Modeling Document-Level Context for Event Detection via Important Context Selection

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Abstract

Event Detection (ED) aims to recognize and classify trigger words of events in text. The recent progress has featured advanced transformer-based language models (e.g., BERT) as a critical component in state-of-the-art models for ED. However, the length limit for input texts is a barrier for such ED models as they cannot encode long-range document-level context that has been shown to be beneficial for ED. To address this issue, we propose a novel method to model document-level context with BERT for ED that dynamically selects relevant sentences in the document for the event prediction of the target sentence. The target sentence will be then augmented with the selected sentences and consumed entirely by BERT for improved representation learning for ED. To this end, the REINFORCE algorithm is employed to train the relevant sentence selection for ED. Several information types are then introduced to form the reward function for the training process, including ED performance, sentence similarity, and discourse relations. Our extensive experiments on multiple benchmark datasets reveal the effectiveness of the proposed model, leading to new state-of-the-art performance.

1 Introduction

Event Detection (ED) is one of the fundamental tasks for Information Extraction. Its goal is to identify the word(s) in text that most clearly evoke events and classifying them into predefined event types (event trigger words). For instance, in the input sentence “After the scandal, David James was fired from the company.”, an ED system needs to recognize the word “fired” as an event trigger and predict its event type as End-Position.

The early methods for ED have involved feature-based models (Ahn, 2006; Liao and Grishman, 2010a; Miwa et al., 2014) while recent work has featured deep learning methods (Nguyen and Grishman, 2015; Chen et al., 2015; Lin et al., 2020; Nguyen et al., 2021). Similar to other NLP tasks, the current best systems for ED leverage transformer-based language models, e.g., BERT (Devlin et al., 2019), as a critical encoding component to achieve state-of-the-art performance (Lai et al., 2020b; Lin et al., 2020). As such, most of the current transformer-based models for ED only focus on sentence-level context in which the scope of context to predict event type for each word is limited to the host sentence (Lu et al., 2019; Wang et al., 2019). However, it has been shown that document-level context also provides important information for deep learning models for ED (Chen et al., 2018; Zhao et al., 2018). For instance, in the document “The troops were retreating cautiously. He was shocked after he heard “Fire!”.”, to correctly predict Attack as the type of the event evoked by “Fire” (i.e., avoiding the confusion with the event type End-Position), it is necessary to consider the previous sentence with the important context words of “troops” and “retreating”. Consequently, in this work, we aim to develop a transformer-based model that can effectively encode document context to boost the performance for ED.

There have been a few recent work that applies BERT-based models for document-level ED (Wang et al., 2020b; Trong et al., 2020). However, as BERT can only encode input texts with up to 512 sub-tokens (due to the quadratic self-attention complexity), current BERT-based document-level models for ED has only constrained their applications to document context that can fit into the BERT length limit. The typical approaches involve only considering short documents (Wang et al., 2020b) or truncating long documents (Trong et al., 2020), as also done for other tasks (Schweter and Akbik, 2020; Luoma and Pyysalo, 2020). These models are thus unable to encode long-range dependencies in document context that go beyond the length limit of BERT to further improve the ED performance.

To alleviate the length limit for BERT-based ED
models, two major approaches from other NLP tasks can be considered: (1) Architecture Change for Self-Attention (Zaheer et al., 2020; Beltagy et al., 2020; Kitaev et al., 2020): In this group, the vanilla self-attention of transformer is replaced with some variant mechanism such as sparse self-attention (Zaheer et al., 2020) that can encode larger context with the same complexity as the original transformer (e.g., Longformer (Beltagy et al., 2020) can consume 4096 sub-tokens compared to 512 sub-tokens in BERT); and (2) Hierarchical Design (Adhikari et al., 2019; Jörke et al., 2020): These works employ the standard transformer-based language models to encode the context with certain length limit. For larger context, they combine the transformer model with other deep architectures to construct the final model for specific tasks. For instance, Adhikari et al. (2019) split the documents into multiple chunks (to fit the length limit of BERT) and send the BERT-based representations of the chunks into a recurrent neural network for document modeling. However, both solutions have their own drawbacks that might not be suitable for ED. For the former, the transformers with variants of vanilla self-attention are still limited to a certain length (e.g., 4096 for Longformer), thus unable to encode important contexts that are farther away in the documents for ED. Moreover, due to the changes in the self-attention mechanism, such variants generally lead to lower performance for NLP tasks compared to vanilla transformer (Beltagy et al., 2020). For the latter, standard transformer architectures are still employed to represent chunks of input texts to the extent of their length limits, thus failing to benefit from the ability of transformer to consume the entire input texts and capture long-range dependencies of documents for representation learning. In particular, the self-attention component of the models in this case is still bounded to the length limit and cannot directly capture the dependencies over the entire document.

To this end, to develop an effective BERT-based document-level model for ED, our motivation in this work is to explicitly select only important/relevant parts of a document for a given sentence and feed those context into BERT for improved representation learning. One the one hand, context selection allows the model to compress an input document into a smaller chunk with important context that can fit entirely into the length limit of BERT to better exploit the capacity of BERT for representation learning. Further, the ignorance of irrelevant context in the input for BERT might also reduce noise and improve representation vectors for ED. In particular, given an input sentence $S_i$ in a document for event prediction, our method seeks to select a subset of sentences for $S_i$ in the document that contain the most important context for the event prediction of $S_i$. The subset is also constrained so its concatenation with $S_i$ (i.e., the compressed document) can fall within the length limit of BERT, thus enabling BERT to encode the compressed document entirely.

As such, the key question in our model is how to design the sentence selection to facilitate the encoding of important context in documents with BERT for ED. To this end, we argue that the important context for an input sentence $S_i$ in a document should be determined by the improved performance of BERT for ED on $S_i$ when $S_i$ is augmented with the context. As such, we propose to use the policy-gradient method REINFORCE (Williams, 1992) to guide the context selection module using the performance of BERT for ED as the reward. In addition, we introduce auxiliary rewards based on linguistic intuition (i.e., semantic and discourse relations between the input sentence $S_i$ and selected context sentences) to enhance the selection process. Our extensive experiments on benchmark datasets show that the proposed method can achieve state-of-the-art results for ED on both the sequence-labeling and the word-classification formulations.

2 Model

In the literature, ED has been formulated as sequence-labeling (Lin et al., 2020; Nguyen et al., 2021) or word-classification (Nguyen and Grishman, 2015) problems. In this work, we explore both formulations of the task. Formally, given the input sentence $S_i = [w_1, w_2, \ldots, w_n]$ (with $n$ words) from the document $D = [S_1, S_2, \ldots, S_N]$ (with $N$ sentences), the goal is to recognize and classify event triggers in $S_i$, leveraging the broader context in $D$. In the sequence-labeling formulation (Lin et al., 2020), as event triggers are allowed to involve multiple words, ED aims to assign a label $y_t$ to each word $w_t \in S_i$ (using the BIO annotation schema) so the label sequence $Y = [y_1, y_2, \ldots, y_n]$ can capture event trigger boundaries and types in $S_i$. For the word-classification formulation (Chen et al., 2015; Nguyen and Grishman, 2015), the model additionally has an index $t$ for the trigger candidate
word \(w_i \in S_i\) as an input and the goal is to predict the event type that \(w_i\) triggers (a multi-class classification problem). Here, we also include a special type \textit{None} to indicate that a word is not an event trigger. As such, in the word-classification setting, the model performs separate event type predictions for each word in the input texts.

As discussed in the introduction, our goal is to design a document-level model for ED that can effectively leverage the representation learning ability of BERT (i.e., entirely encoding important context sentences for \(S_i\) in ED using the powerful BERT and self-attention). To this end, we propose to select a set \(C_i\) that contains the most important context sentences for the event prediction of \(S_i\) in \(D\), i.e., \(C_i \subseteq S_{\text{context}} = \{S_j \in D| j \neq i\}\). The target sentence \(S_i\) will be augmented with the sentences in \(C_i\) to form a shorter document \(D'\) (i.e., \(D' = \{S_i\} \cup C_i\)) for \(D\). In our model, \(D'\) will be constrained to fall within the length limit of BERT, thus allowing BERT to consume \(D'\) entirely for improved representation learning for ED. In this way, the important context with arbitrary distance from \(S_i\) in \(D\) can be reached and packed into \(D'\) to allow effective document-context modeling with BERT for ED. In the rest of this section, for brevity, we remove the subscript \(i\) from \(C_i\). Our model for ED in this work consists of two major components: (I) Prediction Model: This model consumes the shorter document \(D'\) and perform event type prediction for \(S_i\), and (II) Context Selection: This component selects the important context sentence set \(C\) to perform ED for \(S_i\).

### 2.1 Prediction Model

The prediction model \(M^{ED}\) consumes the set of important context sentences \(C\) to perform ED for the target sentence \(S_i\). We will first describe the architecture for the prediction model in this section; the construction of \(C\) will be discussed later. As such, we first divide the set of selected sentences \(C\) into two subsets \(LC\) and \(RC\) for the sentences on the left and right context of \(S_i\) in \(D\), i.e., \(LC = \{S_j \in C | j < i\}\) and \(RC = \{S_j \in C | j > i\}\). Next, the sentences in \(LC\) and \(RC\) are concatenated (following their orders in \(D\)) to form the two word sequences \(\{w_1^{LC}, w_2^{LC}, \ldots, w_n^{LC}\}\) and \(\{w_1^{RC}, w_2^{RC}, \ldots, w_n^{RC}\}\) where \(n_{LC}\) and \(n_{RC}\) are the number of words in \(LC\) and \(RC\) respectively. Afterward, we feed the context-augmented text for \(S_i\), i.e., the short document \(D' = [[CLS], w_1^{LC}, w_2^{LC}, \ldots, w_n^{LC}, [SEP], w_1, w_2, \ldots, w_n, [SEP], w_1^{RC}, w_2^{RC}, \ldots, w_n^{RC}]\) into BERT for representation computation. This is possible as the number of tokens in \(D'\) will be constrained to follow the length limit of BERT. We use the hidden states of the last layer of the BERT model to represent the input tokens: \(E = [e_{CLS}, e_1^{LC}, e_2^{LC}, \ldots, e_n^{LC}, e_{SEP}, e_1^{RC}, e_2^{RC}, \ldots, e_{n_{RC}}]\). Here, for tokens consisting of multiple word-pieces, we take the average of the hidden states of the word-pieces to obtain the representation vectors for the tokens.

Finally, depending on the task formulation, we send the representations of the word(s) \(w_t\) (for word-classification) or \([w_1, w_2, \ldots, w_n]\) (for sequence-labeling) to a two-layer feed-forward layer \(FF\) followed by a the softmax function \(\sigma\) to obtain label probability distributions\(^1\): \(P(|S_i, D', t| = \sigma(FF(e_t))\).

We utilize the negative log-likelihood as the training loss for \(M^{ED}\). In particular, for word classification, the loss function is: \(L_{\text{pred}} = -\log(P(l^*|S_i, D', t))\) while those for sequence labeling is: \(L_{\text{pred}} = -\frac{1}{n} \sum_{j=1}^{n} \log(P(y_j^*|S_i, D', j))\). Here, \(l^*\) is the golden event type for \(w_t \in S_i\) in the word-classification formulation while \(y_j^*\) is the golden BIO label for \(w_j \in S_i\) in sequence labeling.

### 2.2 Context Selection

To select the most important context sentences \(C\) for \(S_i\), our intuition is that a sentence \(S_j\) in \(D\) is important for the event prediction of \(S_i\) if including \(S_j\) into the short document \(D'\) for the base model \(M^{ED}\) can improve the performance for \(M^{ED}\) on \(S_i\). In particular, to prepare the sentences for context selection, we first employ BERT\(_{\text{base}}\) to obtain a representation vector for each sentence \(S_j \in S_{\text{context}}\). As such, to customize the representation of \(S_j\) for \(S_i\) (i.e., our target sentence for ED), we concatenate the two sentences before feeding them to the BERT\(_{\text{base}}\) model. Concretely, the input to the BERT\(_{\text{base}}\) encoder is: \([CLS], w_1^j, w_2^j, \ldots, w_{n_j}^j, [SEP], w_1, w_2, \ldots, w_n\) where \(S_j = [w_1^j, w_2^j, \ldots, w_{n_j}^j]\) with \(n_j\) words. The representation of the \([CLS]\) token from the last layer of BERT\(_{\text{base}}\) is then employed to represent \(S_j\), i.e., denoted by \(x_j\). Next, the representation

\(^1\)For sequence-labeling, the feed-forward layer consumes the representation of every word \(w_i \in S_i\) separately.
vectors $X = \{x_j | S_j \in S_{context}\}$ will be used by subsequent components to select important sentences for $S_i$. Note that the BERT$_{base}$ model for this context selection component is different from those used for the prediction model $M^{ED}$ to facilitate the customization for each component.

Before describing the sentence selection process, we note that the number of words from the selected sentences in $C$ cannot exceed $l_i = 512 - |S_i|$ as we want to make sure that the short document $D'$ can fit into the BERT length limit. We design an iterative process that select important context sentences for $S_i$ via multiple steps. At step $k+1$ in the process ($k \geq 0$), a sentence $S_{i,k+1}$ is chosen over the set of sentences that has not been selected in $S_{context}$, i.e., $S_{context}^k = S_{context} \setminus \{S_{i,1}, \ldots, S_{i,k}\}$, conditioning on the previously selected sentences $S_{i,1}, \ldots, S_{i,k}$. As such, we employ a Long Sort-Term Memory Network (LSTM) LSTM to obtain representation vectors to summarize the sentences that have been chosen in prior steps. At step 0, the initial hidden state $h_0$ for LSTM is set to zero. At step $k+1$, we use the hidden state $h_k$ of LSTM from prior step as a summarization for the sentences selected before. Afterward, we compute a selection score $sc_{j}^{k+1}$ for each sentence $S_{j} \in S_{context}^k$ based on the representation vector $x_j$ of $S_j$ in $X$ and $h_k$: 

$$sc_{j}^{k+1} = \text{sigmoid}(G([x_j : h_k]))$$

where $G$ is a two-layer feed-forward network.

The sentence $S_{j^*}$ with highest selection score, i.e., $S_{j^*} = \arg\max_{S_j \in S^k_{context}} sc_{j}^{k+1}$, is then considered for selection at this step. In particular, if selecting $S_{j^*}$ causes the number of words in the selected sentences so far (i.e., $|S_{\ast}| + \sum_{i=1}^{k} |S_{i,k}|$) exceeds the limit $l_i$, the selection process stops and $S_{j^*}$ is not included in the selected set $C$ (i.e., $C = \{S_{i,1}, \ldots, S_{i,k}\}$ in this case). Otherwise, the selection process continues to the next step and $S_{j^*}$ will be chosen and included in $C$ (i.e., $S_{i,k+1} = S_{j^*}$).

The hidden state of LSTM is also updated for the current step, i.e., $h_{k+1} = \text{LSTM}(h_k, x_{j^*})$, to prepare for the continuation of sentence selection.

### 2.3 Selection Training

As motivated in the introduction, a context sentence $S_j \in S_{context}$ is considered as important for the event prediction of $S_i$ if augmenting $S_i$ with $S_j$ can improve the ED performance for the model. As such, we employ the performance of the prediction model $M^{ED}$ on $S_i$ (i.e., obtained by ruining $M^{ED}$ over the augmented short document $D'$) as the training signal to guide the sentence selection process. In particular, we employ the REINFORCE algorithm (Williams, 1992) to facilitates the use of the ED performance of $M^{ED}$ as the reward to train the context selection in our model. In addition, REINFORCE allows the incorporation of other information into the reward function to better supervise the training process. As such, given the selected context sentences in $C$, we consider the following information for the reward in our model:

1. **Task-level Reward $R_{i}^{\text{task}}$:** This reward is based on the performance of the prediction model $M^{ED}$ for ED on $S_i$. To measure the impact of the selected context $C$, $M^{ED}$ is operated on the augmented short document $D'$. In particular, for the sequence-labeling setting, we use F1 score for the performance-based reward while accuracy is employed for those in the word-classification setting.

2. **Semantics-level Reward $R_{i}^{\text{sim}}$:** In this reward, we propose to prefer context sentences that are semantically similar to the target sentence $S_i$ for ED. The motivation is that similar/related context sentences (e.g., discussing the same events or topics) might provide more relevant information for the event prediction in $S_i$. To this end, we include the semantic similarity between $S_i$ and the selected sentences in $C$ as an auxiliary information for the reward to train our model. In particular, we first obtain representation vectors $\hat{S}_i$ and $\hat{C}$ for $S_i$ and $C$ by max-pooling the representation vectors for their corresponding words in $E$ (i.e., produced by $M^{ED}$ over $D'$): $\hat{S}_i = \text{MAX\_POOL}(e_1, e_2, \ldots, e_n)$ and $\hat{C} = \text{MAX\_POOL}(e_1^{LC}, \ldots, e_n^{LC}, e_1^{RC}, \ldots, e_n^{RC})$. Afterward, the dot-product (i.e., $\odot$) between $\hat{S}_i$ and $\hat{C}$ is used as the similarity-based reward for the model: $R_{i}^{\text{sim}} = \hat{S}_i \odot \hat{C}$.

3. **Discourse-level Reward $R_{i}^{\text{disc}}$:** For this reward, we seek to promote context sentences that are most connected to $S_i$ via the entity coreference relation in the selection process. Here, the motivation is that a context sentence $S_j$ is more relevant/important for the event prediction on $S_i$ if there are more entities mentioned in both $S_j$ and $S_j$. In particular, as entities can serve as arguments in events, mentioning similar entities makes it more likely for $S_j$ and $S_j$ to refer to similar/related events, potentially leading to better relevance and usefulness of $S_j$ for ED on $S_i$. To implement this idea, we first obtain all entity mentions and their coreference clusters in $D$ using the
off-the-shelf tool Stanford CoreNLP. The discourse-level reward to capture our intuition is then computed by: 

$$R^{\text{disc}} = \frac{1}{|\mathcal{C}|} \sum_{S_i \in \mathcal{C}} COR(S_j, S_i)$$

In this formula, \(COR(S_j, S_i)\) counts the number of entities that are mentioned in both \(S_j\) and \(S_i\) normalized by the total number of entities appearing in \(S_j\) and \(S_i\) (i.e., leveraging the detected entity mentions and clusters computed above).

Consequently, the overall reward function to train our context selection module with REINFORCE is 

$$R_i(C^j) = a R^{\text{task}}_i + \beta R^{\text{sim}}_i + \gamma R^{\text{disc}}_i.$$ 

For convenience, we treat \(C\) as the sequence of selected sentences from \(S_{\text{context}}\), i.e., \(C = S_{i_1}S_{i_2} \ldots S_{i_k}\) where \(K\) is the number of sentences in \(C\). With REINFORCE, we seek to minimize the negative expected reward \(R_i\) over the possible choices of \(C\):

$$\mathcal{L}_{\text{sel}} = -\mathbb{E}_{C^j \sim P(C^j|D,S_i)}[R_i(C^j)].$$

The policy gradient is then estimated by:

$$\nabla \mathcal{L}_{\text{sel}} = -\mathbb{E}_{C^j \sim P(C^j|D,S_i)}[(R_i(C^j) - b)\nabla \log P(C^j|D,S_i)].$$

Using one roll-out sample, we further estimate \(\nabla \mathcal{L}_{\text{sel}}\) via the selected sequence \(C^j\):

$$\nabla \mathcal{L}_{\text{sel}} = -(R_i(C) - b)\nabla \log P(C|D, S_i)$$

where \(b\) is the baseline to reduce variance. In this work, we obtain the baseline \(b\) via:

$$b = \frac{1}{|B|} \sum_{j=1}^{B} R_i(C_j),$$

where \(|B|\) is the mini-batch size and \(C_j\) is the selected sequence for the \(j\)-th sample in the mini-batch. Also, the probability of the selected sequence \(C\) is computed via:

$$P(C|D, S_i) = \prod_{k=0}^{K-1} P(S_{i_{k+1}}|D, S_i, S_{i_{\leq k}})$$

where \(S_{i_{\leq k}} = S_{i_1} \ldots S_{i_k}\) and \(P(S_{i_{k+1}}|D, S_i, S_{i_{\leq k}})\) is obtained via the softmax function over selection scores for sentences in \(S_{\text{context}}\) at selection step \(k + 1:\)

$$P(S_{i_{k+1}}|D, S_i, S_{i_{\leq k}}) = \exp(s_{i_{k+1}}) / \sum_{S_{i_{\leq k}}} \exp(s_{i_{j+1}}).$$

In this work, we train the prediction model \(M^{ED}\) and the context selection component in an alternate training fashion. Specifically, at each update step with one batch of data, we employ the current selection component to select important context sentences \(C\) for each target sentence \(S_i\) in the batch and form the short documents \(D^i\). The parameters for the prediction model \(M^{ED}\) will then be updated using the gradient of \(\mathcal{L}_{\text{pred}}\) over the short documents for the current batch. This is followed by the update for the parameters of the selection component using the gradient of \(\mathcal{L}_{\text{sel}}\) (i.e., performance of the current prediction model \(M^{ED}\) is used for the reward at this step). Finally, the same procedure applies for the test time where important context sentences will be first selected and then consumed by the prediction model to perform ED.

### 3 Experiments

**Datasets & Baselines:** To study the effectiveness of the proposed model, called Event Detection with Dynamic Document Context (ED3C), we evaluate its performance on two benchmark datasets ACE 2005 (Walker et al., 2006) and CySecED (Trong et al., 2020). We choose these two datasets as they provide documents that are much longer than the input length limit for BERTbase, thus being more suitable to our focus on document-context modeling for ED\(^2\). We use full document context for the documents in these datasets.

ACE 2005 annotates 599 documents for 33 event types. We use the same data split and preprocessing as prior work (Lin et al., 2020; Lai et al., 2020; Tong et al., 2020) for this dataset. The numbers of documents for the training/test/validation data are 529/40/30 respectively. In prior work, the ED problem on ACE 2005 has been addressed via both the sequence-labeling (Wang et al., 2020b; Lin et al., 2020) and word-classification (Lai et al., 2020; Tong et al., 2020) formulations. The sequence-labeling formulation adheres to the original annotation in ACE 2005 to allow multiple words in event triggers. The word-classification formulation, in contrast, simplifies the problem by only concerning the single most important words in event triggers (Nguyen and Grishman, 2015). We use ACE 2005 to evaluate the systems on both formulations in this work. As such, we compare the performance of EC3C with the current state-of-the-art (SOTA) ED models on ACE 2005, i.e., BiLSTM (Wang et al., 2020b) (for sequence-labeling) and EKD (Tong et al., 2020) (for word-classification).

CySecED is a recent ED dataset that annotates 300 articles for 30 cybersecurity event types. We use the same data split proposed in the original paper (Trong et al., 2020) with 240/30/30 documents for training/test/validation data. Following prior work, we evaluate ED models on the word-classification setting. We compare ED3C with the current SOTA model on CySecED, i.e., DEEB-RNN (word2vec) (Trong et al., 2020; Zhao et al., 2018).

In addition to the aforementioned baselines, we also compare the proposed model with prior state-of-the-art document-level models for ED, including\(^2\)Most of documents in other ED datasets can be fit directly into the BERTmax length limit. For instance, the proportions of documents with length larger than 512 are 9.1% in MAVEN (Wang et al., 2020b) and 0% in RAMS (Ebner et al., 2020).
| Model                  | ACE 2005 (SL) | ACE 2005 (WP) | CySecED |
|-----------------------|--------------|--------------|--------|
|                       | P  | R  | F1 | P  | R  | F1 |        | P  | R  | F1 |
| State-of-the-art      |    |    |    |    |    |    |        |    |    |    |
| BiLSTM                | 77.20 | 74.90 | 75.40 |    |    |    |        | 79.10 | 78.00 | 78.60 |
| DEEB-RNN (BERT)       | 77.89 | 74.35 | 76.08 |    |    |    |        | 70.91 | 79.38 | 74.91 |
| Hierarchical Neighbor Sentences | 77.19 | 73.02 | 75.05 |    |    |    |    | 72.84 | 79.46 | 76.01 |
| BigBird               | 76.04 | 73.85 | 74.93 |    |    |    |        | 74.39 | 79.07 | 76.66 |
| Reformer              | 76.91 | 73.60 | 75.22 |    |    |    |        | 79.32 | 73.24 | 76.16 |
| Longformer            | 75.12 | 77.20 | 76.15 |    |    |    |    | 76.19 | 79.70 | 77.91 |
| ED3C (ours)           | 80.31 | 76.04 | 78.12 | 75.13 | 83.51 | 79.10 | 75.14 | 65.57 | 70.03 |

Table 1: Performance of the models on ACE 2005 and CySecED test sets. SL and WP stand for sequence-labeling and word-classification. The proposed model is significantly better than baselines with \( p < 0.01 \).

ing HBTNGMA (Chen et al., 2018) that employs gated multi-level attention mechanism and DEEB-RNN (BERT) (Zhao et al., 2018) that uses a bi-directional RNN for encoding the sentences of the documents. Note that as BERT is not originally used in these models, we use their provided implementations and inject the BERT\(_{base}\) model into the encoding components for a fairer comparison. Furthermore, we compare ED3C with other variants of pre-trained transformer-based language models capable of encoding input texts with longer length than BERT\(_{base}\) limit. Specifically, we consider three commonly used language models: BigBird (Zaheer et al., 2020) which utilizes sparse self-attention, Reformer (Kitaev et al., 2020) which replaces dot-product attention with locality-sensitive hashing, and Longformer (Beltagy et al., 2020) that utilizes local self-attention together with global task-aware attention. Finally, we compare ED3C with two typical solutions for document encoding using BERT, i.e., Hierarchical (Adhikari et al., 2019) which splits a document into multiple chunks and encode them separately with BERT, a BiLSTM model is then employed to aggregate the representations of the chunks; and Neighbor Sentences (Schweter and Akbik, 2020) which augments the current sentence with sentences immediately appearing before and after the current sentence in the document for BERT-based encoding. Note that for BigBird, Reformer, Longformer, and “Neighbor Sentences”, we use both left and right context sentences for augmentation. The corresponding quota for input length of a model (e.g., \( l_i \) for BERT) is divided evenly for the two types of context.

Hyperparameters: We tune the hyperparameters for the proposed model using a random search. All the hyperparameters are selected based on the F1 scores on the development set of the ACE 2005 dataset (with sequence-labeling setting). The same hyper-parameters from this fine-tuning are then applied for CySecED dataset and word-classification setting for consistency. In our model we use the BERT\(_{base}\) to encode data; 300 dimensions for the hidden states of LSTM and 2 layers for feed-forward neural networks with 200 hidden dimensions. The trade-off parameters \( \alpha, \beta \) and \( \gamma \) are set to 0.5, 0.1, 0.05, respectively. The learning rate is set to 3e-5 for the Adam optimizer and the batch size of 16 are employed during training.

Comparison: The performance of the models are shown in Table 1. There are several observations from this table. First, the modified transformer-based models Longformer outperforms the task-specific architectures that employ the standard BERT\(_{base}\) model (e.g., HBTNGMA or Hierarchical). This is expected in that Longformer employs a variant of self-attention to entirely encode longer context than vanilla self-attention in the BERT (with limited input length), thus better capturing long-range dependencies in the context. The second observation is that the “Neighbor Sentences” baseline is generally worse than other models that attempt to exploit larger document context (e.g., the entire document in Hierarchical and longer neighbor context in Longformer). This confirms the advantage of exploiting long document-level context for ED. Finally, the table shows that the proposed model is significantly better than all baselines and previous SOTA models on all settings and datasets. We attribute the superiority of ED3C to two impor-
important characteristics that cannot be achieved in the baselines: (1) the ability to identify relevant context sentences at arbitrary length in the document to form shorter documents for BERT (thus also avoiding irrelevant sentences), (2) the capacity to encode important context entirely with BERT and self-attention to fully benefit from its representation learning for ED (i.e., avoiding the sacrifice of performance in exchange for efficiency due to the use of less powerful self-attention as in BigBird, Reformer, and Longformer).

Ablation Study: To better understand the proposed model, we conduct an ablation study in which we remove the major components of ED3C and report the performance of the remaining model on the development set of ACE 2005. We use the sequence-labeling setting in this study; however, the same patterns are observed for the word-classification setting. Specifically, we consider the following ablated models: (1) - Sequential Selection (SS): In the selection component, we perform an sequence of selection steps where an LSTM network is employed to obtain a summarization of previously selected sentences, serving as a condition for selecting the next sentence for $C$. To assess the necessity of the multi-step selection with LSTM, we alter the selection process to a one-step selection. In particular, we only perform the sentence selection once where the top $T$ sentences with highest selection scores from the first step (i.e., $sc_i^1$ for $S_j \in S_{context}$) are selected to form the context $C$ (i.e., eliminating LSTM). Here, $K$ is determined such that the resulting short document $D'$ can occupy the the input length limit of BERT$_{base}$ as such as possible; (2) - Task-level Reward (TR): To study the impact of the performance reward, we remove $R_i^{task}$ from the overall reward $R_i(C)$ for the context selection component; (3) - Semantics-level Reward (SR): this model excludes the sentence similarity reward $R_i^{sim}$ from the overall reward $R_i(C)$; (4) - Discourse-level Reward (DR): As such, given the target sentence, these heuristics

| Model                  | P   | R   | F1  |
|------------------------|-----|-----|-----|
| ED3C (full)            | 81.23 | 76.60 | 78.85 |
| - Sequential Selection | 79.21 | 75.00 | 77.05 |
| - Task-level Reward    | 78.72 | 74.10 | 76.06 |
| - Semantics-level Reward | 77.59 | 73.16 | 75.96 |
| - Discourse-level Reward | 78.91 | 75.40 | 77.12 |

Table 2: Performance of the ablated models on the development set of ACE 2005 (using the sequence-labeling formulation).

| Model                  | P   | R   | F1  |
|------------------------|-----|-----|-----|
| Only-Right             | 80.33 | 74.28 | 77.19 |
| Only-Left              | 79.43 | 74.92 | 77.11 |
| Neighbor Sentences     | 76.49 | 75.31 | 75.90 |
| Most Similar           | 78.86 | 73.45 | 76.06 |
| Highest Coreference    | 78.88 | 73.28 | 75.98 |
| ED3C                   | 81.23 | 76.60 | 78.85 |

Table 3: Model performance on the development set of ACE 2005 (with the sequence-labeling setting).

| Document | Gold Label |
|----------|------------|
| Discover. Social Engineering | Red |
| Discover. Backdoor | Red |

Table 4: Case study in CySecED. Trigger words are shown in red. Their hosting sentences are the target sentences $S_i$ for ED. Parts of the documents that are relevant to correctly infer the event types are shown in orange. The sentences containing those parts are successfully selected as important context sentences by ED3C.

Finally, this model eliminates the reward $R_i^{disc}$ to prefer sentences with more discourse-level connections from $R_i(C)$.

The performance of the models are reported in Table 2. It is clear from the table that removing any of the components will hurt the model performance significantly, thus demonstrating their importance for the proposed method. In particular, among all ablated models, the removal of the task-level reward results in the most significant performance loss. This is expected as performance for ED is the most important and direct criteria to determine the salience of a context sentence in our task.

4 Analysis

Context Selection: To demonstrate the benefit of training the context sentence selection, we examine typical heuristics for choosing context sentences in a document $D$ for the target sentence $S_i$ in ED. As such, given the target sentence, these heuristics
can directly suggest a set of context sentences (i.e., no training). The prediction model $M^{ED}$ is then trained on the augmented texts of the suggested context and the target sentence for ED. Note that in these heuristics, context sentences are selected until the BERT$_{base}$ length limit is exceeded; the selected context sentences and target sentence are organized using their order in $D$ to form the augmented short document $D'$ for BERT. In particular, we explore the following selection heuristics in this section: (1) **Only-Right** and **Only-Left**: These approaches only augment the target sentence $S_i$ with its right context sentences (i.e., $S_j \in D$ with $j > i$) and its left context sentences (i.e., $S_j \in D$ with $j < i$); (2) **Neighbor Sentences**: This approach is described in the baselines for ED3C above. It uses both left and right context sentences to augment $S_i$ where the remaining space for context sentences in BERT length limit (i.e., $l_i = 512 - |S_i|$) is distributed evenly for the two context types; (3) **Most Similar**: In this baseline, we select the top context sentences $S_j \in D$ that have the highest similarity with the target $S_i$. As such, we first obtain a representation vector for each sentence $S_j$ by feeding $S_j$ to the pre-trained BERT$_{base}$ model and using the hidden vector for the [CLS] token in the last layer for this purpose. Afterward, the similarity between $S_j$ and $S_j$ is computed via the cosine similarity of their representation vectors; and (4) **Highest Coreference**: Finally, the selection strategy in this approach ranks context sentences $S_j \in S_{context}$ according to $COR(S_j, S_i)$, the normalized number of entities mentioned in both $S_j$ and $S_i$ (i.e., used to compute the reward $R^{disc}_{j}$). The context sentences with the highest $COR(S_j, S_i)$ scores are chosen for augmenting $S_i$.

The results of this analysis are provided in Table 3. As can be seen, the proposed model ED3C outperforms all heuristics-based baselines for context selection, thus demonstrating the benefit of a dynamic and learnable component for context selection in ED3C. Interestingly, selecting only right or left context achieves better results than “Neighbor Sentences”. It suggests that important context sentences might be far away from the target sentence in the document. Centering the target sentence in the context window thus might not be able to reach those sentences, further highlighting the advantage of ED3C on identifying relevant context that is arbitrarily far away for ED.

**Case Study**: To better understand the operation of ED3C, we manually analyze the examples in the development set of CySecED whose event types are not correctly predicted by the baselines (BigBird, Reformer, Longformer, and “Neighbor Sentence”), but can be successfully recognized by ED3C. Two examples for this category is presented in Table 4. The most important insight from our analysis is that the context sentence selection of ED3C allows the model to identify relevant sentences (i.e., as demonstrated in Table 4) and pack them into the short document $D'$ for effective representation learning with BERT. This is in contrast to the baseline models (e.g., Longformer and “Neighbor Sentence”) that augment the target sentence $S_j$ with all neighbor sentences. Noisy/irrelevant sentences might thus be included and impair induced representation vectors for ED. For instance, in Table 4, the immediately preceding sentences are not relevant to the event prediction of the target sentences, but are still introduced into the input texts for transformer-based models. Due to the trained context selection, ED3C can avoid those irrelevant sentences to perform ED correctly in these cases.

5 **Related Work**

ED has been approached with feature-based models earlier (Ahn, 2006; Patwardhan and Riloff, 2009; Liao and Grishman, 2010b; Hong et al., 2011; Li et al., 2013; Yang and Mitchell, 2016). Recently, deep learning (DL) methods are proved to be an effective approach for ED (Nguyen and Grishman, 2015; Chen et al., 2015; Nguyen et al., 2016a; Nguyen and Grishman, 2018; Sha et al., 2018; Zhang et al., 2019; Nguyen and Nguyen, 2019; Yang et al., 2019; Zhang et al., 2020; Le and Nguyen, 2021). Transformer-based language models such as BERT (Devlin et al., 2019) are the core components for current SOTA deep learning models for ED (Lai et al., 2020b; Veyseh et al., 2021). Recently, there have been growing interests to solve ED in the low-shot learning settings to improve the data efficiency of the models (Lai et al., 2020a, 2021). The majority of prior DL models for ED are restricted to sentence-level context. In recent years, encoding document context with DL has also been shown to be helpful for ED (Chen et al., 2018; Zhao et al., 2018; Zheng et al., 2019). However, existing DL methods for document-level ED have not employed transformer-based models, or only utilized them a limited manner (i.e., focusing on short documents or truncating long documents to
fit the BERT length limit).

As described in the introduction, two main approaches have been explored to address the length limitation for transformer-based models: (1) transformers with modified self-attention (Beltagy et al., 2020; Kitaev et al., 2020; Wang et al., 2020a; Tay et al., 2020), and (2) truncating or hierarchical modeling (Adhikari et al., 2019; Luoma and Pyysalo, 2020; Jörke et al., 2020). The major drawback of these approaches involves the inability to capture important context of arbitrarily distance from the target and the failure to entirely consume important context with BERT and self-attention for effective representation learning. These issues are address by ED3C to boost the performance for ED.

6 Conclusion

We introduce a novel method, i.e., ED3C, to model document context for ED with BERT. Our model seeks to group important context sentences for the target sentence into a short document that can be entirely encoded by BERT to produce effective representation vectors for ED. As such, ED3C presents a context selection component that sequentially selects relevant sentences in the document based on LSTM. We use REINFORCE to train the context selection component in ED3C. Our extensive experiments demonstrate the effectiveness of ED3C with SOTA performance on benchmark datasets for ED. In future, we plan to apply the proposed model on other related tasks (e.g., Event Extraction).

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