Efficient Document-level Event Extraction via Pseudo-Trigger-aware Pruned Complete Graph

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Abstract

There are two main challenges in document-level event extraction: 1) argument entities are scattered in different sentences, and 2) event triggers are often not available. To address these challenges, most previous studies mainly focus on building argument chains in an autoregressive way, which is inefficient in both training and inference. In contrast to the previous studies, we propose a fast and lightweight model named as PTPCG. We design a non-autoregressive decoding algorithm to perform event argument combination extraction on pruned complete graphs, which are constructed under the guidance of the automatically selected pseudo triggers. Compared to the previous systems, our system achieves competitive results with lower resource consumption, taking only 3.6% GPU time (pfs-days) for training and up to 8.5 times faster for inference. Besides, our approach shows superior compatibility for the datasets with (or without) triggers and the pseudo triggers can be the supplements for annotated triggers to make further improvements.

Introduction

Event Extraction (EE) is an important task in Information Extraction (IE), which aims at filling event tables with given texts. Different from sentence-level EE (SEE) which focuses on building trigger-centered trees as shown in Figure 1a (Chen et al. 2015; Nguyen, Cho, and Grishman 2016; Liu, Luo, and Huang 2018; Wadden et al. 2019; Lin et al. 2020), document-level EE (DEE) is to decode argument combinations from abundant entities across multiple sentences and fill these arguments into event record tables as shown in Figure 1b, where annotated triggers are often not available.

Compared to SEE, DEE identifies argument entities which may have multiple mentions scattered in different sentences as shown in Figure 1b. For instance, “Hello Group” appears in two sentences. In the widely used dataset ChFinAnn (Zheng et al. 2019), 35.8% of arguments have more than one mention, and 98.2% of event records have arguments scattered across different sentences, making global encoding and entity extraction more difficult. Another challenge for DEE is event argument combination without triggers. In Figure 1a, pledged is a trigger word that most expresses the event occurrence, and the argument combination can be obtained by building a trigger-centered tree. However, such triggers in DEE datasets are either absent or in a low annotation quality since the large-scale datasets are usually generated via distantly supervised (DS) alignment with existing knowledge bases (KB) (Mintz et al. 2009; Chen et al. 2017). For the documents containing multiple records, some entities may be shared, and the absence of triggers makes it harder to extract combinations from these entities. Consequently, the absence of triggers drives the development of trigger-free argument combination methods in recent studies. Yang et al. (2018) first identify a key sentence and then fill the event record table by finding arguments near the sentence, while partial global features and arguments are still missing. Zheng et al. (2019) and Xu et al. (2021) fully utilize the global context and make significant improvements by building an directed acyclic graph (DAG). However, such DAG-based methods require massive computing resources as they rely on an autoregressive fashion to decode argument combinations, which is inefficient in both training and inference for long documents. Meanwhile, building DAGs consumes lots of memories to store previous...
In this paper, we propose a novel non-autoregressive model named as Pseudo-Trigger-aware Pruned Complete Graph (PTPCG). Specifically, we formulate each argument combination as a pruned complete graph, where the important arguments are identified and treated as a group of pseudo triggers with bidirectional connections to each other and other ordinary arguments are linked from these pseudo triggers in a directed manner. Based on the pruned complete graph with the pseudo triggers, we design an efficient algorithm with the non-autoregressive decoding strategy for event argument combination extraction.

The experimental results show that our PTPCG can reach competitive results with only 19.8% parameters of DAG-based SOTA models, just taking 3.6% GPU time (pfs-days) to train and up to 8.5 times faster in terms of inference. Besides, our PTPCG is highly flexible and scalable that can be used as a general architecture for non-autoregressive trigger-based event extraction. If the number of pseudo triggers is one for each combination, the pruned complete graph becomes a trigger-centered tree. Furthermore, for DEE datasets with poorly annotated triggers, pseudo triggers can be adopted as supplements to enhance the annotated-trigger-based methods. It is worth noting that PTPCG can get 2.7% performance gain without these low-quality annotated triggers when the annotated triggers have lower importance than the pseudo ones. Codes, model weights and supplement materials are available at: https://github.com/Spico197/DocEE

In summary, our contributions include:

• We propose a novel non-autoregressive event argument combination paradigm based on pruned complete graph with pseudo triggers, which is compatible in document-level event extraction with (or without) triggers.

• To our best knowledge, our present approach is the first work that explores the effects of using some arguments as pseudo triggers in DEE, and we design a metric to help select a group of pseudo triggers automatically. Furthermore, such metric can also be used for measuring the quality of annotated triggers in DEE.

• Our model is fast and lightweight for end-to-end document-level event extraction and we conduct extensive experiments to show the efficiency and efficacy.

Methodology

As shown in Figure 2, our model can be divided into four components: 1) Event detection performs multi-label classification to identify all possible event types. 2) Entity extraction extracts all entities from the documents and encodes these entities into dense vectors. 3) Combination extraction builds pruned complete graphs and decodes argument combinations from such graphs. 4) Event record generation combines the results of event types and extracted argument combinations to generate the final event records.

Event Detection

For a document D, a bidirectional long short-term memory (BiLSTM) network (Hochreiter and Schmidhuber 1997) is used to encode each sentence s_i into token-wise hidden states (h_i(1), h_i(2), ..., h_i(∥s_i∥)), where h_i(j) ∈ R^{d_h} is the concatenation of two direction representations h_i(j)_+||h_i(j)_− and |s_i| is the length of i-th sentence. The last hidden states in each direction are concatenated to get the sentence representation g_i ∈ G as g_i = h_i[∥s_i∥]|h_i(0).

Subsequently, we follow Doc2EDAG (Zheng et al. 2019) and use event queries with multi-head attention on G to make a binary classification for each event type. The loss function of event detection component L_{det} is defined as a binary cross entropy loss.

Entity Extraction

Mention Extraction. The entity mention extraction task can be formulated as a sequence tagging task in BIO scheme (Zheng et al. 2019). To enhance the entity mention recognition, we add more money, date, percentage ratio and shares entities into the dataset by simple regular expression matching. To deal with the document-level entity extraction, we first split the whole document into sentences and perform a sentence-level mention extraction. Then, we use BiLSTM with CRF (Lample et al. 2016) as sentence encoder instead of transformer and CRF as in Zheng et al. (2019) for reducing the number of parameters, and the parameters of BiLSTM are shared with the event detection task. The training objective of entity extraction is to minimize the negative log-likelihood loss L_{ent} of CRF for each sentence.

Entity Representation: For all tokens of a mention, a max-pooling operation is applied on token-level representations to get the mention representation ˜m_j. As mention types have been proved effective for downstream sub-modules (Zheng et al. 2019; Xu et al. 2021), we convert the predicted discrete mention types into vectors by looking up an embedding table. After concatenating ˜m_j and type embeddings l_j, we get the final mention representation m_j = ˜m_j||l_j ∈ R^{d_m}, where d_m = d_h + d_t and d_t denotes the dimension of l_j. Finally, all the mentions for an entity are aggregated to get the entity representation ˜e_i via another max-pooling. For better modeling entity semantics, an additional BiLSTM layer is applied to get the set of entity representations E = { ˜e_i | 1 ≤ i ≤ |E|}.

Combination Extraction

In this section, we introduce the details of selecting pseudo triggers, building pruned complete graphs, and decoding combinations from the graphs.

Pseudo Trigger Selection It is hard to locate conventional triggers in documents due to the document length and dataset scale. We instead select a group of pseudo triggers for each event type in an automatic way.

Empirically, the triggers are keywords that play two roles: 1) triggers can be used to identify combinations; 2) triggers are fingerprints that can distinguish different combinations. Combinations are made of arguments and we can extract
Figure 2: Overview of our PTPCG. Event types and entity mentions are first extracted with a shared LSTM encoder, then similarities between entity pairs are calculated to help recover the adjacent matrix of pruned complete graph. After combinations are decoded from the adjacent matrix, the extracted types are paired with combinations to generate final event records.

a specific combination by finding all the corresponding arguments, so arguments are able to identify and distinguish combinations naturally. To this end, we design an importance metric that evaluates the possibility of whether a group of arguments can serve as the pseudo triggers. In general, we first select a group of argument roles as candidates for each event type according to the importance scores, and take the corresponding arguments as the pseudo triggers.

Formally, the importance score is obtained by the existence and the distinguishability. For a subset of predefined argument roles in type $t_i$, $\mathcal{R} = \{r_j\}_{j=1}^{|\mathcal{R}|}$ are selected as the pseudo trigger candidates. The existence (Eqn 1) measures whether the arguments of $\mathcal{R}$ can identify combinations. $N_c^{(i)}$ is the number of event records that at least one corresponding argument of $\mathcal{R}$ is not NULL, and $N^{(i)}$ is the number of total records of $t_i$. The distinguishability (Eqn 2) is defined to satisfy that the triggers can distinguish different combinations, where $N_d^{(i)}$ is the number of records that the arguments of $\mathcal{R}$ do not appear in other records in the same document. With the multiplication of existence and distinguishability, pseudo triggers are selected by picking the candidate with the highest importance score.

$$\text{Existence}(\mathcal{R}) = \frac{N_c^{(i)}}{N^{(i)}}, \quad \text{Distinguish}(\mathcal{R}) = \frac{N_d^{(i)}}{N^{(i)}}$$ (1)

$$\text{Importance}(\mathcal{R}) = \text{Existence}(\mathcal{R}) \times \text{Distinguish}(\mathcal{R})$$ (2)

**Pruned complete graph building**  Based on the DEE task setting and data analysis, we propose an assumption that arguments in the same combination are close to each other in the semantic space. Following this assumption, we take the pseudo triggers as the core of argument combinations and formulate each combination as a pruned complete graph. As shown in the pruned complete graph of Figure 2, for any two pseudo triggers $a_t^{(i)}$ and $a_t^{(j)}$ in the same combination, they are bidirectionally connected, where the adjacent matrix $y_A^{(i,j)} = y_A^{(j,i)} = 1$. For a pseudo trigger $a_t^{(i)}$ and an ordinary argument $a_o^{(j)}$ in the same combination, they are connected with a directional link and $y_A^{(i,j)} = 1$. Besides, each argument $a_t^{(i)}$ has a self-loop connection where $y_A^{(i,i)} = 1$. Other entries in $y_A$ are zeros, where entities that do not participate in any combination are isolated nodes in the graph.

After obtaining entity representations, a dot scaled similarity function (Eqn 3) is applied to estimate their semantic distances:

$$\hat{e}_i = e_i \times W_a^T + b_a, \quad \hat{e}_j = e_j \times W_e^T + b_e$$ (3)

$$\hat{A}_{i,j} = \text{sigmoid}\left(\frac{\hat{e}_i^T \hat{e}_j}{\sqrt{d_h}}\right)$$ (4)

where $\hat{A}$ denotes the similarity matrix, $W_a, W_e \in \mathbb{R}^{d_a \times d_a}$ and $b_a, b_e \in \mathbb{R}^{d_a}$ are trainable parameters for semantic space linear projection.

In training, we use binary cross entropy function to formulate the combination loss:

$$\mathcal{L}_{\text{comb}} = -\frac{1}{|\mathcal{A}|} \sum_j \sum_i \left[ y_A^{(i,j)} \log \hat{A}_{i,j} + (1 - y_A^{(i,j)}) \log(1 - \hat{A}_{i,j}) \right]$$ (5)

To predict the binary adjacent matrix $A$ of the pruned complete graph for further decoding, the threshold $\gamma$ is used here (Eqn 6).

$$A_{i,j} = \begin{cases} 1 & \hat{A}_{i,j} \geq \gamma \\ 0 & \text{otherwise} \end{cases}$$ (6)

**Non-Autoregressive Combination Decoding**  Event argument combinations are extracted based on the predicted adjacent matrix $A$ with a non-autoregressive decoding algorithm as shown in Algorithm 1.
First, all the pseudo triggers are identified based on nodes’ out-degree and each pseudo trigger group is recognized as a clique. If the out-degree of an entity is greater than 0 except for self-loop, then the entity is treated as a pseudo trigger. For $|R| = 1$, all the combinations are pseudo-trigger-centered trees (Algorithm1 line 9-13), where each combination is made of a pseudo trigger with its neighbors. Otherwise, Bron-Kerbosch (BK) algorithm (Bron and Kerbosch [1973]) at line 17 is applied first to find all possible cliques. To apply BK algorithm, the links between arguments must be undirected, thus we first extract all bidirectional links as undirected input as shown at line 16 of Algorithm 1.

As shown in Figure 3, the next step is to find the ordinary arguments in the combination. We further exploit all the neighbors of each pseudo trigger in the clique. After that, a connection operation is performed to find commonly shared ordinary arguments. The combination is consist of a pseudo trigger clique and their commonly shared ordinary arguments. For those extreme records that have only one argument in the combinations, all predicted entities are aggregated together as a default combination.

Since there is no multi-step graph link dependencies as in DAG-based methods, this non-autoregressive decoding design could speed up both training and inference.

**Event Records Generation**

After the set of combinations $C$ are obtained from the pruned complete graphs, the next step is to fill these combinations into event tables. First, all the combinations should match with event types. Since event detection is a multiple-label classification task, there may be more than one type prediction. For all type predictions $T_p = \{t_j\}_{j=1}^{T_p}$ and combinations $C$, we perform a Cartesian product and get all type-combination pairs $\{< t_j, c_k > | 1 \leq j \leq |T_p|, 1 \leq k \leq |C|\}$.

For each pair $< t_j, c_k >$, we use an event-relevant feed-forward network (FFN) as classifier to get possible role results for all arguments $E_{k}$. And the loss function here is a binary cross entropy as below.

$$p_{role}(r_j|c_k) = \text{sigmoid}(\text{FFN}_j(E_k))$$  

(7)

(8)

1. We tried to use a type-relevant combination extraction module to make less confusion, but did not get much performance gain, so we take a Cartesian product operation here and keep the simplicity.

**Algorithm 1: Combination decoding**

**Input**: adjacent matrix $A$, number of pseudo triggers $|\mathcal{R}|$, number of entities $|\mathcal{E}|$

**Output**: A set of combinations $C$

1: Initialize $C \leftarrow \{\}$, pseudo triggers $\mathcal{O}_p \leftarrow \{\}$ and updated pseudo trigger set $\mathcal{U} \leftarrow \{\}$
2: //get all pseudo triggers from $A$
3: for $i = 1$ to $|\mathcal{E}|$ do
4: if $\sum_{i} A_i \setminus A_i > 0$ then
5: $\mathcal{O}_p \leftarrow \mathcal{O}_p \cup i$
6: end if
7: end for
8: if $|\mathcal{R}| = 1$ then
9: for $o_j$ in $\mathcal{O}_p$, do
10: // $\mathcal{N}(u)$ denotes the directional neighbors of node $u$
11: $c \leftarrow \{o_j\} \cup N(o_j)$
12: $C \leftarrow C \cup c$
13: end for
14: else
15: //find max cliques
16: $A’ = A \& A^T$
17: $C_{max} \leftarrow \text{BronKerbosch}(A’)$
18: for $c_k$ in $C_{max}$ do
19: $\mathcal{U} \leftarrow \mathcal{U} \cup c_k$
20: $N \leftarrow \text{find neighbors that are connected from all pseudo triggers in } c_k$
21: $C \leftarrow c_k \cup N$
22: end for
23: //single trigger-aware combinations that are mixed with the others
24: for $u$ in $\mathcal{O}_p \setminus \mathcal{U}$ do
25: $c \leftarrow \{u\} \cup \mathcal{N}(u)$
26: $C \leftarrow C \cup c$
27: end for
28: end if
29: return $C$

$$L_{role} = - \sum_{k} \sum_{j} \left[ y_{role}^{(j,k)} \log p_{role}^{(j)}(t_j|c_k) + (1 - y_{role}^{(j,k)}) \log \left(1 - p_{role}^{(j)}(t_j|c_k)\right) \right]$$

(8)
be dropped.

\[ i^* = \arg \max_{q} i_{role}(j_i) | q_k \]  \hspace{1cm} (9)

**Optimization**

Our PTPCG is an end-to-end model with joint training and scheduled sampling (Bengio et al. 2015) strategy. The overall loss is a weighted sum of all losses as below:

\[ \mathcal{L} = \alpha_1 \mathcal{L}_{det} + \alpha_2 \mathcal{L}_{ent} + \alpha_3 \mathcal{L}_{comb} + \alpha_4 \mathcal{L}_{role} \]  \hspace{1cm} (10)

where \( \alpha_1, \alpha_2, \alpha_3, \alpha_4 \) are hyper-parameters to reduce the unbalanced loss effect.

**Experiments**

**Datasets**

We use ChFinAnn (Zheng et al. 2019) to get main results and DuEE-fin (Li 2021) for compatibility evaluation.

1. **ChFinAnn** is by far the largest DEE dataset constructed by distantly supervised alignment without trigger annotations. This dataset contains 32k financial announcements and 48k event records, in which 29% documents have more than one record and 98% of records have arguments scattered across different sentences. On average a document contains 20 sentences and the longest document contains 6.2k Chinese characters.

2. **DuEE-fin** is another dataset for DEE with trigger annotations. It contains 13 event types and 11.7k documents, where the test set is evaluated online. Each record in DuEE-fin has a labeled trigger word without specific positions, and 36% of records share the same trigger in a document.

**Experiment Settings**

We choose the hyper-parameters of our system according to the performance on the development set in ChFinAnn. In PTPCG, we use 2 layers of shared BiLSTM for event detection and entity extraction, and another 2 layers of BiLSTM for entity encoding. We use the same vocabulary as (Zheng et al. 2019) and randomly initialize all the embeddings where \( d_{e}=768 \) and \( d_l=32 \). Adam (Kingma and Ba 2015) optimizer is used with a learning rate of 5e-4 and the mini-batch size is 64. The weights in Equation (10) are 0.5, 1.0, 1.0, and 1.0. Following the setting in Zheng et al. (2019), we train our models for 100 epochs and select the checkpoint with the best F1 score on the development set to evaluate on the test set. For more experiment setting and hyper-parameter details, please refer to the supplementary material.

**Baselines and Metrics**

**Baselines:**

1. **DCFEE** (Yang et al. 2018) has two variants here: DCFEE-O extracts only one record from one document while DCFEE-M extracts records as much as possible.

2. **Doc2EDAG** (Zheng et al. 2019) constructs records as argument chains (DAG) and uses an auto-regressive way to extract final results.

3. **GreedyDec** is a baseline from Zheng et al. (2019) which fills one event table greedily.

4. **GIT** (Xu et al. 2021) is another variant of Doc2EDAG and utilizes a graph neural network to further encode entities and add more features in DAG generation.

5. **DE-PPN** (Yang et al. 2021) uses limit number of record queries to extract combinations. We further discuss these systems in the related work and please refer to the papers for more details.

**Metrics:**

We use the same evaluation setting as in the previous studies (Zheng et al. 2019; Xu et al. 2021; Yang et al. 2021). For each predicted record, a golden record is selected without replacement by matching the record that has the same event type and the most shared arguments. F1 scores are calculated by counting correct arguments and we report the overall F1 scores.

**Main Results**

Compared to the previous works in Table 1, the results show that our PTPCG achieves the best macro- and micro-F1 scores on documents with single record. In multi-record documents, our PTPCG is less powerful, showing 1.0% and 1.7% drop in macro- and micro-F1 scores compared to Doc2EDAG. For overall micro-F1 scores, our model outperforms Doc2EDAG and is very close to GIT.

Among all the models, PTPCG is the most lightweight one and is in the same scale with DCFEE, while the overall results outperforms DCFEE with 19.2% and 16.2% absolute gain in macro- and micro-F1 scores. Without considering 16M vocabulary embedding parameters, PTPCG takes only 33.3% and 19.8% parameters of Doc2EDAG and GIT respectively and reaches the competitive results.

As \(|\mathbb{R}|\) ranges from all (complete) to 1, metric results are continuously going up in both macro- and micro-F1 scores. This indicates that the complete graph assumption may be too strong, and semantic distances in combinations can be modeled better when connections are pruned.

**Comparison on Speed**

Benefiting from the lightweight architecture design and non-autoregressive decoding style, our PTPCG is fast in both

| Model            | #Params(w/oE) | S      | M      | All    | S      | M      | All    |
|------------------|--------------|--------|--------|--------|--------|--------|--------|
| DCFEE-O          | 12M(16M)     | 62.5   | 41.0   | 51.4   | 72.4   | 52.4   | 63.2   |
| DCFEE-M          | 32M(16M)     | 57.9   | 47.7   | 55.3   | 68.1   | 52.6   | 60.7   |
| GreedyDec        | 64M(48M)     | 75.1   | 38.1   | 60.4   | 80.4   | 37.7   | 63.0   |
| Doc2EDAG         | 64M(48M)     | 81.1   | 67.1   | 76.0   | 86.2   | 70.8   | 79.0   |
| GIT              | 97M(81M)     | 83.1   | 76.1   | 78.2   | 86.8   | 72.3   | 79.9   |
| DE-PPN\( \|\mathbb{R}\|=3 \) | -       | 83.9   | 68.7   | 77.9   | -      | -      | -      |
| PTPCG\( \|\mathbb{R}\|=3 \) | 32M(16M)     | 74.1   | 62.2   | 69.5   | 78.7   | 60.1   | 69.5   |
| PTPCG\( \|\mathbb{R}\|=5 \) | -       | 75.2   | 63.0   | 70.4   | 81.6   | 64.0   | 73.1   |
| PTPCG\( \|\mathbb{R}\|\leq4 \) | -       | 76.6   | 62.3   | 71.1   | 82.6   | 64.7   | 74.0   |
| PTPCG\( \|\mathbb{R}\|\leq3 \) | -       | 78.7   | 63.5   | 72.8   | 83.1   | 65.9   | 74.9   |
| PTPCG\( \|\mathbb{R}\|\leq2 \) | -       | 81.6   | 65.0   | 75.1   | 86.3   | 68.1   | 77.7   |
| PTPCG\( \|\mathbb{R}\|\leq1 \) | -       | 84.1   | 66.1   | 76.6   | 88.2   | 69.1   | 79.4   |

Table 1: Comparison with previous works on ChFinAnn. w/oE is the number of parameters without vocabulary embeddings. S and M denote the evaluation results on documents with only one or multiple records respectively. To better compare the results, we reproduce the results of baselines using their open-source codes. DE-PPN does not report micro scores in the paper, and we are trying to reproduce the results.
Table 2: Comparison on training time. Doc2EDAG and GIT do not support trigger centred graph construction, hence we take the trigger as the first argument role for each trigger selection, we select groups of pseudo triggers with the middle and the lowest importance scores instead of the annotated triggers, and we think this is the reason that leads the outcome, which also validates the efficacy of our trigger selection strategy based on importance scores. Compared to DAG-based models, PTPCG reaches the best F1 scores in online evaluation. Besides, we find the pseudo triggers (Tgg is $\boxtimes$) could assist the trigger words to identify combinations and bring 0.7% improvement in offline dev evaluation and 0.8% improvement in the online test set. Pseudo-trigger-only results have similar patterns as in Table 1 where the growing number of $|\mathcal{R}|$ might be challenging for similarity calculation and adjacent matrix prediction that leads to a performance decline.

| Model      | Tgg | $|\mathcal{R}|$ | Impt. | Dev   | Online Test |
|------------|-----|----------------|-------|-------|-------------|
| Doc2EDAG   | $\times$ | - | - | 70.8 | 55.3 | 62.1 | 66.7 | 50.0 | 57.2 |
| GIT        | ✓   | 2 | 73.7 | 59.8 | 66.0 | 67.1 | 51.3 | 58.1 |
| PTPCG      | ✓   | - | - | 77.4 | 64.1 | 67.7 | 70.3 | 46.0 | 55.6 |

Table 3: Results on DuEE-fin. Tgg means whether annotated triggers are used. Impt. denotes the importance. Doc2EDAG and GIT do not support trigger centred graph construction, here we take the trigger as the first argument role for each type and build DAGs.

Validation of Importance Scores and $|\mathcal{R}|$ Selection

To validate the effectiveness of importance scores for pseudo trigger selection, we select groups of pseudo triggers with the middle and the lowest importance scores instead of the highest ones and analyze the results in Table 1. The results show that there is a positive correlation between the importance and overall scores within the same $|\mathcal{R}|$. However, the highest importance score (88.3%) is not equal to 100.0%, which may limit the upper bound of decoding. We will explain more about error analysis in the future discussion section.

| $|\mathcal{R}|$ | Impt. | Macro   | Micro   |
|----------------|-------|---------|---------|
|                | S | M | All | S | M | All |
| 1              | 88.3 | 84.1 | 66.1 | 76.6 | 88.2 | 69.1 | 79.4 |
| 2              | 85.7 | 81.6 | 65.0 | 75.1 | 86.3 | 68.1 | 77.7 |
| 3              | 76.1 | 80.2 | 58.0 | 72.0 | 88.7 | 53.9 | 73.9 |
| 4              | 40.1 | 84.2 | 49.2 | 70.1 | 89.2 | 51.7 | 73.4 |

Table 4: PTPCG results with different importance levels on ChFinAnn.

Figure 4: Inference speed comparison with Doc2EDAG (left) and with different $|\mathcal{R}|$ (right). Experiments are conducted on 1 NVIDIA V100 GPU for all models.

Training and Inference

As Table 2 shows, it takes 90.6 minutes for Doc2EDAG to train one epoch with 4 GPUs, while PTPCG only takes 14.9 minutes with one GPU, which is 6.1 times faster than Doc2EDAG and 8.8 times faster than GIT in terms of training speed. Besides, PTPCG takes only 14.1 hours to get the best checkpoint, while Doc2EDAG needs 123.8 hours and GIT needs 152.2 hours. Furthermore, PTPCG is 26.2 and 27.4 times smaller than Doc2EDAG and GIT in pfs-days.

These facts indicate that PTPCG is more efficient in training and requires much lower computation resource cost than Doc2EDAG and GIT.

According to the inference speed test in Figure 4, PTPCG is more scalable than other models. With the growth of batch size, PTPCG becomes faster and finally stabilized near 125 documents per second, while Doc2EDAG and GIT are barely growing with batch size, peaking at 19 and 15 docs/s respectively. PTPCG is up to 7.0 and 8.5 times faster than Doc2EDAG, GIT is 21.2% slower than Doc2EDAG on average, and raises OOM error on a 32GB memory GPU of Doc2EDAG, GIT is 21.2% slower than Doc2EDAG on average, and raises OOM error on a 32GB memory GPU.
### Ablation Study

Here we perform an ablation study to verify correctness of three mechanisms or sub-modules: (1) **AdditionalEntities**: add additional entities by regular expression matching in the entity extraction task; (2) **EntityBiLSTM**: further encoding on extracted entities; and (3) **DefaultCombination**: If no combinations are decoded out, then all the entities are combined to become a default combination.

Table 5 shows the results. We find that entity extraction is an important component in DEE, and the model can get higher overall scores if we increase the supervised signal by adding similar entities that do not participate in any combination. Further encoding is confirmed to be useful in GIT (Xu et al. 2021), and the results here show that using an additional BiLSTM module is better for representation encoding. Default combination is designed for extreme cases in the dataset, which also shows its efficacy in single-record documents improvements.

| Model             | Macro  | Micro  |
|-------------------|--------|--------|
|                  | S  | M  | All  | S  | M  | All  |
| PTCPG\(|R| = 1\)   | 84.1 | 66.1 | 76.6 | 88.2 | 69.1 | 79.4 |
| - AdditionalEntities | -1.8 | -0.1 | -1.0 | -1.6 | -0.6 | -1.2 |
| - EntityBiLSTM    | -5.9 | -12.1 | -8.6 | -5.1 | -9.9 | -7.6 |
| - DefaultCombination | -2.0 | +0.2 | -1.0 | 1.0 | +0.9 | -0.3 |

Table 5: Ablation study on PTCPG\(|R| = 1\).  

### Future Discussion

Although pruned complete graph structure is efficient for training and inference, it is not perfect in similarity calculation (adjacent matrix prediction) and combination decoding. Here we analyze the upper bounds of Algorithm 1 and discuss the future directions for better modeling.

Results in Table 6 show that models with the lower number of pseudo triggers are better. However, Table 6 shows that models with more pseudo triggers have higher upper bounds for decoding and have higher importance scores. Why models with more pseudo triggers have greater importance but still result in lower performance? Results in Table 6 and 7 may answer this question. Models with the same \(|R| = 1\) has a strong correlation that higher importance brings higher metric scores which validates the effectiveness of the pseudo trigger selection strategy based on importance scores. However, more pseudo triggers bring more links to connect, and the model is not robust enough for predicting each connection correctly, leading to an adjacent accuracy decline.

Overall, it is a trade-off that more pseudo triggers improves the upper bounds and reduces combination error rates, but also brings new challenges to recover connections between entities and it becomes harder to retrieve perfect graphs. We believe it is the future direction to improve the similarity calculation and adjacent matrix prediction.

### Related Work

DS-constructed datasets can hardly match triggers to records, so triggers are likely to be absent. Yang et al. (2018) propose a simple model to extract event records using entities in a window of key sentences. It is efficient but misses lots of information from other sentences. To fully utilize all entities in the whole document, Doc2EDAG (Zheng et al. 2019) uses all entities in documents and formulates the argument combination to be a directed acyclic graph (DAG), making great progress in DEE. GIT (Xu et al. 2021) is a variant of Doc2EDAG where a graph neural network is added to help entity encoding and further exploit the global memory mechanism during decoding. DAG extracts combinations in an auto-regressive way, which is very time consuming and needs huge space in global memory module to store all previous paths. Besides, Doc2EDAG and GIT are both large models with lots of parameters, where Doc2EDAG and GIT use 12 and 16 layers of transformer encoders. To train such models, a minimum of four 32GB GPUs would have to be run for almost a week. DE-PPN (Yang et al. 2021) is a multi-granularity model that can generate event records via limit number of record queries. It outperforms Doc2EDAG but still needs lots of computing resources since the model contains 8 layers of transformer encoder, 4 layers of transformer decoder and 4 layers of self-designed attention-based decoder. Besides, DE-PPN must set the maximal number of event records in advance, which is less flexible to adapt datasets automatically. To speedup trigger-free argument combination decoding, we propose a pruned complete graph-based non-autoregressive model, which is up to 8.5 times faster for inference compared to GIT and get competitive overall evaluation results. Besides, our approach is flexible for decoding and is not limited by preset maximal number of event record.

### Table 6: Analysis of combination decoding errors on ChFiAnn. SE, ME, TotE are error rates on single-record documents, multiple-record documents, and overall error respectively. #links is the number of connected links among all graphs in the test set. Adj Acc is the accuracy of adjacent matrix prediction given golden entities.

| N  | Imp. | SE  | ME  | TotE | #links | Adj Acc. |
|----|------|-----|-----|------|--------|----------|
| 1  | 88.3 | 5.0 | 37.5 | 14.6 | 10,502 | 65.8     |
| 2  | 95.7 | 1.0 | 20.4 | 6.7  | 23,847 | 59.1     |
| 3  | 97.2 | 0.9 | 18.0 | 5.9  | 55,961 | 56.7     |
| 4  | 97.6 | 0.5 | 16.9 | 5.3  | 75,334 | 58.2     |
| 5  | 97.8 | 0.4 | 13.9 | 4.4  | 88,752 | 59.5     |
| all| 97.8 | 0.2 | 13.4 | 4.1  | 140,989| 60.1     |

### Conclusion

Pursuing fast and general document-level event extraction (DEE), we propose a non-autoregressive model named as PTCPG. For DEE without triggers, we first select a group of pseudo triggers to build pruned complete graphs, and then train a lightweight model to extract all possible combinations, which enables non-autoregressive decoding and is up to 8.5x faster compared to SOTA models. For DEE with annotated triggers, pseudo triggers also show the power to make improvement and are even better than annotated trigger-only method.

Although PTCPG is not perfect in adjacent matrix prediction, we believe it has the ability to combine different DEE tasks and needs more explorations.
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