

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

Supplementary Material

Abstract

In this supplementary material, we introduce more about the implementation details for better understanding our approach and reproducibility.

- Section I provides details of event detection component as used in Doc2EDAG (Zheng et al. 2019), GIT (Xu et al. 2021) and PTPCG;
- Section II lists the regular expressions used in entity extraction section in the main content;
- Section III introduces the pseudo trigger selection and pruned complete graph building process with an example;
- Section IV lists the pseudo trigger roles and corresponding importance scores of the ChFinAnn (Zheng et al. 2019) dataset;
- Section V introduces more about the DAG-based methods and differences compared with PTPCG;
- Section VI introduces the Bron-Kerbosch algorithm;
- Section VII lists all the hyper-parameters used in the experiments;
- Section VIII provides the results of Doc2EDAG, GIT and PTPCG on the development set during training;
- Section IX shows more inference speed test results;
- Section X provides additional PTPCG experimental results.

I Event Detection Details

As introduced in the main content, event detection is a multi-label classification task. In this section, we explain more details about the event type classification.

For all sentence representations $\mathcal{G} = \{g_i\}_{i=1}^{|\mathcal{D}|}$, we follow the same method as reported in Doc2EDAG and GIT. An event query $q_j \in \mathbb{R}^{1 \times d_h}$ of type t_j is applied to an event-related document representation \mathcal{P}_j via the multi-head attention (Vaswani et al. 2017) mechanism with query, key and value as inputs:

$$\mathcal{P}_j = \text{MultiHeadAttention}(q_j, \mathcal{G}, \mathcal{G}) \in \mathbb{R}^{1 \times d_h} \quad (\text{I.1})$$

$$p(\mathcal{P}_j | \mathcal{G}) = \text{sigmoid}(\mathcal{P}_j \times W_p^\top + b_p) \quad (\text{I.2})$$

where $W_p \in \mathbb{R}^{d_h \times d_h}$ and $b_p \in \mathbb{R}^{d_h}$ are trainable parameters.

The cross entropy function is used to calculate the loss of event detection component. To get final prediction results, an argmax operation is applied for each type.

$$\mathcal{L}_{det} = - \sum_{j=1}^{|\mathcal{T}|} y_{type} \log p(\mathcal{P}_j | \mathcal{G}) \quad (\text{I.3})$$

$$o_{type}^j = \text{argmax}(p(\mathcal{P}_j | \mathcal{G})) \quad (\text{I.4})$$

where $|\mathcal{T}|$ denotes the number of event types, y_{type} is the golden type labels, and o_{type}^j is the event type prediction.

II Regular Expression for Additional Entities

In the entity extraction component, we add additional entities into the dataset for data augmentation. These additional entities are matched via regular expressions as listed in Table II.1.

Type	Regular Expression
money	$\backslash d+ (\backslash . \backslash d+)? \text{元}$
date	$\backslash d\{4\} \text{年} \backslash d\{1,2\} \text{月} \backslash d\{1,2\} \text{日}$
percentage ratio	$\backslash d+ (\backslash . \backslash d+)? \%$
shares	$(\backslash d+ \text{股}) [^\wedge \text{票}]$

Table II.1: Regular expressions for additional entities.

III Example of Pseudo Trigger Selection and Pruned Complete Graph Building

For better explaining the pseudo trigger selection and pruned complete graph building, we present a simple example in Figure X.4.

IV Pseudo Triggers and Importance Scores

All the pseudo trigger roles \mathcal{R} and importance scores for each type in the ChFinAnn dataset are listed in Table X.3.

V Different Event Argument Combination Methods

Figure V.1 shows different event argument combination strategies.

With annotated triggers, it is easy to identify combinations by building trigger-centered trees as shown on the top of Figure V.1 (Chen et al. 2015; Nguyen, Cho, and Grishman 2016; Liu, Luo, and Huang 2018; Wadden et al. 2019; Lin et al. 2020). However, annotating the triggers and identifying the event records in documents are difficult and costly. To speedup the annotation process, Chen et al. (2017) borrow the idea of distant supervision (DS) (Mintz et al. 2009) and use an event knowledge base to align raw texts and generate records automatically. However, it is difficult to match the automatically extracted triggers with DS-constructed event records, and the triggers are often not available.

DAG-based argument combination strategy is shown in the left bottom of Figure V.1. For each argument role in type t_i , all the predicted entities are classified via a type-specific role classifier to determine whether such entities are arguments of this role. If there are multiple entities recognized as the same argument role, the DAG is split into two branches. Finally, each path represents a possible argument combination. This strategy makes significant progress in trigger-free document-level event extraction, but the resource consumption shortcoming is obvious. To build DAGs, devices have to store all the previous paths, and each node in the graph has different previous memories. This auto-regressive decoding strategy requires massive memories and huge computing resources, so the training and inference speed are both very slow.

We instead use the pruned complete graphs (right bottom of Figure V.1) to represent event argument combinations and further exploit the non-autoregressive decoding algorithm to extract final records. The experimental results show that our approach is fast in both training and inference.

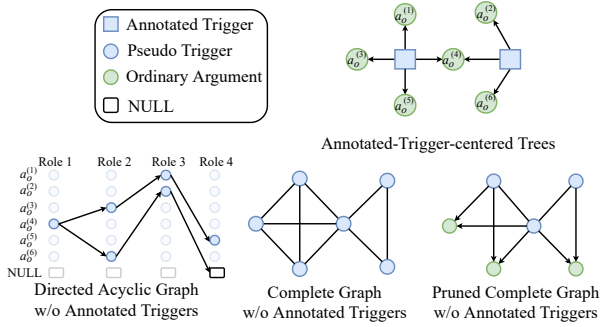


Figure V.1: Event argument combination comparison (best viewed in color).

VI Bron-Kerbosch Algorithm

In the combination extraction section of the main content, we introduce the non-autoregressive combination decoding algorithm. In this section, we list more details about the Bron-Kerbosch algorithm (Bron and Kerbosch 1973) used at line 17 of Algorithm 1 in the main content. To apply the recursive Algorithm VI.1, the input of adjacent matrix A must be symmetric, thus we perform the operation at line 16 of Algorithm 1. After that, the Algorithm VI.1 is applied to find possible pseudo trigger cliques.

Algorithm VI.1: Bron-Kerbosch

Input: Adjacent matrix A .

Output: Pseudo-trigger cliques \mathcal{C} .

```

1: for  $c \in \text{BK-Kernel}(\emptyset, \{1, 2, \dots, |A|\}, \emptyset)$  do
2:    $\mathcal{C} \leftarrow \mathcal{C} \cup c$ 
3: end for

```

Algorithm VI.2: BK-Kernel

Input: Possible clique of arguments \mathcal{Q} , set of candidate vertices \mathcal{S} , set of excluded vertices \mathcal{X}

Output: A clique of vertices.

```

1: if  $\mathcal{S} = \emptyset$  and  $\mathcal{X} = \emptyset$  and  $|\mathcal{Q}| \geq 2$  then
2:   return  $\mathcal{Q}$ 
3: end if
4: if  $\mathcal{S} \cup \mathcal{X} = \emptyset$  then
5:    $\mathcal{W} \leftarrow \mathcal{S}$ 
6: else
7:    $u \leftarrow$  random choice from  $\mathcal{S} \cup \mathcal{X}$ 
8:   // here  $\mathcal{N}(u)$  denotes the neighbors of  $u$ 
9:    $\mathcal{W} \leftarrow \mathcal{S} \setminus \mathcal{N}(u)$ 
10: end if
11: for  $v \in \mathcal{W}$  do
12:    $\mathcal{F} \leftarrow \mathcal{S} \cap \mathcal{N}(v)$ 
13:    $\mathcal{H} \leftarrow \mathcal{X} \cap \mathcal{N}(v)$ 
14:   return  $\text{BK-Kernel}(\mathcal{Q} \cup v, \mathcal{F}, \mathcal{H})$ 
15:    $\mathcal{S} \leftarrow \mathcal{S} \setminus v$ 
16:    $\mathcal{X} \leftarrow \mathcal{X} \cup v$ 
17: end for

```

VII Hyper-Parameters

We list all the hyper-parameters in Table VII.2 for reproducibility.

VIII Results on Development Set in Training

As Figure VIII.2 shows, PTPCG is the fastest to get convergence and reach the max micro-F1 score at the 57th epoch, while Doc2EDAG and GIT suffers from parameter updating in the first 20 epochs and get the max scores on the development set until the 82th and the 96th epoch.

IX Inference Speed Comparison

Figure IX.3 shows the inference speed test results on Doc2EDAG, GIT, TransPTPCG ($|\mathcal{R}| = 1$) and PTPCG with different batch sizes. Specially, GIT raises the ‘‘Out of Memory’’ error when batch size is 128. Our PTPCG outperforms Doc2EDAG and GIT in all batch size settings.

X Additional Experimental Results

We report additional performance results of PTPCG, including overall scores for each event type (Table X.4), performance on single & multiple record documents (Table X.5) and results of each separate component (Table X.6).

We also provide a case predicted by PTPCG ($|\mathcal{R}| = 3$) in Figure X.5. This example is picked from ChFinAnn. To better show this example, we have reduced the document length.

Name	Setting
learning rate	5e-4
batch size	64
epoch	100
embedding dim d_h	768
mention type dim d_l	32
max sentence length	128
max number of sentence	64
minimal teacher prob	0.1
scheduled sampling start epoch	10
scheduled sampling end epoch	20
α_1	0.05
α_2	1.0
α_3	1.0
α_4	1.0
γ	0.5
#heads of multi-head att in event detection	1
layers of BiLSTM for token encoding	2
layers of BiLSTM for entity encoding	2

Table VII.2: Hyper-parameter details for implementation.

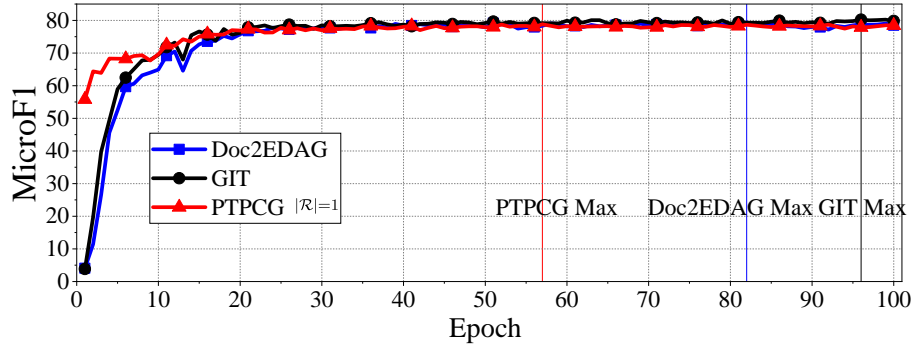


Figure VIII.2: Micro F1-scores on development set during training.

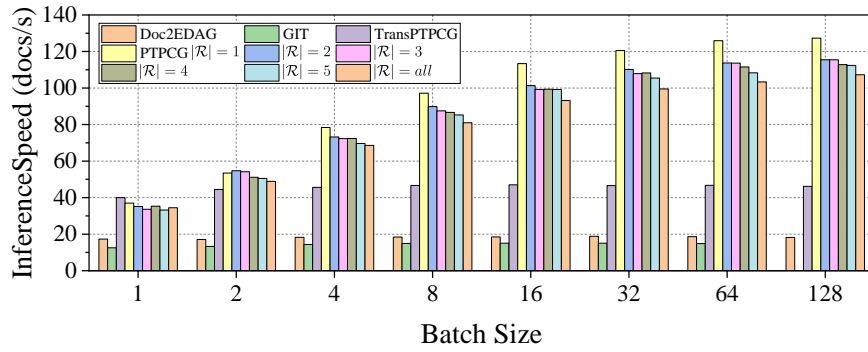
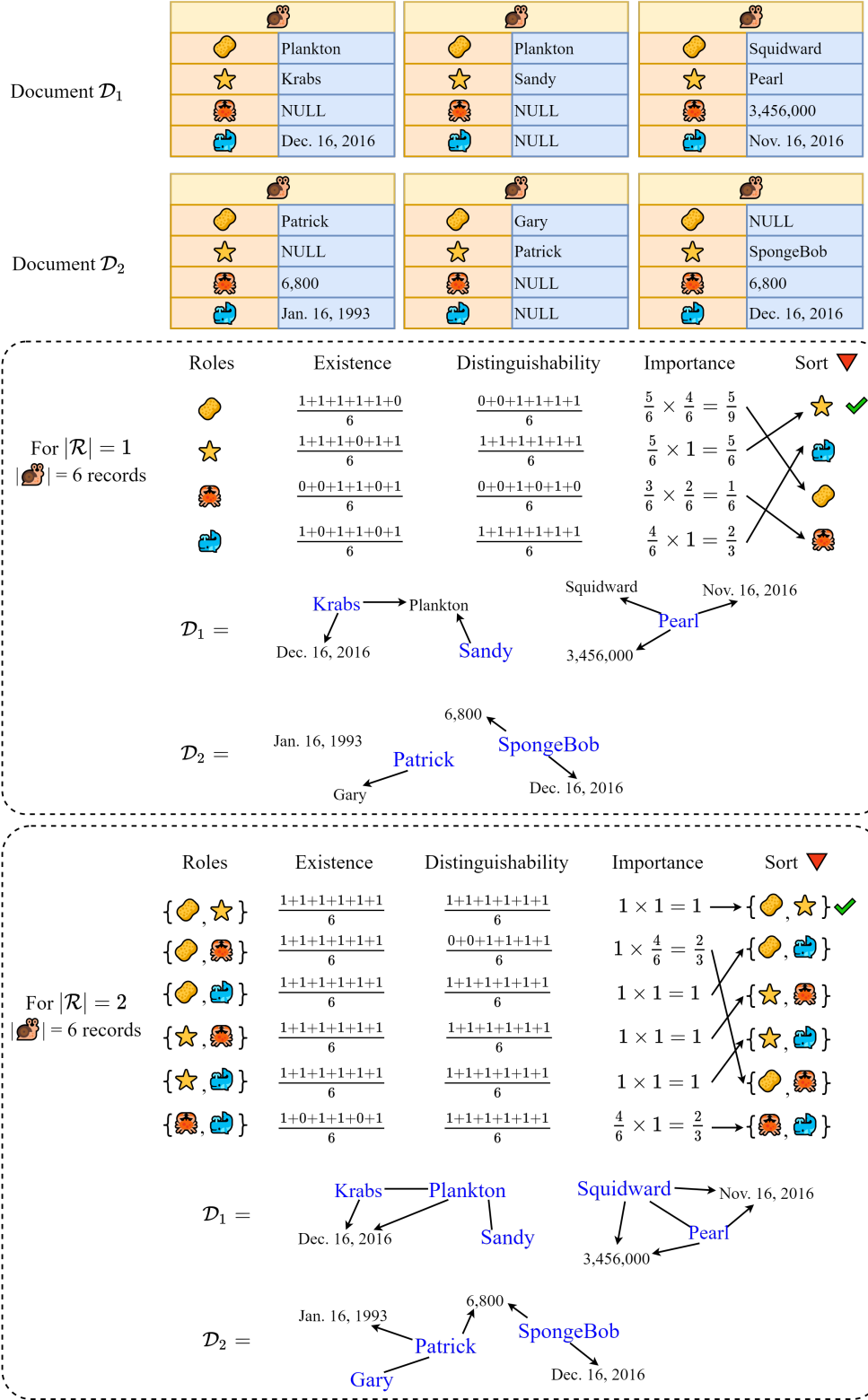


Figure IX.3: Inference speed comparison (best viewed in color).



Event Type	R	Importance (%)	Pseudo Trigger Roles
EquityPledge	1	88.47	PledgedShares
	2	92.39	PledgedShares, StartDate
	3	94.08	EndDate, PledgedShares, StartDate
	4	95.00	EndDate, PledgedShares, ReleasedDate, StartDate
	5	95.43	EndDate, PledgedShares, Pledgee, ReleasedDate, StartDate
	6	95.61	EndDate, PledgedShares, Pledgee, Pledged, ReleasedDate, StartDate
	7	95.65	EndDate, PledgedShares, Pledgee, Pledged, ReleasedDate, StartDate, TotalPledgedShares
EquityRepurchase	1	97.18	RepurchasedShares
	2	99.19	RepurchaseAmount, RepurchasedShares
	3	100.00	ClosingDate, RepurchaseAmount, RepurchasedShares
	4	100.00	ClosingDate, CompanyName, RepurchaseAmount, RepurchasedShares
	5	100.00	ClosingDate, CompanyName, HighestTradingPrice, RepurchaseAmount, RepurchasedShares
	6	100.00	ClosingDate, CompanyName, HighestTradingPrice, LowestTradingPrice, RepurchaseAmount, RepurchasedShares
EquityOverweight	1	93.25	TradedShares
	2	99.60	EquityHolder, StartDate
	3	99.80	EquityHolder, StartDate, TradedShares
	4	100.00	EquityHolder, LaterHoldingShares, StartDate, TradedShares
	5	100.00	EndDate, EquityHolder, LaterHoldingShares, StartDate, TradedShares
	6	100.00	AveragePrice, EndDate, EquityHolder, LaterHoldingShares, StartDate, TradedShares
EquityFreeze	1	70.61	LegalInstitution
	2	87.58	FrozeShares, LegalInstitution
	3	92.42	FrozeShares, LegalInstitution, StartDate
	4	93.03	EquityHolder, FrozeShares, LegalInstitution, StartDate
	5	93.33	EquityHolder, FrozeShares, LegalInstitution, StartDate, TotalHoldingRatio
	6	93.64	EquityHolder, FrozeShares, LegalInstitution, StartDate, TotalHoldingRatio, UnfrozeDate
	7	93.64	EquityHolder, FrozeShares, LegalInstitution, StartDate, TotalHoldingRatio, TotalHoldingShares, UnfrozeDate
	8	93.64	EndDate, EquityHolder, FrozeShares, LegalInstitution, StartDate, TotalHoldingRatio, TotalHoldingShares, UnfrozeDate
EquityUnderweight	1	91.88	TradedShares
	2	99.74	EndDate, EquityHolder
	3	99.74	EquityHolder, StartDate, TradedShares
	4	99.74	EndDate, EquityHolder, StartDate, TradedShares
	5	99.74	EndDate, EquityHolder, LaterHoldingShares, StartDate, TradedShares
	6	99.74	AveragePrice, EndDate, EquityHolder, LaterHoldingShares, StartDate, TradedShares

Table X.3: Pseudo trigger roles with highest importance scores for each type in ChFinAnn.

\mathcal{R}	EquityFreeze			EquityRepurchase			EquityUnderweight			EquityOverweight			EquityPledge			Average			Total (micro)		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
1	80.8	63.9	71.4	90.9	92.3	91.6	80.2	64.6	71.5	77.5	67.5	72.2	81.7	71.7	76.4	82.2	72.0	76.6	83.7	75.4	79.4
2	75.0	66.0	70.2	91.3	90.4	90.8	73.2	64.4	68.5	74.4	68.4	71.3	74.7	74.5	74.6	77.7	72.8	75.1	78.6	76.7	77.7
3	68.5	69.6	69.0	86.5	91.2	88.8	70.4	67.0	68.6	63.7	68.1	65.9	68.2	75.3	71.6	71.5	74.2	72.8	72.3	77.7	74.9
4	65.9	67.4	66.6	85.9	91.2	88.5	61.9	67.3	64.5	61.2	69.1	64.9	67.5	75.0	71.1	68.5	74.0	71.1	70.9	77.5	74.0
5	56.5	69.9	62.5	82.6	92.8	87.4	65.7	67.4	66.5	63.3	68.4	65.8	64.1	77.0	69.9	66.4	75.1	70.4	67.9	79.1	73.1
all	63.9	71.6	67.5	81.7	92.0	86.6	64.0	65.9	64.9	59.9	68.8	64.0	55.8	76.0	64.4	65.1	74.9	69.5	62.4	78.4	69.5

Table X.4: PTPCG overall scores on ChFinAnn.

\mathcal{R}	EquityFreeze		EquityRepurchase		EquityUnderweight		EquityOverweight		EquityPledge		Average		Total (micro)	
	S	M	S	M	S	M	S	M	S	M	S	M	S	M
1	83.6	59.9	93.7	73.8	77.3	63.6	79.7	62.8	86.1	70.5	84.1	66.1	88.2	69.1
2	77.4	63.7	93.2	70.8	76.7	57.3	76.9	64.1	83.7	69.3	81.6	65.0	86.3	68.1
3	73.6	64.7	91.0	69.4	74.9	60.4	74.7	55.6	79.3	67.2	78.7	63.5	83.1	65.9
4	71.2	62.3	90.9	68.3	70.7	56.3	69.9	58.9	80.3	65.8	76.6	62.3	82.6	64.7
5	63.2	61.8	89.6	70.3	71.4	60.0	71.9	58.3	79.7	64.6	75.2	63.0	81.6	64.0
all	69.5	65.7	88.6	69.9	69.4	58.8	69.4	57.4	73.6	59.3	74.1	62.2	78.7	60.1

Table X.5: PTPCG performance on documents with single and multiple records in ChFinAnn.

\mathcal{R}	EventDetection			EntityExtraction			Combination			Overall		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
1	99.0	98.8	98.9	97.5	99.4	98.4	40.9	40.9	40.9	83.8	75.4	79.4
2	99.0	98.9	99.0	97.3	99.5	98.4	35.4	40.2	37.7	78.6	76.7	77.7
3	99.2	98.9	99.0	97.4	99.4	98.4	32.5	41.4	36.4	72.3	77.7	74.9
4	99.2	98.9	99.0	97.4	99.5	98.4	31.1	40.7	35.2	70.9	77.5	74.0
5	99.1	98.9	99.0	97.5	99.4	98.4	31.6	43.8	36.7	67.9	79.1	73.1
all	99.1	99.0	99.1	97.3	99.5	98.4	26.4	41.4	32.2	62.4	78.4	69.5

Table X.6: PTPCG performance of each component on ChFinAnn.

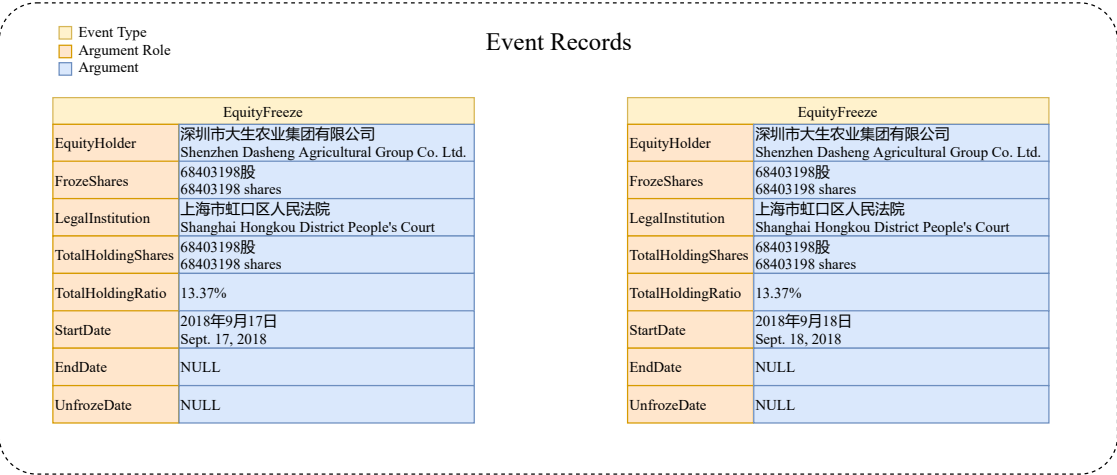
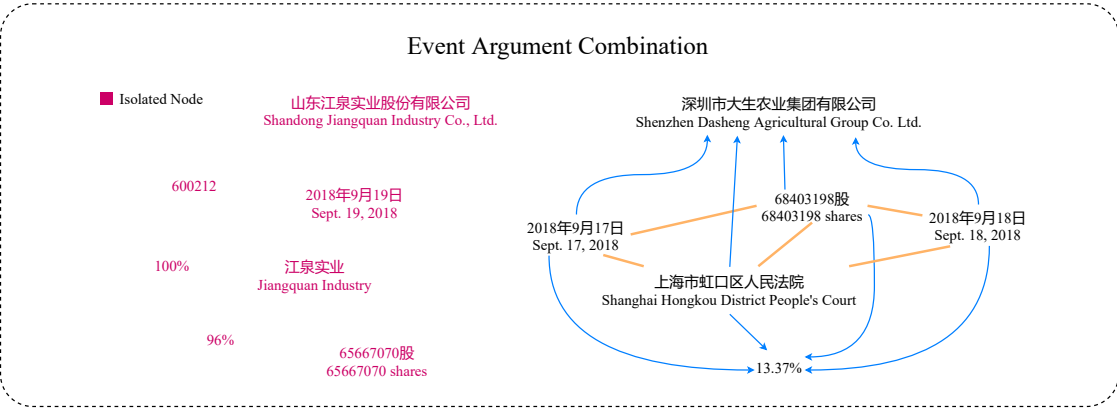
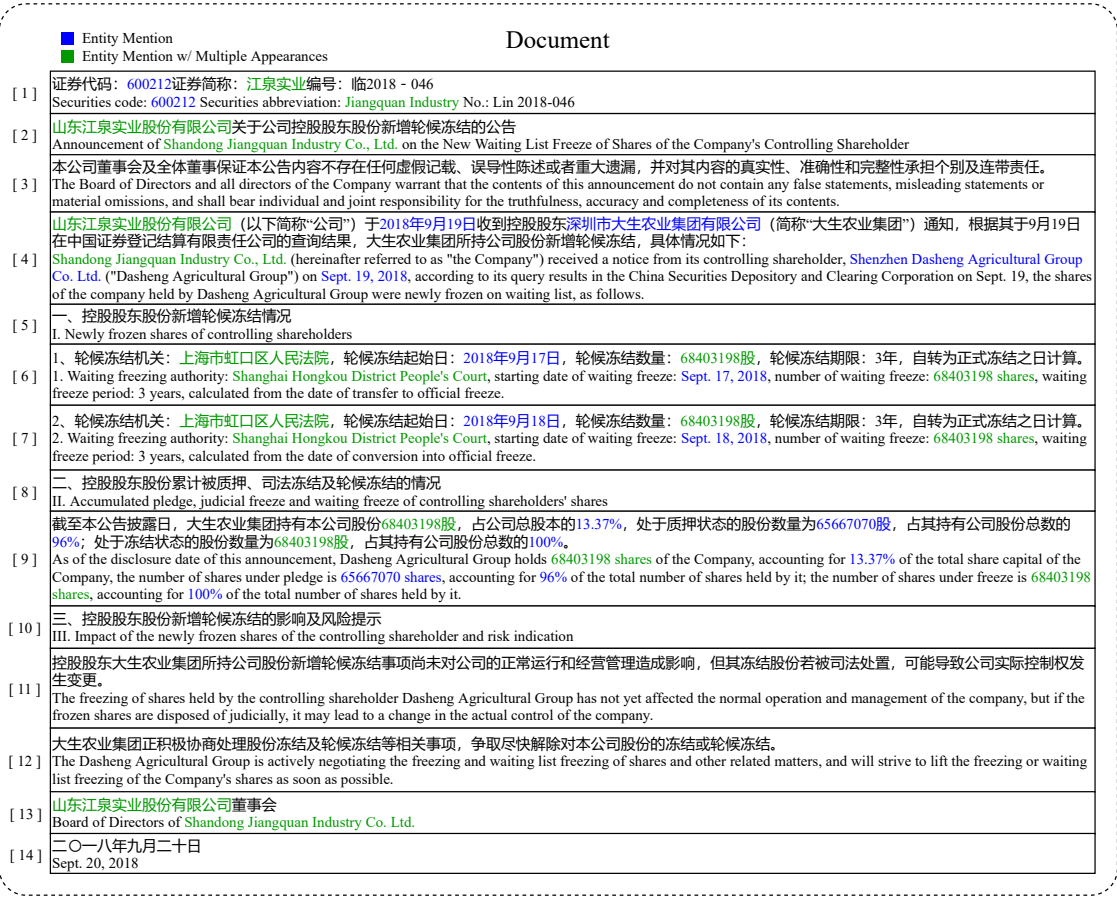


Figure X.5: PTPCG ($|\mathcal{R}| = 3$) prediction.

References

- Bron, C.; and Kerbosch, J. 1973. Algorithm 457: Finding All Cliques of an Undirected Graph. *Commun. ACM*, 16(9): 575–577.
- Chen, Y.; Liu, S.; Zhang, X.; Liu, K.; and Zhao, J. 2017. Automatically Labeled Data Generation for Large Scale Event Extraction. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 409–419. Vancouver, Canada: Association for Computational Linguistics.
- Chen, Y.; Xu, L.; Liu, K.; Zeng, D.; and Zhao, J. 2015. Event Extraction via Dynamic Multi-Pooling Convolutional Neural Networks. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 167–176. Beijing, China: Association for Computational Linguistics.
- Lin, Y.; Ji, H.; Huang, F.; and Wu, L. 2020. A Joint Neural Model for Information Extraction with Global Features. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 7999–8009. Online: Association for Computational Linguistics.
- Liu, X.; Luo, Z.; and Huang, H. 2018. Jointly Multiple Events Extraction via Attention-based Graph Information Aggregation. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, 1247–1256. Brussels, Belgium: Association for Computational Linguistics.
- Mintz, M.; Bills, S.; Snow, R.; and Jurafsky, D. 2009. Distant supervision for relation extraction without labeled data. In Su, K.; Su, J.; and Wiebe, J., eds., *ACL 2009, Proceedings of the 47th Annual Meeting of the Association for Computational Linguistics and the 4th International Joint Conference on Natural Language Processing of the AFNLP, 2-7 August 2009, Singapore*, 1003–1011. The Association for Computer Linguistics.
- Nguyen, T. H.; Cho, K.; and Grishman, R. 2016. Joint Event Extraction via Recurrent Neural Networks. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 300–309. San Diego, California: Association for Computational Linguistics.
- Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, Ł.; and Polosukhin, I. 2017. Attention is all you need. In *Advances in neural information processing systems*, 5998–6008.
- Wadden, D.; Wennberg, U.; Luan, Y.; and Hajishirzi, H. 2019. Entity, Relation, and Event Extraction with Contextualized Span Representations. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, 5784–5789. Hong Kong, China: Association for Computational Linguistics.
- Xu, R.; Liu, T.; Li, L.; and Chang, B. 2021. Document-level Event Extraction via Heterogeneous Graph-based Interaction Model with a Tracker. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 3533–3546. Online: Association for Computational Linguistics.
- Zheng, S.; Cao, W.; Xu, W.; and Bian, J. 2019. Doc2EDAG: An End-to-End Document-level Framework for Chinese Financial Event Extraction. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, 337–346. Hong Kong, China: Association for Computational Linguistics.