Event Presence Prediction Helps Trigger Detection Across Languages

Parul Awasthy and Tahira Naseem and Jian Ni and Taesun Moon and Radu Florian
IBM Research AI
Yorktown Heights, NY 10598
{awasthyp, tnaseem, nij, tsmoon, raduf}@us.ibm.com

Abstract
The task of event detection and classification is central to most information retrieval applications. We show that a Transformer based architecture can effectively model event extraction as a sequence labeling task. We propose a combination of sentence level and token level training objectives that significantly boosts the performance of a BERT based event extraction model. Our approach achieves a new state-of-the-art performance on ACE 2005 data for English and Chinese. We also test our model on ERE Spanish, achieving an average gain of 2 absolute $F_1$ points over prior best performing models.

1 Introduction and Prior Work
Event Extraction (EE) is an important subfield in Information Extraction. It usually comprises two subtasks: (1) Event Detection (ED) which extracts from text nuggets of information that signals occurrence of an event; (2) Event Argument Extraction (EAE) which extracts the participants of an event. The task is challenging as there are various ways to express the same event, and the same phrase can express different events. For example, pay could mean event Transaction, as in figure 1, or could mean Justice, as in “...pay a fine of...”.

Events have been used by applications like Question Answering (Yang et al., 2003), Information Retrieval (Basile et al., 2014), Narrative Schema extraction (Chambers and Jurafsky, 2009), Reading Comprehension (Cheng and Erk, 2018), and to build knowledge resources.

Traditionally, EE models were feature based, with careful feature engineering to generate rich set of features (Ahn, 2006; Ji and Grishman, 2008; Li et al., 2013; Araki and Mitamura, 2015). With the rise of deep learning based methods, recent works have used CNNs (Chen et al., 2015; Lin et al., 2018), RNNs (Nguyen et al., 2016), LSTMs (Hong et al., 2018; Feng et al., 2018), Tree LSTMs (Yu et al., 2020), Graph CNNs (Nguyen and Grishman, 2018) to extract events. DMBERT (Wang et al., 2019) was the first transformer based model. Since then Wang et al. (2019); M’hamdi et al. (2019); Lin et al. (2020) have also used transformers for EE.

Work in other languages has been largely language dependent (Chen and Ji, 2009). Chinese EE models have relied on features or language characteristics to improve performance (Chen and Ng, 2012; Lin et al., 2018). Feng et al. (2018) and Lin et al. (2020) have developed language independent models on English, Chinese and Spanish.

The best performing EE models rely on advanced architectures or language specific features. Here, we propose a Transformer based model called sepBERT which uses multiple objectives to improve performance. The idea of learning additional objectives that exploit labels that are available with the data is used successfully by Mikolov et al. (2013); Devlin et al. (2019); Logeswaran and Lee (2018), etc.

We focus on Event Detection (ED) and model the ED problem as a sequence labeling task. We introduce a simple and intuitive sentence level objective that greatly improves model performance. We show that for ED:

- Adding an auxiliary objective function helps achieving the state-of-the-art performance.
- Highly contextualized Transformer models can be effectively used for ED without additional features or layers on top, performing better than more elaborate Transformer based models.
- Our model can be applied to different languages and can still achieve the state-of-the-art performance.
2 Event Extraction Task

Event Extraction is defined for Automatic Content Extraction (ACE) evaluation (Walker et al., 2006) as follows:

- Event Trigger is a phrase that most clearly expresses the occurrence of an event. It is denoted by a type and subtype.
- Event Arguments are the mentions (entity, value or time) that serve as a participant or attribute with a specific role in the event. They are denoted by a role.

As shown in figure 1, pay is an event trigger of type Transaction and subtype Transfer-Ownership with two arguments The company with role Buyer and Yukos with role of Artifact. We focus on Event Trigger Extraction, also referred to as Event Detection (ED) in the literature.

3 Methodology

Most of the previous work on Trigger Extraction has focused on one word triggers (Nguyen and Grishman, 2018; Li et al., 2013; Chen et al., 2015), etc. Such methods classify each word of the sentence as a trigger, ignoring multi-word triggers. Lin et al. (2020) predicts the start and end positions of the triggers to capture multi-word triggers. We treat the task as a sequence labelling task to implicitly capture multi-word triggers, as is done by (M’hamdi et al., 2019).

3.1 Trigger Extraction

Figure 2 shows the architecture of our system, which builds on top of a pre-trained BERT model. We model trigger extraction as a token sequence labeling task. We combine the token-level classification loss $L_t$ with a novel sentence-level event presence prediction loss $L_{sep}$:

$$L = L_t + L_{sep}$$

For the token-level component of our model, we use the IOB2 encoding (Sang and Veenstra, 1999) where each token is labeled with its trigger label $l$ and an indicator of whether it starts or continues a trigger. We introduce a linear classification layer on top of the token-level BERT output vectors. The parameters of the layer are trained via cross entropy loss, a standard approach for BERT based sequence labeling models (Devlin et al., 2019). This is equivalent to minimizing the negative log-likelihood of the true labels,

$$L_t = - \sum_{i=1}^{n} \log(P(l_{w_i}))$$

Although each token is classified independently, the BERT transformer layers help capture the context across all tokens via a multi-head self-attention mechanism.

In addition, we introduce a simple yet effective sentence-level objective that serves as an auxiliary task. This is a binary classification objective, where truth $y = 1$ if the sentence contains an event and $y = 0$ otherwise. We model this by adding a classification layer over the BERT output of the [CLS] token – a token added to the beginning of all BERT inputs,

$$L_{sep} = - \log(P(y))$$

As many sentences do not have events, this loss acts as a discriminator. It offers the system a global representation of when events show up in sentences. We call this loss sentence event presence (SEP) loss and our model sepBERT.
4 Experiments

4.1 Dataset

For English and Chinese we conduct our experiments on ACE (Walker et al., 2006), a popular event extraction dataset. ACE defines 8 event types and 33 subtypes.

As ACE does not have an official test split, for English we follow the work of (Li et al., 2013) and use their pre-defined split of the documents to create a test set with the same 40 newswire documents, development set of 30 mixed documents and training set of the remaining 529. For Chinese, we follow the split proposed by (Feng et al., 2018), and randomly split the data into 60 development, 60 test, and the remaining 513 training documents.

For our Spanish language experiments we use the Entities, Relations and Events (ERE) corpus from LDC2015E107 catalog. ERE defines 9 event types, and 38 subtypes. We follow (Lin et al., 2020)’s split to split the 154 documents into 10 dev, 10 test and 134 train documents.

4.2 Experimental Setup

Details of our setup are mentioned below. For contextualized word embedding, we use the HuggingFace PyTorch implementation of Transformers (Wolf et al., 2019). We train monolingual models on three languages, English, Spanish and Chinese, using the same method as described in 3. We denote the language-specific models as sepBERTlang. We use the out-of-the-box pre-trained transformer models, and fine-tune them with the event data, updating all layers. Our English model uses bert-base-uncased and the Chinese and Spanish model uses bert-base-multilingual-cased with the standard BERT hyperparameters; we ran 20 epochs with 5 seeds each, dropout of 0.3, learning rate of $3 \cdot 10^{-5}$ or $5 \cdot 10^{-5}$, and training batch sizes of 30 for English, and 15 for Arabic and Spanish. We train our models on various seeds and learning rate combinations, and select the model that performs the best on the development set and report the test score for that model. Our sepBERT model takes about 2 minutes per epoch to train on a k80 GPU.

4.2.1 Metrics

We adopt the formal ACE evaluation criteria to evaluate our model: A trigger is correctly classified if its offsets, event type, and subtype match those of a reference trigger. We use Precision, Recall and F1-Measure to score the performance.

4.3 Baselines

We create an ablation baseline, stdBERT, where we formulate the task as sequence labeling, but train without the SEP objective. This is a standard out-of-the-box sequence labeling model.

We compare our model with the following external English baselines:

- Feature-based: Li et al. (2013) is the best performing feature-based model.
- Neural net, pre-transformer: JRNN (Nguyen et al., 2016) is a joint RNN based system. BiLSTM+GAN (Hong et al., 2018) is an ED only NN model. GCN-ED (Nguyen and Grishman, 2018) is a joint model that uses graph CNN to model dependency trees to capture event information.
- Transformer-based: DMBERT+Boot (Wang et al., 2019) uses bert-base-uncased and models GANs to generate more training data for ED. They also have a vanilla baseline DMBERT, which does not use additional training data. BERT-CRF (M’hamdi et al., 2019) is an ED only transformer based model that uses a CRF layer on top of bert-base model. ONEIE (Lin et al., 2020) is a joint transformer based model, that extracts mentions, events and relations at the same time. They use bert-large-cased for the English model. We report their score on what they call ACE-E+ dataset, as that matches our data.

For Chinese, we compare our model with the following external baselines:

- Language dependent: Rich-C (Chen and Ng, 2012) is a feature-based model that adds language specific features to improve performance. NPN (Lin et al., 2018) is a Chinese only Neural Net model that learns a hybrid representation for each character from both characters and words.
- Language independent: HNN (Feng et al., 2018) is a BiLSTM based Neural Net model. ONEIE (Lin et al., 2020) is a transformer based model that uses bert-base-multilingual-cased.

*BERT-CRF* (M’hamdi et al., 2019) although we have listed BERT-CRF Chinese language scores, their numbers are not comparable to ours as they “limit the maximum sequence length of sentences to 128, padding or cutting otherwise.” This leads to reduction in the ground truth making their total event count 2521, when there are 3333 total events in the Chinese data set. ¹

Our Spanish baseline is ONEIE.

¹It is to be noted that their English event count does not suffer from this problem, possibly due to the shorter length of ACE05 English sentences.
Table 1: Trigger Classification Performance on English, Chinese, and Spanish. stdBERT_{lang} and sepBERT_{lang} are trained on monolingual lang data; J is used to differentiate Joint EE models.

### 5 Results and Discussion

Table 1 shows our results. The sepBERT model consistently achieves state-of-the-art results across languages. Some baselines systems, annotated with J in Table 1 are joint event extraction model, optimizing a global objective over event triggers and arguments. Our model outperforms them and the Event Detection only models like DMBERT, BERT-CRF, BiLSTM+GAN with an average gain more than 2F points.

On English, our ablation baseline stdBERT_{en}, performs better than the feature-based model and the JRNN model by a good margin. It performs at par with the GCN-ED and BiLSTM+GAN, but does worse than the transformer based baselines. Our full model sepBERT_{en} performs 1F point better than BERT-CRF, and 1.8F points better than DMBERT, both of which are transformer based methods. It performs 1.2F points better than DMBERT+Boot, system that augments the training data, and more than 3F points better than the more elaborate neural net models GCN-ED and BiLSTM-GAN. It is 3.5F points better than DMBERT+Boot, which is a larger model built using bert-large.

Similarly, on Chinese our ablation baseline stdBERT_{zh} does better than all other models, except transformer based ONEIE. sepBERT_{zh} is again the best model, performing 1.1F points better than ONEIE, also based on bert-base-multilingual, and 1.9+F points better than language specific models like NPN and Rich-C. It is also 3.7F points better than the other language independent baseline HNN. *As mentioned in 4.3 BERT-CRF is not comparable with our model.

On Spanish sepBERT_{es} is 5.2F points better than ONEIE. The stdBERT_{es} also scores 3.8F higher than ONEIE.

Results show that the stdBERT baseline has a lower precision than sepBERT. By comparing their output we see that stdBERT_{en} produces 30% more false positives than sepBERT_{en}. This suggests that the added event presence objective helps make sepBERT_{en} more precise. To further investigate, we measure the sentence level event prediction accuracy of both systems, i.e. we measure ratio of number of times system is correct in predicting presence of an event with total number of times a system predicts any event in a sentence. We find for all languages, sepBERT is more accurate than stdBERT, by as much as 3 points, suggesting the SEP loss works as desired.

We also find that both sepBERT_{en} and stdBERT_{en} misclassify around 5% of the events, i.e., they label a trigger of type x as y, where both x,y are valid trigger types and not "O". This suggests that the added objective does not make the model more accurate on the identified events.

### 6 Conclusion

In this paper, we proposed a method for event trigger extraction (sepBERT), which formulates the task as sequence labeling to capture multi-word triggers. With the help of an added auxiliary objective, sepBERT achieves the state-of-the-art performance. We show that our model effectively uses the pre-trained Transformer without additional features or layers on top, performing better than more elaborate Transformer based models. Moreover, our model can be applied to different languages and can still achieve the state-of-the-art performance in those languages, attaining an average gain of 2 absolute F1 points over past best performing models.
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