Rapid Customization for Event Extraction

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Abstract

We present a system for rapidly customizing event extraction capability to find new event types and their arguments. The system allows a user to find, expand and filter event triggers for a new event type by exploring an unannotated corpus. The system will then automatically generate mention-level event annotation automatically, and train a Neural Network model for finding the corresponding event. Additionally, the system uses the ACE corpus to train an argument model for extracting Actor, Place, and Time arguments for any event types, including ones not seen in its training data. Experiments show that with less than 10 minutes of human effort per event type, the system achieves good performance for 67 novel event types. The code, documentation, and a demonstration video will be released as open source on github.com.

1 Introduction

Event extraction is the task of identifying events of interest with associated participating arguments in text. For instance, given the following sentence:

S1: 21 people were wounded in Tuesday's southern Philippines airport blast.

We want to recognize that there are two events (Injury and Attack), anchored or *triggered* by the words "wounded" and "blast" respectively. We also recognize that "21 people" and "airport" are the participating arguments of both events, taking the event argument roles affected-Actor and Place respectively. Event extraction is important for understanding complex scenarios, intelligence analysis, etc.

Current supervised event extraction systems usually assume a predefined event ontology and learn from a corpus of manually labeled examples that are specific to that ontology. For instance, the popular Automatic Content Extraction (ACE) (Doddington et al., 2004) corpus contains more than 500 documents manually annotated with examples for 33 event types such as Attack, Injury, Election, etc. To extend extraction capabilities to a new event type, one needs to manually annotate a large amount of training examples for that new event type. This is very labor intensive.

In this paper, we present a system that uses a minimally supervised approach for rapid extension of extraction capabilities to a large number of novel event types.

Briefly, we first manually provide a few triggers or keywords for each novel event type. We then automatically expand these initial triggers by leveraging WordNet (Miller, 1995) and word embeddings (Baroni et al., 2014). These expanded trigger words are then adjudicated, culminating in a final set of trigger words. Our system then automatically gathers event trigger training examples via distant supervision (Mintz et al., 2009; Craven and Kumlien, 1999) on an unannotated corpus. We summarize the contributions of this paper as follows:

- We present an approach to rapidly gather event trigger examples for *new* event types, with minimal human effort.
- We show how to leverage annotations of *existing* event types, to train a classifier that extracts event arguments for the *new* event types.
- We demonstrate the practical utility of our approach by applying it on a set of 67 novel event types.
- We develop a User Interface (UI) to further expedite and improve the time efficiency of our approach. The code, documentation, and a demonstration video will be released as open source on github.com.

We first describe the task of event extraction in the next section. We then show how to rapidly gather event trigger examples for new event types in Section 3. In Section 4, we show how to extract

Figure 1: A user interface that allows a user to provide, expand, and filter event triggers for new types. Each column shows an event type name at the top, followed by event triggers (in red) and text snippets (clickable to expand to full sentence) mentioning these triggers. The user can drag and drop a trigger or sentence from one event to another. The user can also click on "−" to remove an event, a trigger with its snippets, or just a snippet. The first column to the left is reserved for displaying similar triggers found by word similarity tools.

event arguments for novel event types. In Section 5, we describe our model architecture. We present experiment results in Section 6 and perform analysis in Section 7. We discuss related work in Section 8 before concluding in Section 9.

2 Event Extraction

Given an English sentence, we perform event extraction using a two-stage process:

- Trigger classification: Labeling words in the sentence with their predicted event type (if any). For instance, in sentence S1, the extraction system should label "wounded" as a trigger of an Injury event, and label "blast" as a trigger of an Attack event.
- Argument classification: If a sentence contains predicted event triggers $\{t_i\}$, we pair each t_i with each entity and time mention $\{m_j\}$ in the sentence to generate candidate event arguments. Given a candidate event argument (t_i, m_j), the system predicts its associated event role (if any). For instance, given the candidate event argument ("wounded", "airport"), the system should predict the event role $Place$.

3 Trigger Examples for New Events

In this section, we describe how we rapidly gather event trigger examples for new event types with minimal human effort, aided by the UI shown in Figure 1. Our approach is as follows:

Initial triggers Given a new event type, we first ask a user to provide a few discriminative keywords $\mathcal{K}$.

Expanded triggers Next, we add words that are related to $\mathcal{K}$ using two approaches:

- Leverage word embeddings to gather words $\mathcal{W}_e$ that have a high cosine similarity to $\mathcal{K}$.
- Leverage WordNet to gather hyponyms[1] $\mathcal{W}_h$ of $\mathcal{K}$.

We then ask the user to filter $\mathcal{W}_e$ and $\mathcal{W}_h$, only keeping words $\mathcal{W}_r \subseteq (\mathcal{W}_e \cup \mathcal{W}_h)$ that are relevant to the new event type.

Distant supervision We then locate occurrences of $\mathcal{K} \cup \mathcal{W}_r$ in an unannotated text corpus and gather them as event trigger examples for the new event type.

In practice, over a set of 67 new event types, the user spent an average of 4.5 minutes to provide 8.6 initial triggers, and 5 minutes interacting with the UI to filter the expanded triggers, for a total of less than 10 minutes per event type.

4 Argument Extraction for New Events

Current event argument extraction systems learn from training examples annotated for a predefined ontology. For instance, the ACE corpus contains argument annotations such as the Agent and Victim of Injury events, the Attacker and Target of Attack events, etc.

When given a candidate event argument (t_i, m_j) where t_i is a predicted event trigger, state-of-the-art systems such as DMCNN (Chen et al., 2015), usually use the predicted event type of t_i as a feature in its model. While this generally helps to improve performance, the learned system will not be able to label arguments for new event types not seen in the training data.

In this paper, we propose a simple approach to learn a $generic$ event argument model that could be applied to extract Actor, Place, and Time arguments for new event types. In particular, we map

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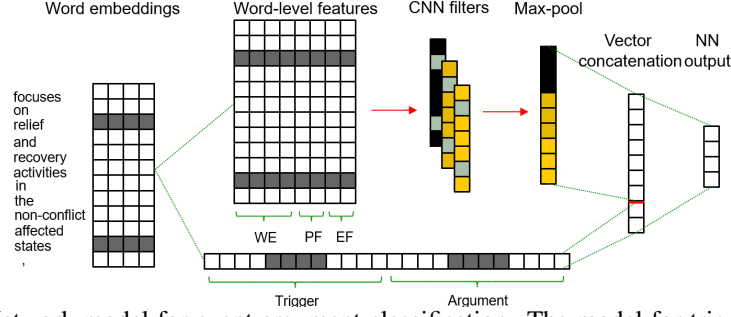[1]X is a hyponym of Y if X is a (kind of) Y.

Figure 2: A Neural Network model for event argument classification. The model for trigger classification omits the argument features that are shown at the bottom. Chen et al. (2015) models event type using event embeddings features (EF), but we omit this when training a *generic* event argument model.

Actor-*like* argument roles (e.g. Attacker, Victim, Target, etc.) in ACE to a common Actor role label, and omit using event type of t_i as a feature in the argument role classifier. The Place and Time arguments in ACE are kept as they are. The complete list of ACE event argument roles that we mapped to Actor are as follows:

- Person, Agent, Victim, Artifact, Buyer, Seller, Giver, Recipient, Org, Attacker, Target, Entity, Defendant, Prosecutor, Plaintiff
- Adjudicator of event types: Convict, Sentence, Fine, Acquit, Pardon

Using the above approach, we build a classifier that could extract Actor, Place, and Time arguments for any event type.

5 Neural Network Model

To perform event trigger and argument classification, we developed a convolution neural network (CNN) model based on the work of Chen et al. (2015), which achieves competitive performance for event extraction. The authors also added a dynamic multi-pooling (DM) layer for CNN, which provides further improvements for event extraction over CNN. Since our focus in this paper is on rapid customization of extraction capabilities to new event types, we leave the implementation of DM to future work.

We show our CNN model in Figure 4, which primarily uses unsupervised pre-trained word embeddings as input features. In this work, we use the word embeddings[2] trained by Baroni et al. (2014), which achieved state-of-the-art results in a variety of NLP tasks. The embeddings provide representation for about 300K words (lowercased, non-lemmatized). It was trained on the concatenation of ukWaC[3], the English Wikipedia,

and the British National Corpus using the Skip-gram model with 5-word context window, 10 negative samples, and 400 dimensions. Briefly, the Skip-gram model trains the embeddings of words $w_1, w_2, ..., w_m$ by maximizing the average log probability:

$$\frac{1}{m} \sum_{t=1}^{m} \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j}|w_t) \qquad (1)$$

where c is the window size and $p(w_{t+j}|w_t)$ is defined as:

$$\frac{\exp(e_{t+j}^{'T} e_t)}{\sum_{w=1}^{m} \exp(e_w^{'T} e_t)} \qquad (2)$$

where m is the vocabulary of the unlabeled text and $e_i^{'}$ is another embedding for e_i

Given a sentence, our CNN model constructs word-level features using the following:

- Word Embeddings (WE): We represent each word in the sentence with its word embeddings vector.
- Position Feature (PF): For every word w_i in the sentence, this captures its relative token distance to the predicted trigger or candidate argument. For instance, in Figure 4, the relative distances of "on" and "recovery" to the trigger "relief" are -1 and $+2$ respectively. These distance values to the trigger are represented by $PF_{trigger}$ embedding vectors which is learnt during training. When performing argument classification, we similarly use PF_{arg} embedding vectors to capture token distances to the candidate argument.

The WE and PF embeddings are fed into the convolution and max-pooling layers. As shown at the bottom of Figure 4, we also construct a vector consisting of the word embeddings of the candidate trigger, the candidate argument, and the embeddings of words in their local window (i.e.

words on their left and right). This vector is then concatenated with the max-pooled vector and fed into the output layer for classification. In this paper, we set the dimension of PF to 5, and the window size as 3. For more details, we refer the reader to (Chen et al., 2015).

6 Experiments

We use the following criteria to judge the correctness of our event extractions:

- A trigger is correctly classified if its event subtype and offsets match those of a reference trigger.
- An argument is correct classified if its event subtype, event argument role, and offsets match any of the reference event arguments

For all our experiments reported in this paper, we follow (Chen et al., 2015) by tuning the model parameters (batch size and number of CNN filter maps) on the development documents. We also tried different number of epoches: 5, 10, or 20. In addition, since the ratio of positive vs negative examples is relatively skewed (for instance, most words in a sentence are not triggers), we also tried different weights for the positive examples: 1, 3, 5, or 10. Finally, we follow (Chen et al., 2015) by using the Adadelta update rule with parameters $\rho = 0.95$ and $\epsilon = 1e^{-6}$, and a dropout rate of 0.5.

To evaluate the effectiveness of our event extraction system in customizing extractors for new event types, we present experiment results in the rest of this section, based on the Common Core Ontologies[4] (CCO). CCO comprises 11 ontologies and is aimed at representing semantics for many domains of interests. The CCO event ontology covers a wide variety of actions, events, processes, and change of states. We sampled 67 event types that are not in existing event schemas (such as ACE and TAC-KBP[5]), to evaluate how well our system does on novel event types. As our experiment corpus $\mathcal{C}$, we use 6,000 allafrica.com news articles, published between 2016-2017.

6.1 Trigger Classification

Given the set of 67 new event types, we first ask our annotator to provide an initial set of keywords or triggers for each event type, then perform expansion and filtering as described in Section 3. On average for each event type, we obtain a set of 21.5

	$\mathcal{C}_d$	$\mathcal{C}_h$	$\mathcal{C}_s$	Dev	Test
#Docs	818	618	618	274	273
#Egs	1674	1171	1258	643	752

Table 1: A set of 1,365 allafrica.com articles are gathered via distance supervision (DS) of trigger examples. A set of 274 and 273 documents are manually annotated and set aside as dev and test data. The DS examples within the remaining set of 818 documents are also manually filtered for correctness, resulting in a smaller set of adjudicated examples associated with 618 documents $\mathcal{C}_h$.

	Precision	Recall	F1
T_d	0.69	0.50	0.58
T_h	0.69	0.46	0.55
T_s	0.62	0.40	0.48

Table 2: Event trigger results on new event types.

final set of triggers from an initial set of 8.6 triggers.

Applying the distant supervision (DS) approach, we use the final set of triggers to automatically gather trigger examples from $\mathcal{C}$ as follows:

- Automatically gather a maximum of 60 DS trigger examples per event type. When doing this, we gathered trigger examples from a total of 1,365 documents.
- We randomly do a 60/20/20 split of these documents into training, development, and test data. For instance, as shown in Table 1, we obtain a set of 818 documents $\mathcal{C}_d$, which we use to train a DS trigger model T_d.
- $\mathcal{C}_d$ contains only DS trigger examples. To compare against the traditional approach of learning from manually annotated examples, we adjudicated and filtered $\mathcal{C}_d$, obtaining a smaller set of adjudicated examples associated with 618 documents $\mathcal{C}_h$, which we use to train a supervised trigger model T_h.

We tune model parameters for T_d and T_h on the development data and report their performance on the test data in Table 2. The results show that our proposed DS trigger model T_d achieves an F1 score of 0.58 on the test data, while the traditional approach of training a supervised trigger model T_h achieves an F1 score of 0.55. We were expecting the manually supervised model T_h to perform better than the DS model T_d. One possible explanation for the observed lower performance of T_h is that $\mathcal{C}_h$ is substantially smaller than $\mathcal{C}_d$. We will show this is exactly the case in Section 7.

Model	Overall			F1		
	P	R	F1	Actor	Place	Time
A_s	0.53	0.47	0.50	0.47	0.43	0.64
A_m	0.65	0.41	0.50	0.49	0.37	0.61
A_n	0.41	0.62	0.49	0.49	0.45	0.62

Table 3: Event argument results using gold triggers. A_s: argument model trained as normal, but predictions and reference roles are mapped to a common Actor role. A_m: argument model by mapping Actor-$like$ argument roles to a common Actor role. A_n: Since the motivation is for the argument model to decode on new event types not previously seen during training, we conduct n-fold experiments, where in each fold i, we omit (Actor, Place, Time) argument examples associated with event type i from the training data.

Model	Overall			F1		
	P	R	F1	Actor	Place	Time
A_s	0.38	0.34	0.36	0.34	0.31	0.45
A_m	0.46	0.28	0.35	0.34	0.27	0.43
A_n	0.32	0.44	0.37	0.36	0.32	0.53

Table 4: Event argument results using predicted triggers.

6.2 Argument Classification

In Section 4, we describe our approach of learning an event argument model that could be applied to extract Actor, Place, and Time arguments for new event types, by mapping Actor-$like$ argument roles in ACE to a common Actor role. In this section, we evaluate this approach by performing experiments on the ACE corpus.

We applied the above mapping approach to learn an argument model A_m on the ACE training data, showing its performance on the ACE test data when using gold triggers (Table 3) and predicted triggers (Table 4). In the second column of the tables, we show the overall Precision (P), Recall (R), and F1 scores over Actor, Place, and Time in aggregate. Next, we also show the F1 scores for each individual role.

For comparison, we evaluated an alternative approach where we train an event argument model as per normal (i.e. using the original ACE event roles), but report results after mapping predictions and reference roles to a common Actor role. We show the results of this experiment as rows A_s.

We note that both A_s and A_m train on the entire ACE training data. However, the motivation of our approach is for the argument model to decode on new event types not previously seen in its training data. Hence, we conduct an additional set of leave-1-out experiments A_n. Specifically, ACE defines event types at a coarse-grained (8 types) level and a fine-grained (33 types) level. For instance, the $Attack$ and $Demonstrate$ event types are grouped into $Conflict$ as a coarser-grained

event type. We thus perform an 8-fold experiment where in each fold i, we omit from the training data, (Actor, Place, Time) argument examples associated with event type i. We then proceed to calculate test performance for that fold, on just the argument examples associated with event type i, which was not seen during training. We aggregate the test results over the 8 folds and present them as row A_n. We note that A_n achieves reasonable performance when compared against A_s and A_m. In particular, we note from Table 3, which shows argument extraction performance when using gold triggers (so that we could isolate the performance of the argument extractor), that the overall F1 score of A_n is very close to that of A_m.

7 Analysis

In Section 6.1, we note that, contrary to our expectations, T_h has a lower performance than T_d. C_d (used to train T_d) consists entirely of trigger examples gathered via distance supervision. C_h (used to train T_h) is a subset of C_d, where only trigger examples that are judged to be correct for the event types are kept. Table 1 shows that C_h contains substantially fewer examples than C_d (1171 examples in 618 documents vs 1674 examples in 818 documents). To investigate the difference in number of examples as a plausible reason for T_d's higher performance, we randomly down-sampled C_d to have the same number of documents as C_h. From the resulting C_s (which still consists entirely of distant supervision examples), we trained the trigger model T_s and show its results in Table 2. Here, we see that T_s performs worse than T_h, which matches our expectations.

In Section 6.2, we provide experiment results of our argument model on the ACE corpus. We now evaluate its performance on the 273 test documents listed in Table 1, which contains 67 new event types not found in ACE. Using T_h and A_m as the trigger and argument models on these documents, we randomly selected 78 Actor, 8 Place, and 14 Time arguments (for a total of 100) predicted by A_m. Of these, we determine that 62 Actor, 7 Place, and 10 Time arguments are correctly predicted, for an overall precision of 0.79.

8 Related Work

Event extraction are often sentence-level pipeline (Ahn, 2006) models with high-level features (Huang and Riloff, 2012; Ji and Grishman, 2008). There are growing interests in Neural

Network models (Chen et al., 2015) for event extracion. Chen et al., (2015) apply dynamic multi-pooling CNNs for event extraction in a pipelined framework. (Nguyen et al., 2016a) propose joint event extraction using recurrent neural networks.

Nguyen et al. (2016b) proposed a two-stage Neural Network model for event type extension. Given a new event type with a small set of seed examples, they leverage examples from other event types. In another work, Peng et al. (2016) developed a minimally supervised approach to event trigger extraction by leveraging trigger examples gathered from the ACE annotation guidelines.

A closely related direction is rapid customization (Gupta and Manning, 2014; Akbik et al., 2013) of IE systems. The ICE (Integrated Customization Environment) system (He and Grishman, 2015) allows a user to create an information extraction (IE) system for a new domain by building new classes of entities and relations interactively. The main ideas are user-in-the-loop entity set expansion and boostrap learning for relation extraction. The WIZIE (Li et al., 2012) system guides users to write rules for IE.

9 Conclusion and Future Work

We presented a system which allows a user to rapidly build event extractors to find new types of events and their arguments. We plan to use clustering techniques to automatically discover salient event trigger words in a new corpus, to further reduce human effort involved in the customization process.

Acknowledgments

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