Scale Up Event Extraction Learning via Automatic Training Data Generation

Abstract

Event extraction, which detects the occurrence of events with specific types and extract arguments (i.e. typed participants or attributes) that are associated with an event, is an important technique that underpins many natural language processing applications. Supervised learning is an effective method for building event extraction systems. The effectiveness of the learning is bound by the number and the quality of the training instances. Currently, training data must be manually generated through a combination of expert domain knowledge and trial and error. However, due to drastic efforts involved in annotating text, the resulted datasets are usually small, which severally affects the quality of the learned model, making it hard to generalize.

Our work develops an automatic approach for generating training data for event extraction. Our technique allows us, for the first time, to construct training data with millions of instances instead of just thousands, and it does this at a much lower cost than a manual approach. We achieve this remarkable result by employing distant supervision to automatically create event annotations from unlabelled text using existing structured knowledge bases or tables. We then develop a neural network model with post inference to transfer the knowledge extracted from structured knowledge bases to automatically annotate event types for sentences in another corpus. We evaluate our approach by using the knowledge extracted from Freebase to label texts from Wikipedia articles. Experimental results show that our approach can generate a large number of high-quality training instances. We show that this large volume of training data not only leads to a better event extractor, but also allows us to detect multi-typed events – a feature that none of the existing event extractors can offer.

Introduction

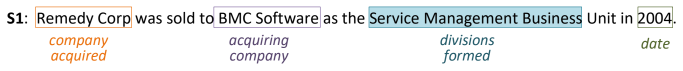
Event extraction, as represented by the Automatic Content Extraction (ACE) task, is a key enabling technique for many natural language processing (NLP) applications. Current event extractors are typically built through applying supervised learning to learn over labelled datasets. This means that the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

Constructing high-quality training data for event extraction is, however, an expensive and error-prone process (Aguilar et al. 2014; Song et al. 2015). This requires the involvement of linguists to design annotation templates and rules for a set of predefined event types, and the employment of annotators to manually label large datasets. Because of the drastic efforts required for manual labeling, existing training datasets are usually small, covering only a small set of event types. As a result, current event extraction systems built upon of human-annotated datasets have two major drawbacks. They can only handle (1) single-token triggers[1] and (2 scenarios where each event is merely associated with a single type. In our real-world, however, there are countless examples where trigger annotations are unavailable (FIX:ZW: This has nothing to do with single-token triggers?? or or one event is associated with multiple types. To make event extractors more practical, we need to find ways to support these scenarios.

This paper presents a novel approach for automatic training data generation, specifically targeting event extraction. Our approach advances prior work in two aspects: (1) it does not rely on expert-annotated texts (hence it reduces expert involvement) and (2) supports multi-typed event extraction. The former is achieved by automatically collecting training data through indirect supervision from structured knowledge bases or knowledge tables to automatically label event structures from plain text. The later is achieved by proposing a novel neural network model with post inference to detect multi-typed events without relying on explicit trigger annotations.

Our first insight is that structured knowledge bases (`KB`) typically organize complex structured information in tables; and such knowledge tables often share similar structures with ACE event definitions, i.e., a particular entry of such tables usually implies the occurrence of certain events. Recent studies (Mintz et al. 2009; Zeng et al. 2015) have demonstrated the effectiveness of `KB` as distant supervision (`DS`) for binary relation extraction. In this paper, we aim to extend `DS` to extract events of n-ary relations and multiple arguments (rather than just binary relation). One of the hurdles for doing this is the lacking of explicit trigger information in existing `KB`. Our solution is to use a group of **key arguments**

[1]In the event extraction task, a trigger is the word or phrase that most clearly expresses the occurrence of an event. For example, *ex* in *ex-husband* may trigger a *divorce* event.


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

(a) An example sentence from Wiki text

id	company_acquired	acquiring_company	date	divisions_formed
m.07bh4j7	Remedy Corp	BMC Software	2004	Service Management Business Unit

(b) Entry of `business.acquisition` in Freebase

Figure 1: The event type of the sentence shown in (a) can be automatically inferred using the structured table given by Freebase in (b).

rather than explicit triggers to capture a particular event. For example, we can use *spouse* as the key argument to identify *marriage* events.

Our second innovation is that unlike previous studies which focus on tasks defined by the ACE evaluation framework (Ahn 2006; Li, Ji, and Huang 2013; Chen et al. 2015; Nguyen, Cho, and Grishman 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, Xu, and Yu 2015; Lample et al. 2016), we utilize BLSTM-CRF models to label key arguments and non-key arguments in 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-typed events.

We evaluate our approach by applying it to automatically collect training data with both Freebase and Wikipedia tables. Our proposed event extractor is used to identify typed event mentions with typed roles. Our experimental results on both automatic and manual evaluations show that our approach can effectively extract a rich types of events without expert-annotated training data.

Motivation

As a motivation example, consider a sentence from the Wiki text dataset, shown in Figure 1 (a). This sentence describes a business acquisition event. It consists of four **arguments**, *company acquired* (Remedy Corp), *acquiring company* (*BMC Software*), *formed division* (Service Management Business Unit) and *date* (2004). To learn an event extractor, existing supervision-based approaches all require manually identifying the event type by examining the event trigger and arguments from each individual training instance; for this examples, the trigger "*sold*" and the acquired/acquring company arguments suggest that there is a business acquisition event.

The problem of manually labeling is that it takes a lot of time to construct a training dataset and in many cases the resulted dataset is too small to learn an effective event extractor. For example, it took FIX:man-months to label the FIX:xxx instances in the ACE dataset. To make the learning process fast and cheap, we must take humans out of the loop of data labeling. For this particular motivation sentence, we discover that the structural knowledge of Freebase (`FB`) (Bollacker et al. 2008) already provides sufficient information to allow us to automatically label the event type. Figure 1 (b) shows a Compound Value Type (`CVT`) entry of `FB`. A `CVT` organizes complex structured data with multiple *properties* as a table[2]. After examining this `CVT` schema, one can find that this schema implies there could be a *business.acquisition* event if the text contains properties (and arguments) like, `company_acquired` (Remedy Corp), `acquiring_company` (BMC Software) and date (2004) – all these are the identical arguments if they were extracted manually. If we can utilize such `CVT` information, we can then label the sentence shown in Figure 1 (a) without needing to identify the trigger (which is usually done by manual annotation to ensure the quality of the generated training dataset).

A natural question to ask is that "How useful are `CVTs`?". Later in this paper, we show that structured knowledge base, tables or lists that are used to sum up certain activities can be a useful source of supervision data generation for event extraction. For example, using just 24 `CVTs`, we are able to automatically generate FIX:2.8 billions FIX:is this true? instances from a subset of the Wikipedia articles (FIX:Section **??**).

This work develops a simple, yet effective technique to automatically generate training data by exploiting the prior `CVT` knowledge from various datasets, including `FB` and Wikiedia pages. Our work shows that it is possible to scale up training data generation for event extraction with little human involvement. In the next section, we describe g our approach of automatic traning data generation in more details.

Training Data Generation

Our approach exploits structural information like `FB CVT` tables to automatically annotate event mentions[3] in order to generate training data to learn an event extractor. Such an approach is known as Distant Supervision (Mintz et al. 2009). Essentially, we use the knowledge extracted from a known knowledge base to *distantly supervise* the process of training data generation using another dataset.

We use the arguments of a `CVT` table entry to infer what event a sentence is likely to express. A `CVT` table entry can have multiple arguments but not all of the arguments are useful in annotation. For example, the `divisions_formed` argument in Figure 1 (b) is not as important as the other three arguments when determining if a sentence expresses a `business.acquisition` event. Therefore, our first step is to identify the key arguments from a `CVT` table en-

[2]Therefore, we also use the term "argument" to refer to a `CVT` property for the rest of the paper.

[3]An event mention is a phrase or sentence within which an event is described, including its type and arguments.

try. A **key argument** is an argument that plays an important role in one event, which helps to distinguish with other events. If a sentence contains all key arguments of an entry in an event table (e.g. a CVT table), it is likely to express the event expressed by the table entry. If a sentence is labelled as an event mention of a CVT event, we also record the words or phrases that match the entrys properties as the involved arguments, with the roles specified by their corresponding property names. For instance, sentence S1 shown in Figure 1 (a) is a mention of business.acquisition type, its involved arguments are "Remedy Corp", "BMC Software", and "2004", and the roles of the three arguments are company_acquired, acquiring_company and date respectively.

In addition to use the raw information given by a CVT entry, we also use alias information (such as Wikipedia redirect) to match two arguments that have different literal names but refer to the same entity (e.g. Microsoft and MS).

Determining Key Arguments

We use the following formula to calculate the importance value, $I_{cvt,arg}$, of an argument *arg* (e.g., date) to its event type *cvt* (e.g., business.acquisition):

$$I_{cvt,arg} = log\frac{count(cvt, arg)}{count(cvt) \times count(arg)} \qquad (1)$$

where $count(cvt)$ is the number of instances of type cvt within a CVT table, $count(arg)$ is the number of times arg appearing in all CVT types within a CVT table, and $count(cvt, arg)$ is the number of cvt instances that contain arg across all CVT tables. FIX:explain how do you come up with this formula.

Our strategy for selecting key arguments of a given event type is described as follows:

P1 For a CVT table with n arguments, we first calculate the important value of each argument. Next, we sort the arguments according to their importance values in descending order, so that arguments with the highest importance values will appear on the top of the list. We then consider the top half $\lceil n/2 \rceil$ (rounding up) arguments on the sorted list as key arguments.

P2 We find that time-related arguments are useful in determining the event type, so we always include time-related arguments (such as date) in the key argument set.

P3 We also remove sentences from the generated dataset in which the dependency distances between any two key arguments are greater than 2.

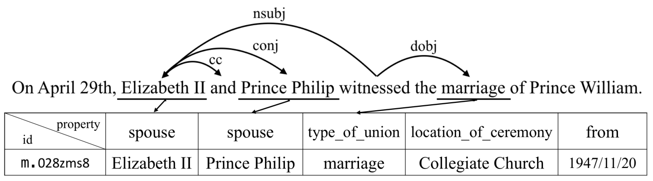
Using this strategy, the first three argument of the CVT entry are considered to be key arguments for event typ business.acquisition. FIX:Here we should give the importance values for all arguments in S1.

Key Argument Selection Parameters

To determine how many arguments should be chosen (step P1 in our strategy), we have conducted a series of evaluations on the quantity and quality of the datasets using different policies. We found that choosing the top half arguments

Table 1: CVT entry of business.acquisition in FB.

id	company_acquired	acquiring_company	date	divisions_formed
m.05nb3y7	aQuantive	Microsoft	2007	N/A


nsubj
conj
cc
dobj
On April 29th, Elizabeth II and Prince Philip witnessed the marriage of Prince William.

property / id	spouse	spouse	type_of_union	location_of_ceremony	from
m.028zms8	Elizabeth II	Prince Philip	marriage	Collegiate Church	1947/11/20

Figure 2: The dependency tree of S3, which partially matches a CVT entry of *people.marriage* from FB.

(sorted by their importance scores) gives the best accuracy for event labeling.

We use three example sentences from the Wiki text dataset to explain steps P2 and P3 in our key argument selection strategy described above. The three sentences are:

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.

We regard a sentence as *positive* when it mentions the occurrence of an event, or *negative* otherwise. For example, S1 in Figure 1 (a) and S2 (with its arguments in italics and underlined) are positive examples, while S3 and S4 are negative. We wish to minimize the number of negative sentences to be labelled as positive (i.e., false positive) and to maximize the number of true positive sentences to be labelled as their correct events.

Although time-related arguments are often missing in the currently imperfect KBs, they are crucial to identify the actual occurrence of an event. As an example, suppose we want to use the CVT entry shown in Table 1 to determine if sentence S3 is a business.acquistion event. This sentence contains *Microsoft* as acquiring_company and *aQuantive* as company_acquired. If we ignore the time-related argument (i.e., date in this case), this setence could be mistakenly considered as a positive sample for event business.acquisition. Therefore, we always consider time-related arguments as key arguments (step P2) if these are given on the CVT entry.

Finally, step P3 is based on our intuitions that two arguments involved in the same event mention are likely to be closer within the syntactic structure. As an example, consider S4. The dependency parse tree of this sentence is given in Figure 2. As can be seen from the diagram, although both *Prince Philip* and *marriage* can be matched as key arguments in a people.marriage entry, but with a distance of 3 (i.e., far from each other under our criterion) on the dependency parse tree, thus S4 will be labelled as negative.

Limitations

Our approach relies on structured tables or lists to automatically label text. The table can be obtained from an existing knowledge base or hand-crafted by developers. We want to highlight that providing a table incurs much less overhead than manually tagging each training sentence, as a single table entry can be automatically applied to many sentences. Like all supervision-based event extractors, our approach does not support detecting new event types that are not seen in the training data. However, our approach does offer an easy way to extend the structured table to support new types, i.e., by adding new entries to the table.

Our current implementation does not disambiguate pronouns. There are co-reference methodsFIX: () that can be used to find out which word a pronoun refers to. These works are therefore complementary to our approach. Integrating our work with co-reference methods is our future work.

Event Detection and Argument Extraction

Once we have automatically labeled a large number of training instances, we can then use the training data to learn a model to detect the occurrence of events and the associated arguments from *unseen* text. In this section, we present a novel neural network based model which does not rely on explicit trigger information (and hence it eliminates the need for manually labeling triggers to generate training data).

Previous event extraction systems mainly rely on explicit trigger identification to detect the occurrence of an event, which is then used to decide its event type and label its arguments. Because identifying triggers is widely considered as a difficult task, human involvement is requiredFIX: (). 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 the following two steps:

Event detection 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 mention of this specified type.

Argument detection To identify other non-key arguments for each event in the sentence.

Take S1 as an example, in event detection, *Remedy Corp*, *BMC Software*, and *2004* will be identified as `company_acquired`, `acquiring_company`, and `date`, respectively, indicating that S1 may mention a `business.acquisition` event. During argument detection, *Service Management Business Unit* will be identified as `divisions_formed`, which, together with the detected key arguments, form a full mention for a `business.acquisition` event.

Event Detection

Because 68% of arguments in our dataset consist of more than one word, we formulate each subtask in a sequence labeling paradigm rather than word-level classifications. Each word in the given sentence is tagged using the standard begin-inside-outside (`BIO`) schemeFIX:(), 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.

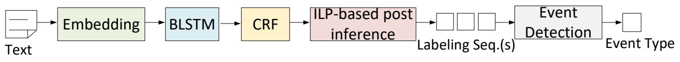


Figure 3: Our event detection model.

Remedy	Corp	was	sold	to	BMC	
`B-com._acq.`	`I-comp._acq.`	`O`	`O`	`O`	`B-acq._comp.`	
Software	as	the	Service	Management	Business	Unit
`I-acq._comp.`	`O`	`O`	`O`	`O`	`O`	`O`
in	2004	.				
`O`	`B-date`					

Figure 4: The labeling sequence for sentence S1 shown in Figure 1 (a). Each token of the sentence is tagged using the `BIO` scheme.

Figure 3 provides an overview of our event detection model. The model has two key components, a Bidirectional LSTM (BLSTM) network with a conditional random field (CRF) layer and an Integer Linear Programming (ILP) based post inference. The input to our model is the raw text. The embedding layer maps the input text to a vector of real values, where each token of the text is given an integer value. The BLSTM and CRF layers find the optimal label sequence which will then be post-processed by an ILP solver. As an output, the labeling sequence tags each word with its role using the `BIO` scheme. Figure 4 illustrates the labeling sequence for sentence S1 given in Figure 1 (a). Using the labeling sequence, an event detector can then simply map the sentence to a specific event type, using the detected key arguments and their properties. It is to note that our model may generate multiple labeling sequences for multi-typed events, one sequence for an event type.

BLSTM The Long Short-Term Memory (LSTM) network (Hochreiter and Schmidhuber 1997) is a natural fit for sequence labeling, which maintains a memory based on historical contextual information. Formally, given a sentence $\boldsymbol{w} = \{w_1, w_2, \ldots, w_n\}$ 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 t, a forward LSTM layer takes $\mathbf{x}_t$ as input and computes the output vector $\overrightarrow{\mathbf{h}}_t$ of the past context, while a backward LSTM layer reads the same sentence in reverse and outputs $\overleftarrow{\mathbf{h}}_t$ given the future context. We concatenate these two vectors to form the output vector of a BLSTM, which 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 the BLSTM output. However, this greedy strategy ignores the dependencies between labels, thus cannot guarantee the best sequence. Therefore, we introduce a CRF layer over the BLSTM output, which is shown to be effective in various sequence labeling tasks (Collobert et al. 2011; Huang, Xu, and Yu 2015).

We consider $\mathbf{P}$ to be a matrix of confidence scores output by BLSTM, 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 $\boldsymbol{w}$ along with a path of labels $\boldsymbol{y} = \{y_1, y_2, \ldots, y_n\}$ is measured by the sum of BLSTM outputs and transition scores:

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

During test, given a sentence $\boldsymbol{w}$, 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 Essentially, event detection is a structure prediction problem. However, the output sequences of BLSTM-CRF do not necessarily satisfy the structural constraints. For instance, regardless of how many key arguments are correctly identified by BLSTM-CRF, if there is one key argument missing, this detection should be considered as failed.

We thus propose to apply ILP to further globally optimize the BLSTM-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 $\boldsymbol{w}$ 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:

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

where we consider the following four constraints:

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

$$\sum\nolimits_{l,l'} v_{i,l,l'} = 1 \qquad (3)$$

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.:

$$v_{i,l,l'} = \sum\nolimits_{l^*} v_{i+1,l',l^*} \qquad (4)$$

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

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

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:

$$\sum\nolimits_{i,l'} v_{i,\texttt{B-arg}_1,l'} \leq n * \sum\nolimits_{j,l^*} v_{j,\texttt{B-arg}_2,l^*} \qquad (6)$$

where n is the length of the sentence.

Multi-typed Events There are scenarios where one event is associated with multiple types, but all current event extractors only map a sentence to one event. FIX:zw: we need an example here. One of the advantages of our approach is that it can be easily extended to support multi-typed events. To do so, we allow our ILP solver to output multiple optimal sequences. Specifically, after our model outputs the best sequence $\boldsymbol{s}^t$ at time t, we remove the previously best solutions $\{\boldsymbol{s}^1, \ldots, \boldsymbol{s}^t\}$ from the solution space, and re-run our solver to obtain the next optimal sequences $\boldsymbol{s}^{t+1}$. We repeat the optimization procedure until the difference between the scores of $\boldsymbol{s}^1$ and $\boldsymbol{s}^T$ is greater than a threshold λ, and consider all solutions $\{\boldsymbol{s}^1, \boldsymbol{s}^2, \ldots, \boldsymbol{s}^{T-1}\}$ as the optimal label sequences. We use Gurobi (Gurobi Optimization 2016) as our ILP solver and set $\lambda = 0.05 \times n$, which averagely produce 1.07 optimal sequences for each sentence.

Argument Extraction

After event detection, a sentence will be classified into a or more than one event types, and labeled with its corresponding key arguments. Next, we will identify the remaining non-key arguments in the sentence.

We adopt the same BLSTM-CRF architecture (that is used for event detection) 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 BLSTM-CRF. Note that we do not need post inference here.

Experiments

Our experiments are designed to answer the following questions, 1) whether it is possible to automatically collect training data for event extraction, 2) whether extractors trained on such data can detect events of interest and identify their corresponding arguments, and 3) whether our solution can work with other knowledge resources for more types of event.

Dataset Evaluation

Let us first evaluate **different data-collecting strategies discussed in Section XXXX**: (1) *ALL*: all arguments are regarded as key arguments; (2) *IMP*: we select the top half arguments with highest importance values as key arguments; (3) *IMP&TIME* means adding a time-related argument with the highest importance value to *IMP*; (4) *DIS*: we eliminate sentences where the dependency distances between any two key arguments are greater than 2. We follow the above methods to collect datasets using Freebase and the English Wikipedia dump of 2016-11-20, randomly select 100 sentences from each dataset, and ask two annotators to decide whether each sentence implies a given type of event.

As shown in Table 2, it is not surprising that *T1*, as the most strict, guarantees the quality of the collected data, but only contributes 203 sentences covering 9 event types, which is far from sufficient for further applications. *T2* relaxes *T1* by allowing the absence of non-key arguments, which expands the resulting dataset, but introduces more noise. We can also see that the dependency constraint (DIS)

No.	Strategy	Sent.	Type	Post.
T1	*ALL*	203	9	98%
T2	*IMP*	318K	24	22%
T3	*IMP+DIS*	170K	24	37%
T4	*IMP&TIME*	112K	24	83%
T5	*IMP&TIME+DIS*	46K	24	91%

Table 2: Statistics of the datasets built with different strategies. *Sent.* is the number of sentences found. *Type* the number of different CVT types found. *Post.* is the percentage of sentences mentioning the given events explicitly.

improves the data quality (*T3*). Compared with *T2*, the significant quality improvement by *T4* proves that time-related arguments within CVT schemas are critical to imply an event occurrence. Among all strategies, the dataset by *T5* achieves the best quality, while still accounting for 46735 sentences with 50109 events, almost 8 times more than the ACE dataset, showing that it is feasible to automatically collect quality training data for event extraction without either human-designed event schemas or **extra** human annotations.

Our final dataset, **FBWiki**, using *T5*, contains 46735 positive sentences and 79536 negative ones[4] a random split of 101019 for training and 25252 for testing. Note that there are averagely 4.8 arguments per event, and in total, 5.5% instances labeled with more than two types of events.

On ACE : We also test our strategy on the ACE dataset. We first collect all annotated events, without triggers, as the knowledge base to compute the importance values for all arguments, and select the key arguments for each ACE event type accordingly. We follow *T5* to examine every sentence whether it can be selected as an annotated instance within the ACE event types. Eventually, we correctly find 3448 sentences as positive instances, covering 64.7% of the original ACE dataset. We find that the main reason for the missing 35.3% is that many arguments in the ACE dataset are pronouns, where our strategy is currently unable to treat a pronoun as an key argument. However, if a high-precision coreference resolution tool is available to preprocess the document, our solution would be able to automatically label more instances as training data. **ANYTHING NOVEL that traditional ACE does not have??? multple types? multiple events?**

Extraction Setup

Next, we evaluate our event extractor on the collected datasets, in terms of popular metrics in event extraction, i.e., precision (P), recall (R), and F-measure (F) for each subtask. These metrics are computed according to the following standards of correctness: For *event classification*, an event is correctly classified if its reference sentence contains **all key arguments** of this event type. For *key argument detection*, an event is correctly detected if its type and all its key arguments match a reference event within the same sentence. For *all argument detection*, an event is correctly extracted if its type and all its arguments match a reference event within the same sentence.

Training: All hyper-parameters are tuned on a development split in the training set. During 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 and fine tuned during training. We apply dropout (0.5) on both input and output layers.

Baselines: We compare our proposed model with three baselines. The first is a BLSTM model that takes word embeddings as input, and outputs the label for each word with the maximum probability. For feature-based methods, we apply Conditional Random Field (Lafferty, McCallum, and Pereira 2001) (with the CRF++ toolkit (Kudo 2005)) and Maximum Entropy (Berger, Pietra, and Pietra 1996) (Le Zhang's MaxEnt toolkit) 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, Ji, and Huang 2013).

All models are first required to predict each word with a label indicating whether **it is in an key argument, and add the resulting label of each word as a supplementary feature to predict whether it is in a non-key argument**.

Compare with Automatic Annotations

Firstly, we compare the model output against with the automatically obtained event annotations. As shown in Table 3, 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 position features. Although 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, especially in recall, since they can make better use of word semantic features. Specifically, BLSTM can capture longer dependencies and richer contextual information, instead of neighbouring word features only. And the CRF component brings an averagely 2% improvement in all metrics, and by adding the ILP-based post inference module, our full model, BLSTM-CRF-ILP$_{multi}$, achieves the best performance among all models.

The CRF Layer: It is not surprising that every model with a CRF layer over its BLSTM layer is superior to the one with a BLSTM layer only. Compared with vanilla BLSTM, BLSTM-CRF achieves higher precisions and recalls in all

[4]To train a better system, besides trivial negative samples that have no arguments, we then randomly sample 34837 negative instances that contain serveral but not all key arguments, and 21866 sentences whose key arguments violate the dependency constraint.

Model	Event Classification			Key Argument Detection			All Argument Detection		
	P	R	F	P	R	F	P	R	F
CRF	88.9	11.0	19.6	36.1	4.47	7.96	19.9	3.06	5.30
MaxEnt	**95.2**	12.4	21.9	41.6	5.40	9.56	22.5	3.40	5.91
BLSTM	89.8	63.0	74.1	**64.9**	45.5	53.5	42.9	27.7	33.7
BLSTM-CRF	86.4	67.4	75.7	63.6	49.6	55.8	**44.4**	31.0	36.5
BLSTM-CRF-ILP$_1$	84.4	74.1	78.9	62.3	53.8	57.3	42.7	33.8	37.7
BLSTM-CRF-ILP$_{multi}$	85.3	**79.9**	**82.5**	60.4	**55.3**	**57.7**	41.9	**34.6**	**37.9**

Table 3: System performance when compared with automatic annotations (%).

subtasks by significantly reducing the invalid labelling sequences (e.g., `I-arg` appears right after `O`). During prediction, instead of tagging each token independently, BLSTM-CRF takes into account the constraints between neighbouring labels, and potentially increases the co-occurrences of key arguments regarding the same event type.

The ILP Post Inference: As shown in Table 3, ILP-based post inference considerably improves the overall system performance, especially in *event type classification*. With the help of constraint **C4**, dubious key arguments can be correctly inferred through other key arguments from their context. Compared with BLSTM-CRF, BLSTM-CRF-ILP$_1$ produces an F1 gain of 3.2% in event classification, 1.5% in key argument detection, and 1.2% in all argument detection.

Multi-type Events: Among all methods, BLSTM-CRF-ILP$_{multi}$ is the only model that can deal with multi-type event mentions. The proposed strategy in BLSTM-CRF-ILP$_{multi}$ helps detect more event mentions for a sentence, contributing to the increase of recalls, and F1 scores with a little drop of precisions. BLSTM-CRF-ILP$_{multi}$ can correctly identify 132 sentences with multi-type events, with an accuracy of 95.6%, and for each involved event, our model maintains a high performance in identifying its corresponding arguments, achieving the F1 scores of 45.5%, and 29.1% for key argument detection and all argument detection, respectively.

Manual Evaluation

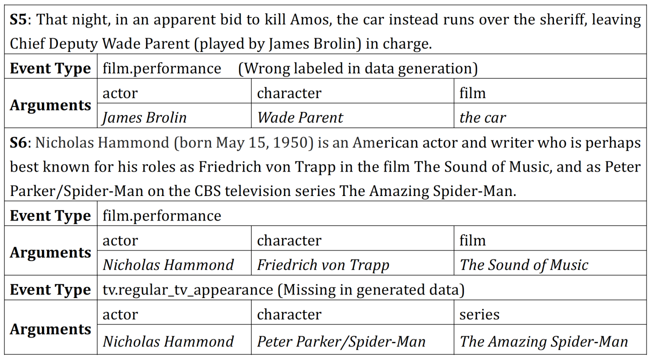
To provide a deep investigation about our dataset and models, we randomly sample 150 sentences from the test set. Two annotators are asked to annotate all arguments to each sentence following two steps. First, determine whether a given sentence is positive or negative, and assign **all existing** event types to positive ones. Next, label all related arguments and their roles according to the event types for all positive instances. Two annotators will independently annotate each sentence, and discuss to reach an agreement. The inter-annotator agreement is 87% for event types and 79% for arguments.

By comparing the automatic and manual annotations on the 150 sentences, we find that the main issue for the automatic annotation is that some automatically labeled sentences do not imply any event while still matching all key properties of certain CVT entries in Freebase. We find 16 such instances that are mistakenly labeled as positive. For example in Figure 5, although the phrase *the car* in S5 matches a film name, it does not indicate that film. This is mainly because that we currently do not have a strong entity linker to verify those entities, which we leave for future work. But, interestingly, during manual investigation, we find that BLSTM-CRF-ILP$_{multi}$ manages to detect 6 of them as negative.

Model	EC	KAD	AAD
BLSTM-CRF	75.4	54.7	35.5
BLSTM-CRF-ILP$_1$	77.2	56.1	35.7
BLSTM-CRF-ILP$_{multi}$	**80.7**	**56.4**	**36.3**

Table 4: The F1 scores of different systems on the manually annotated data. EC, KAD, AAD denote the event type classification, key argument detection and all key argument detection, respectively.

Table 4 summarizes the performances of different models on the manually annotated dataset, where we can observe similar trends with Table 3, that both CRF and ILP$_{multi}$ greatly improve the overall performance and BLSTM-CRF-ILP$_{multi}$ remains the most effective model.



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 5: Example outputs of BLSTM-CRF-ILP$_{multi}$.

Remarkably, our BLSTM-CRF-ILP$_{multi}$ model can find more CVT instances that are currently not referenced in Freebase. Our model detects two events in S6, while the arguments of the second event do not match any existing CVT instances in Freebase, which do not receive any credit during automatic evaluation, but should be populated into Freebase. This phenomenon suggests that by learning from distant supervision provided by Freebase, our model can be used to populate or update Freebase instances in return.

On BBC News: We further apply our event extractor, trained on the FBWiki, to 397 BBC News articles (from 2017/04/18 to 2017/05/18 in Politics, Business and TV sections), and manually examine the extraction results. We find that our model is able to identify 117 events, and 53 events, almost half of which are not covered in the currently used Freebase.

Tables as Indirect Supervision

To investigate the applicability of our approach to other structured knowledge/tables besides Freebase CVT tables, we automatically build a new dataset, TBWiki, with the supervision provided by Wikipedia tables, which characterize events about business acquisition, winning of the Olympics games, and winning prestigious awards in entertainment (Table 5).

Event type	Entr.	Sent.	EC	KAD	AAD
Acquisition	690	414	87.0	72.0	69.6
Olympics	2503	1460	77.2	64.5	38.6
Awards	3039	2217	95.0	82.8	58.6

Table 5: Statistics of the TBWiki dataset and the performance of our model on TBWiki. *Entr.* is the number of table entries. *Sent.* is number of positive instances.

We train our BLSTM-CRF-ILP$_{multi}$ on this dataset and evaluate it on 100 manually annotated sentences. We can see that without extra human annotations, our model can learn to extract events from the training data weakly supervised by Wikipedia tables. Given a specific event type, as long as we can acquire tables implying events of such type, it is possible to automatically collect training data from such tables, and learn to extract structured event representations of that type.

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, Ji, and Huang 2013) or neural-network-based methods (Chen et al. 2015; Nguyen, Cho, and Grishman 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 $<subj$, rel, $obj>$ 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 *T1*. 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.

Conclusions and Future Work

In this paper, we propose a novel event extraction paradigm without expert-designed event templates by leveraging structured knowledge bases or tables to automatically acquire event schema and corresponding training data. We propose a BLSTM-CRF model with ILP-based post inference to extract multi-typed event mentions without explicit trigger annotations. Experimental results on both manual and automatic evaluations show that it is possible to learn to identify both typed events and typed roles with indirect supervision from Freebase or Wikipedia tables. In the future, we will first further investigate how to better characterize key arguments for a certain event type, and extend our work to update a structured knowledge base according to news events.

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