentences, showing that it is feasible to automatically collect quality training data for event extraction without either human-designed event schemas or extra human annotations.

4.3 Baselines

We compare our proposed models with three baseline extraction systems, including traditional feature-based methods and neural network models. All baselines are trained following the two-step pipeline, i.e., event detection and argument detection. For neural network method, we train a simple LSTM model that takes word embeddings as input, and outputs the label with the maximum probability among all possible labels. For feature-based methods, we apply Conditional Random Field (Lafferty et al., 2001) and Maximum Entropy (Berger et al., 1996) to explore a variety of elaborate features, such as lexical, syntactic and entity-related features, according to the state-of-art feature-based ACE event extraction system (Li et al., 2013). Note that during argument detection stage, we add the label of each word output by event detection as a supplementary feature. We use Stanford CoreNLP (Manning et al., 2014) for feature extraction, and utilize the CRF++ toolkit (Kudo, 2005) and Le Zhang’s MaxEnt toolkit² to train the CRF and Max Entropy classifiers, respectively.

4.4 Automatic Evaluation

As shown in Table 4, traditional feature-based models perform worst in both event detection and argument detection. One of the main reasons is the absence of explicit event trigger annotations in our dataset, which makes it impossible to include trigger-related features, e.g., trigger-related dependency features and positions of triggers. Al-

²<https://github.com/lzhang10/maxent>

though traditional models can achieve higher precisions, they only extract a limited number of events, resulting in low recalls. Neural-network methods perform much better than feature-based models, since they can make better use of word semantic features, especially, LSTM can capture longer range dependencies and richer contextual information, instead of neighboring word features. And the CRF component brings an averagely 4% improvement in all metrics, and by adding the ILP-based post inference module, our full model, LSTM-CRF-ILP_{multi}, achieves the best performance among all models.

Multi-word Argument Detection Committing to the multi-word argument issue, we treat each subtask as a sequence labeling problem. Evaluated on multi-word arguments, the F1 scores of LSTM-CRF, LSTM-CRF-ILP₁ and LSTM-CRF-ILP_{multi} in argument detection are 71.3%, 80.5%, and 81.0%, respectively.

Effect of CRF Layer Every model which has a CRF layer over its LSTM output layer is superior to the one with a simple LSTM layer. Compared with LSTM model, LSTM-CRF achieves higher precisions and recalls in all subtasks by significantly reducing the invalid labeling sequences (e.g., I-arg appears right after O). During prediction, instead of tagging each token independently, LSTM-CRF takes into account the constraints between neighbor labels, and increases the cooccurrences of key arguments with regard to the same event type in some way.

Effect of Post Inference As shown in Table 4, post inference based on ILP considerably improve the overall system performance, especially in event classification. With the help of constraint C4, some dubious key arguments can be inferred through other key arguments from their contexts. Compared with LSTM-CRF, LSTM-CRF-ILP₁ produces a gain of 7.4 in event classification, 1.8 in event detection, and 4.6 in argument detection, with respect to the F1.

Multi-type Event Extraction We further investigate the effect of LSTM-CRF-ILP_{multi}, which is the only model that can deal with the multi-type event mention issue. As we can see from Table 4, the proposed strategy in LSTM-CRF-ILP_{multi} helps detect more event mentions, contributing to the increase of recalls, and F1 scores

with a little drop of precisions. Evaluated on the sentences containing multi-type event mentions, the F1 scores of LSTM-CRF-ILP_{multi} in event classification, argument detection and event detection are 70.7%, 26.9% and 58.4%, respectively.

4.5 Manual Evaluation

We randomly sample 150 unlabeled sentences from test data set. Annotators are asked to annotate the events and arguments to each sentence following two steps. First, determine whether a given sentence is positive or negative, and assign event types to positive sentences. Next, label all related arguments and their roles according to the types of events in the positive sentences. Each sentence is independently annotated by two annotators, and the inter-annotator agreement is 87% for event types and 79% for arguments.

Table 5 presents the average F1 score of manual evaluations. We can draw similar conclusions about the comparison of performances between different models as automatic evaluation. We demonstrate that LSTM-CRF-ILP_{multi} is the most effective model in event extraction as it achieves the highest F1 score in both manual and automatic evaluation.

S5: That night, in an apparent bid to kill Amos, the car instead runs over the sheriff, leaving Chief Deputy Wade Parent (played by James Brolin) in charge.			
Event Type	film.performance (Wrong labeled in data generation)		
Arguments	actor	character	film
	James Brolin	Wade Parent	the car
S6: Nicholas Hammond (born May 15, 1950) is an American actor and writer who is perhaps best known for his roles as Friedrich von Trapp in the film The Sound of Music, and as Peter Parker/Spider-Man on the CBS television series The Amazing Spider-Man.			
Event Type	film.performance		
Arguments	actor	character	film
	Nicholas Hammond	Friedrich von Trapp	The Sound of Music
Event Type	tv.regular_tv_appearance (Missing in generated data)		
Arguments	actor	character	series
	Nicholas Hammond	Peter Parker/Spider-Man	The Amazing Spider-Man

Figure 3: Example outputs of LSTM-CRF-ILP_{multi}.

Moreover, manual evaluation helps us to gain a deep insight of our data and models. We further conduct automatic evaluation on the manually annotated dataset and list the top 5 event types whose F1 scores of LSTM-CRF-ILP_{multi} differ greatly from automatic evaluation in Table 6.

Most of the performance differences are caused by data generation. Figure 3 examples two types of errors in data generation. Some automatically labeled sentences do not imply any event while still matching all key properties of certain instances. Take S5 as an example. Although the phrase *the car* matches a film name, it does not in-

Model	Event Classification			Argument Detection			Event Detection		
	P	R	F	P	R	F	P	R	F
CRF	96.8	9.93	18.0	64.8	6.54	11.9	29.8	3.06	5.55
MaxEnt	97.9	11.4	20.3	64.5	7.28	13.1	29.3	3.40	6.08
LSTM	97.2	62.4	75.1	77.1	53.9	63.5	51.0	32.8	39.9
LSTM-CRF	97.3	67.2	79.5	78.0	60.2	68.0	54.4	37.6	44.4
LSTM-CRF-ILP ₁	93.4	81.4	86.9	74.1	71.1	72.6	49.6	43.3	46.2
LSTM-CRF-ILP _{multi}	93.2	81.9	87.2	74.0	71.5	72.7	49.5	43.5	46.3

Table 4: Overall system performance of automatic evaluations. (%)

Model	EC	AD	ED
CRF	21.2	13.3	5.30
MaxEnt	17.7	11.7	5.44
LSTM	80.2	65.1	42.2
LSTM-CRF	81.6	68.6	44.1
LSTM-CRF-ILP ₁	85.4	70.2	44.2
LSTM-CRF-ILP _{multi}	85.5	70.4	44.6

Table 5: Average of F1 scores of system performance of manual evaluations by two annotators. EC, AD, ED denote the event classification, argument detection and event detection, respectively.

dicating this film, and there is no explicit evidence expressing that an actor starring in a film. This is a bottleneck of our data generation strategy. During manual evaluation, we find 16 negative sentences which are mistakenly labeled due to this reason. Unfortunately, our model fails to rectify 10 of them.

Remarkably, our LSTM-CRF-ILP_{multi} model can help find more CVT instances that are not referenced in Freebase. There are two events mentioned in S6, while the arguments of the second event do not match any CVT instances in Freebase, leading to a missing event in data generation. This phenomenon suggests that learning from distant supervision provided by Freebase, our model can help complete and update properties of Freebase instances in return.

Event type	P	R	F
olympics.medal_honor	↓ 25.0%	↓ 5.0%	↓ 13.8%
film.performance	↓ 21.4%	↑ 3.1%	↓ 10.3%
business.acquisition	→	↓ 7.1%	↓ 5.4%
tv.appearance	↓ 9.5%	↑ 3.0%	↓ 3.1%
film.release	↓ 7.7%	↑ 5.6%	↓ 0.55%

Table 6: Top 5 event types whose performances on event classification differ most from automatic evaluation. The evaluated model is LSTM-CRF-ILP_{multi}

5 Related Work

Most event extraction works are within the tasks defined by several evaluation frameworks (e.g., MUC (Grishman and Sundheim, 1996), ACE (Doddington et al., 2004), ERE (Song et al., 2015) and TAC-KBP (Mitamura et al., 2015)), all of which can be considered as a template-filling-based extraction task. These frameworks focus on limited number of event types, which are designed and annotated by human experts and hard to generalize to other domains. Furthermore, existing extraction systems, which usually adopt a supervised learning paradigm, have to rely on those high-quality training data within those frameworks, thus hard to move to more domains in practice, regardless of feature-based (Gupta and Ji, 2009; Hong et al., 2011; Li et al., 2013) or neural-network-based methods (Chen et al., 2015; Nguyen et al., 2016).

Besides the works focusing on small human-labeled corpus, Huang et al. (2016) propose a novel Liberal Event Extraction paradigm which automatically discovers event schemas and extract events simultaneously from any unlabeled corpus. In contrast, we propose to exploit existing structured knowledge bases, e.g., Freebase, to automatically discover types of events as well as their corresponding argument settings, without expert annotation, and further automatically construct training data, with the essence of distant supervision (Mintz et al., 2009).

Distant supervision (DS) has been widely used in binary relation extraction, where the key assumption is that sentences containing both the subject and object of a $\langle \text{subj}, \text{rel}, \text{obj} \rangle$ triple can be seen as its support, and further used to train a classifier to identify the relation rel . However, this assumption does not fit to our event extraction scenario, where an event usually involves several arguments and it is hard to collect enough training sentences with all arguments appearing in, as indicated by the low coverage of **H1**. We therefore

investigate different hypotheses for event extraction within the DS paradigm and propose to utilize time and syntactic clues to refine the DS assumption for better data quality. We further relieve the reliance on event trigger annotations by previous event extractors, and define a novel event extraction paradigm with key arguments to characterize an event type.

6 Conclusions and Future Work

In this paper, we propose a new event extraction paradigm without expert-designed event templates by leveraging structured knowledge bases to automatically acquire event schema and corresponding training data. We propose an LSTM-CRF model with ILP-based post inference to extract events without explicit trigger annotations. Experimental results on both manual and automatic evaluations show that it is possible to learn to extract KB-style events on automatically constructed training data. Furthermore, our model can extract information not covered by Freebase which indicates the possibility to extend this work to knowledge base population.

References

- David Ahn. 2006. The stages of event extraction. In *Proceedings of the Workshop on Annotating and Reasoning about Time and Events*. Association for Computational Linguistics, pages 1–8.
- Adam L Berger, Vincent J Della Pietra, and Stephen A Della Pietra. 1996. A maximum entropy approach to natural language processing. *Computational linguistics* 22(1):39–71.
- Kurt Bollacker, Colin Evans, Praveen Paritosh, Tim Sturge, and Jamie Taylor. 2008. Freebase: a collaboratively created graph database for structuring human knowledge. In *SIGMOD 2008*. ACM, pages 1247–1250.
- Yubo Chen, Liheng Xu, Kang Liu, Daojian Zeng, and Jun Zhao. 2015. Event extraction via dynamic multi-pooling convolutional neural networks. In *ACL 2015*. pages 167–176.
- Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. 2011. Natural language processing (almost) from scratch. *Journal of Machine Learning Research* 12(Aug):2493–2537.
- George R Doddington, Alexis Mitchell, Mark A Przybocki, Lance A Ramshaw, Stephanie Strassel, and Ralph M Weischedel. 2004. The automatic content extraction (ace) program-tasks, data, and evaluation. In *LREC 2004*. volume 2, page 1.
- Ralph Grishman and Beth Sundheim. 1996. Message understanding conference-6: A brief history. In *COLING 1996*. volume 96, pages 466–471.
- Prashant Gupta and Heng Ji. 2009. Predicting unknown time arguments based on cross-event propagation. In *ACL-IJCNLP 2009*. Association for Computational Linguistics, pages 369–372.
- Inc. Gurobi Optimization. 2016. *Gurobi optimizer reference manual*. <http://www.gurobi.com>.
- Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation* 9(8):1735–1780.
- Yu Hong, Jianfeng Zhang, Bin Ma, Jianmin Yao, Guodong Zhou, and Qiaoming Zhu. 2011. Using cross-entity inference to improve event extraction. In *ACL 2011*. Association for Computational Linguistics, pages 1127–1136.
- Lifu Huang, T Cassidy, X Feng, H Ji, CR Voss, J Han, and A Sil. 2016. Liberal event extraction and event schema induction. In *ACL 2016*.
- Zhiheng Huang, Wei Xu, and Kai Yu. 2015. Bidirectional lstm-crf models for sequence tagging. *arXiv preprint arXiv:1508.01991*.
- Taku Kudo. 2005. Crf++: Yet another crf toolkit. *Software available at <http://crfpp.sourceforge.net>*.
- John Lafferty, Andrew McCallum, and Fernando Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In *ICML 2001*. volume 1, pages 282–289.
- Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. 2016. Neural architectures for named entity recognition. *arXiv preprint arXiv:1603.01360*.
- Qi Li, Heng Ji, and Liang Huang. 2013. Joint event extraction via structured prediction with global features. In *ACL 2013*. pages 73–82.
- Christopher D Manning, Mihai Surdeanu, John Bauer, Jenny Rose Finkel, Steven Bethard, and David McClosky. 2014. The stanford corenlp natural language processing toolkit. In *ACL 2014*. pages 55–60.
- Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In *NIPS 2013*. pages 3111–3119.
- Mike Mintz, Steven Bills, Rion Snow, and Dan Jurafsky. 2009. Distant supervision for relation extraction without labeled data. In *ACL-IJCNLP 2009*. Association for Computational Linguistics, pages 1003–1011.

- Teruko Mitamura, Yukari Yamakawa, Susan Holm, Zhiyi Song, Ann Bies, Seth Kulick, and Stephanie Strassel. 2015. Event nugget annotation: Processes and issues. In *Proc. of the Workshop on EVENTS at the NAACL-HLT*. pages 66–76.
- Thien Huu Nguyen, Kyunghyun Cho, and Ralph Grishman. 2016. Joint event extraction via recurrent neural networks. In *NAACL-HLT 2016*. pages 300–309.
- Lawrence R Rabiner. 1989. A tutorial on hidden markov models and selected applications in speech recognition. *Proc. of the IEEE* 77(2):257–286.
- Zhiyi Song, Ann Bies, Stephanie Strassel, Tom Riese, Justin Mott, Joe Ellis, Jonathan Wright, Seth Kulick, Neville Ryant, and Xiaoyi Ma. 2015. From light to rich ere: annotation of entities, relations, and events. In *Proc. of the Workshop on EVENTS at the NAACL-HLT*. pages 89–98.
- Daojian Zeng, Kang Liu, Yubo Chen, and Jun Zhao. 2015. Distant supervision for relation extraction via piecewise convolutional neural networks. In *EMNLP 2015*. pages 1753–1762.

950
951
952
953
954
955
956
957
958
959
960
961
962
963
964
965
966
967
968
969
970
971
972
973
974
975
976
977
978
979
980
981
982
983
984
985
986
987
988
989
990
991
992
993
994
995
996
997
998
999