Document-Level Multi-Event Extraction with Event Proxy Nodes and Hausdorff Distance Minimization

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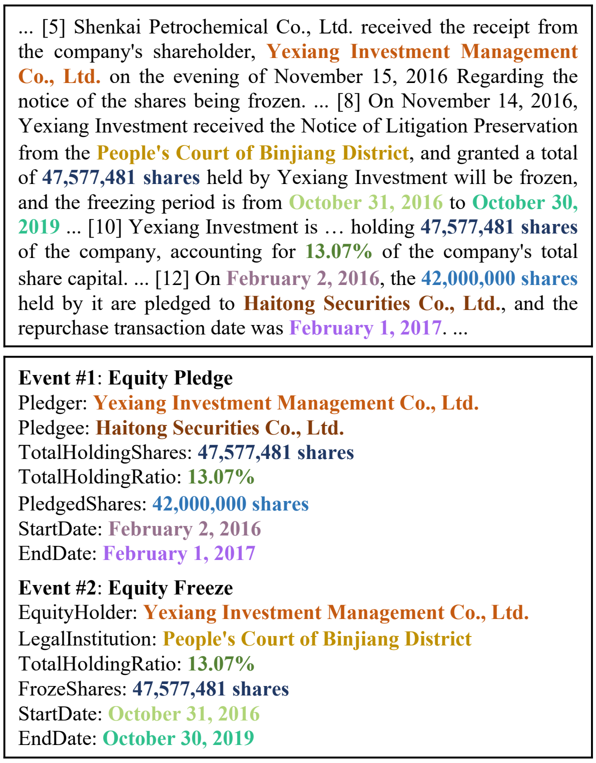
Abstract

Document-level multi-event extraction aims to extract the structural information from a given document automatically. Most recent approaches usually involve two steps: (1) modeling entity interactions; (2) decoding entity interactions into events. However, such approaches ignore a global view of inter-dependency of multiple events. Moreover, an event is decoded by iteratively merging its related entities as arguments, which might suffer from error propagation and is computationally inefficient. In this paper, we propose an alternative approach for document-level multi-event extraction with event proxy nodes and Hausdorff distance minimization. The event proxy nodes, representing pseudo-events, are able to build connections with other event proxy nodes, essentially capturing global information. The Hausdorff distance makes it possible to compare the similarity between the set of predicted events and the set of ground-truth events. By directly minimizing Hausdorff distance, the model is trained towards the global optimum directly, which improves performance and reduces training time. Experimental results show that our model outperforms previous state-of-the-art method in F1-score on two datasets with only a fraction of training time. [1]

1 Introduction

Event extraction aims to identify event triggers with certain types and extract their corresponding arguments from text. Much research has been done on sentence-level event extraction (Du and Cardie, 2020; Lin et al., 2020; Lu et al., 2021). In recent years, there have been growing interests in tackling the more challenging task of document-level multi-event extraction, where an event is represented by a cluster of arguments, which may scatter across multiple sentences in a document. Also, multiple events in the same document may share some common entities. For example, as shown in Figure 1, the two events, *Equity Pledge* and *Equity Freeze*, have their arguments scattered across the document. The same entity mentions, *Yexiang Investment Management Co., Ltd.* and *13.07%*, are involved in both events, with the former taking different argument roles ('*Pledger*' and '*Equity Holder*'), while the latter having the same argument role ('*Total Holding Ratio*'). In such a setup, an event is not associated with a specific event trigger word or phrase, as opposed to the common setup in sentence-level event extraction. These challenges make it difficult to distinguish various events and link entities to event-specific argument roles.



... [5] Shenkai Petrochemical Co., Ltd. received the receipt from the company's shareholder, **Yexiang Investment Management Co., Ltd.** on the evening of November 15, 2016 Regarding the notice of the shares being frozen. ... [8] On November 14, 2016, Yexiang Investment received the Notice of Litigation Preservation from the **People's Court of Binjiang District**, and granted a total of **47,577,481 shares** held by Yexiang Investment will be frozen, and the freezing period is from **October 31, 2016** to **October 30, 2019** ... [10] Yexiang Investment is … holding **47,577,481 shares** of the company, accounting for **13.07%** of the company's total share capital. ... [12] On **February 2, 2016**, the **42,000,000 shares** held by it are pledged to **Haitong Securities Co., Ltd.**, and the repurchase transaction date was **February 1, 2017**. ...

Event #1: **Equity Pledge**
Pledger: **Yexiang Investment Management Co., Ltd.**
Pledgee: **Haitong Securities Co., Ltd.**
TotalHoldingShares: **47,577,481 shares**
TotalHoldingRatio: **13.07%**
PledgedShares: **42,000,000 shares**
StartDate: **February 2, 2016**
EndDate: **February 1, 2017**

Event #2: **Equity Freeze**
EquityHolder: **Yexiang Investment Management Co., Ltd.**
LegalInstitution: **People's Court of Binjiang District**
TotalHoldingRatio: **13.07%**
FrozeShares: **47,577,481 shares**
StartDate: **October 31, 2016**
EndDate: **October 30, 2019**

Figure 1: An example of a document that contains two events. [·] denotes the sentence numbering. Words highlighted in colors denote different entities.

Document-level multi-event extraction can be typically formulated as a table-filling task that fills

[1] Code is available at https://github.com/xnyuwg/procnet

Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics
Volume 1: Long Papers, pages 10118–10133
July 9-14, 2023 ©2023 Association for Computational Linguistics

the correct entities into a pre-defined event schema as shown in Figure 1. Here, an event is essentially represented by a cluster of arguments. Existing approaches (Zheng et al., 2019; Yang et al., 2021; Huang and Jia, 2021; Xu et al., 2021; Liang et al., 2022) usually involve two steps: (1) first model the entity interactions based on contextual representations; (2) then design a decoding strategy to decode the entity interactions into events and arguments. For example, Zheng et al. (2019) and Xu et al. (2021) transformed this task into sequential path-expanding sub-tasks. Each sub-task expands a path sequentially by gradually merging entities in a pre-defined order of event argument roles.

The aforementioned approaches suffer from the following limitations: (1) They decode events from entity information and tend to produce local optimal results without considering the inter-dependency of multiple events globally in a document. (2) Event decoding by iteratively merging entities suffers from error propagation that an event type or an entity that has been incorrectly classified cannot be corrected later. (3) Every decoding decision requires iterating all entity mentions in a document, which is computationally inefficient.

To address the above limitations, we propose an alternative approach for document-level multi-event extraction with event proxy nodes and Hausdorff distance minimization, named as **Pro**xy Nodes **C**lustering **Net**work (`ProCNet`). The event proxy nodes aim to capture the global information among events in a document. The Hausdorff distance makes it possible to optimize the training loss defined as the difference between the generated events and the gold standard event annotations directly. This is more efficient compared to existing decoding approaches.

Our method involves two main steps: *Event Representation Learning* and *Hausdorff Distance Minimization*. For *Event Representation Learning*, we create a number of proxy nodes, each of which represents a pseudo-event, and build a graph to update proxy nodes. Entities mentioned in text are treated as nodes connecting to the proxy nodes. All the proxy nodes are interconnected to allow information exchange among the potential events. We employ a Hypernetwork Graph Neural Network (GNN) (Ha et al., 2017) for updating proxy node representations. After *Event Representation Learning*, each proxy node essentially resides in a new event-level metric space by aggregating information from the entity-level space.

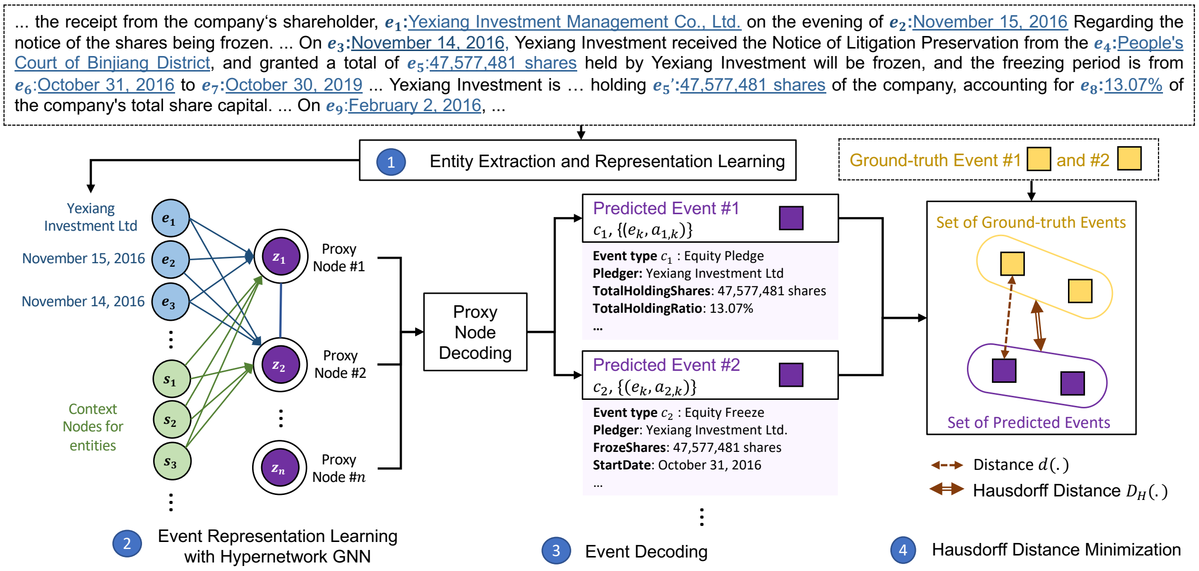
For *Hausdorff Distance Minimization*, we regard the predicted events as a set and the ground-truth events as another set, and compute the Hausdorff distance between these two sets, which simultaneously consider all events and all their arguments. We then minimize the Hausdorff distance via gradient descent, where the model is trained to directly produce a globally optimal solution without the need of using decoding strategies as in existing approaches.

In this way, our model learns globally and does not suffer from the problem of existing approaches that decode events based on local entity information. Each entity is linked to every proxy node, and the association between an entity and a proxy node is updated at each training iteration. As such, our model avoids the error propagation problem caused by the iterative decoding strategy. In addition, our approach naturally addresses the problem that the same entity mention may be involved in multiple events since the entity will be mapped to a different event-level metric space depending on its associated proxy node. Moreover, as our approach replaces iterative computation in decoding with parallel computation, it is computationally more efficient compared to existing path-expansion approaches, as will be shown in our experiments section. In summary, our main contributions are:

- We propose a new framework for document-level multi-event extraction by learning event proxy nodes in a new event-level metric space to better model the interactions among events.
- We propose to utilize the Hausdorff distance in our learning objective function to optimize the difference between the generated events and the gold standard events directly. The proposed mechanism not only simultaneously considers all events but also speeds up the training process.
- Experimental results show that our model outperforms previous state-of-the-art method in F1 on two datasets with only a fraction of training time.

2 Related Work

Early research on event extraction (EE) largely focused on sentence-level event extraction (SEE), aiming to classify the event trigger and arguments in a sentence. Chen et al. (2015) decomposes SEE


... the receipt from the company's shareholder, e_1:Yexiang Investment Management Co., Ltd. on the evening of e_2:November 15, 2016 Regarding the notice of the shares being frozen. ... On e_3:November 14, 2016, Yexiang Investment received the Notice of Litigation Preservation from the e_4:People's Court of Binjiang District, and granted a total of e_5:47,577,481 shares held by Yexiang Investment will be frozen, and the freezing period is from e_6:October 31, 2016 to e_7:October 30, 2019 ... Yexiang Investment is … holding e_5':47,577,481 shares of the company, accounting for e_8:13.07% of the company's total share capital. ... On e_9:February 2, 2016, ...

Event type c_1 : Equity Pledge
Pledger: Yexiang Investment Ltd
TotalHoldingShares: 47,577,481 shares
TotalHoldingRatio: 13.07%
…

Event type c_2 : Equity Freeze
Pledger: Yexiang Investment Ltd.
FrozeShares: 47,577,481 shares
StartDate: October 31, 2016
…

1 Entity Extraction and Representation Learning
Ground-truth Event #1 and #2
Yexiang Investment Ltd
November 15, 2016
November 14, 2016
e_1
e_2
e_3
s_1
s_2
s_3
Context Nodes for entities
z_1
z_2
z_n
Proxy Node #1
Proxy Node #2
Proxy Node #n
Proxy Node Decoding
Predicted Event #1
$c_1, \{(e_k, a_{1,k})\}$
Predicted Event #2
$c_2, \{(e_k, a_{2,k})\}$
Set of Ground-truth Events
Set of Predicted Events
Distance $d(.)$
Hausdorff Distance $D_H(.)$
2 Event Representation Learning with Hypernetwork GNN
3 Event Decoding
4 Hausdorff Distance Minimization

Figure 2: Overview of ProCNet with the example in Figure 1, where Entity 1, 5, 8, 9 are arguments of Event #1; Entity 1, 4, 5, 6, 7, 8 are arguments of Event #2; Entity 2, 3 do not belong to any events. Before training, proxy node embeddings are randomly initialized. Entities are first mapped to entity representations in the entity-level space by *Entity Representation Learning*. Then in *Event Representation Learning*, a hypernetwork heterogeneous graph is constructed with entity and context nodes connected with proxy nodes, and proxy nodes interconnected with each other. Proxy nodes are updated to represent pseudo-events. Afterwards, the proxy nodes and entity nodes are decoded into events, each of which is represented by an event types and a set of argument role-entity pairs in the *Event Decoding* step. Finally, *Hausdorff Distance Minimization* minimizes the distance between the set of predicted events and the set of ground-truth events to perform a global training in the new event-level metric space.

into two sub-tasks: *event trigger detection* and *event argument labeling*. More work has been done on joint-learning of the two sub-tasks (Nguyen and Nguyen, 2019; Lin et al., 2020). Recently, multi-turn Question-Answer (QA) methods have been investigated for EE with hand-designed or automatically generated questions (Du and Cardie, 2020; Li et al., 2020; Wang et al., 2020; Liu et al., 2020; Lyu et al., 2021). Apart from QA-based approaches, sequence-to-sequence learning has also been explored, where the event annotation is flattened as a sequence (Paolini et al., 2021; Lu et al., 2021; Li et al., 2021; Lu et al., 2022b). More recently, prompt-based learning has been explored using the knowledge in pre-trained language models (Lin et al., 2021; Hsu et al., 2021; Ma et al., 2022).

Compared to SEE, document-level event extraction (DEE) appears to be more challenging. DEE requires methods to model long-term dependencies among entities across multiple sentences. Simply employing SEE approaches for DEE may lead to incomplete and uninformative extractions (Li et al., 2021). To address the problem, conditional generation have been proposed, which are conditioned on pre-specified templates or prompts (Du et al., 2021; Huang et al., 2021; Ma et al., 2022).

DEE can also be formulated as a table-filling task where each event is represented as a cluster of arguments and an event type. In such a setup, it is usually not possible to associate a particular event trigger word or phrase with an event. Yang et al. (2018) proposed a key-event detection model. Zheng et al. (2019) transformed event tables into a directed acyclic graph with path expansion. Huang and Jia (2021) constructed a graph to build sentence communities. Lu et al. (2022a) captured event clues as a series of intermediate results. Xu et al. (2021) constructed a heterogeneous GNN with a tracker mechanism for partially decoded events. Liang et al. (2022) modeled the relation between entities with Relation-augmented Attention Transformer. These methods mainly focus on modeling entity inter-relations and rely on carefully-designed event decoding strategies. In contrast, we model events in the event-level metric space within a more global view and with less training time.

3 Methodology

3.1 Problem Setup

Different from the trigger-based event extraction task, where an event is represented by a trigger and a list of arguments, in our task, an event is defined by an event type category c, a list of entities $\{e_i\}$ and their corresponding argument types $\{a_i\}$ as shown in Figure 1. Therefore, the target output is a list of "entity-argument" pairs $\{(e_i, a_i)\}$ and c as $\big(c, \{(e_i, a_i)\}\big)$. Proxy node is defined as z. An overview of ProCNet is shown in Figure 2. In what follows, we present each module in detail.

3.2 Entity Representation Learning

Given an input document, the first step is to identify the entities which might be potential arguments. This can be framed as a sequence labeling problem that, given a word sequence, the entity recognition model outputs a label sequence with the BIO (Beginning and Inside of an entity span, and Other tokens) tagging. We use BERT (Devlin et al., 2019) as a sequence labeler to detect entities at sentence-level. As an entity span may contain multiple tokens, we drive its representation by averaging the hidden states of its constituent tokens. For a document, a total of $|e|$ entity representations are extracted as $\{\boldsymbol{h}_{e_i}\}_{i=1}^{|e|}$. The loss of the BIO sequence tagging is defined as $\mathcal{L}_{\text{er}}$.

In order to make the entity representations encode the knowledge of entity associations, we introduce a simple auxiliary learning task to predict whether two entities belong to the same event, where entity representations will be updated during learning. Specifically, it is a binary classification task, with the predicted output computed as:

$$\hat{y}_{\text{epc}_{(i,j)}} = \phi\left(\text{MLP}([\boldsymbol{h}_{e_i}; \boldsymbol{h}_{e_j}])\right), \tag{1}$$

where ϕ denotes the sigmoid function, $[;]$ denotes the concatenation, and $\hat{y}_{\text{epc}_{i,j}}$ indicates the probability if entities i and j are from the same event. We use the binary cross-entropy (CE) loss here:

$$\mathcal{L}_{\text{epc}} = -\sum_i \sum_j \text{CE}(y_{\text{epc}_{(i,j)}}, \hat{y}_{\text{epc}_{(i,j)}}) \tag{2}$$

where $y_{\text{epc}_{i,j}}$ is the label. The loss for entity representation learning is defined as $\mathcal{L}_{\text{e}} = \mathcal{L}_{\text{er}} + \mathcal{L}_{\text{epc}}$.

3.3 Event Representation Learning with Proxy Nodes

In this section, we construct a graph to map entity representations in the entity-level space into event representations in a new event-level metric space.

We define n proxy nodes, which serve as pseudo-events, and randomly initialize their embeddings $\{\boldsymbol{h}_{z_i}^{(0)}\}_{i=1}^{n}$, which are only initialized once before training and will be updated during training. n is a hyper-parameter and can be simply set to a much larger value than the expected number of extracted events, as proxy nodes can also represent *null* events (see Section 3.4). We initialize entity node embeddings $\{\boldsymbol{h}_{e_i}\}_{i=1}^{|e|}$ and context node embeddings $\{\boldsymbol{h}_{s_i}\}_{i=1}^{|s|}$ by their corresponding entity and [CLS] representations, respectively.

We define the graph as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, and the node set $\mathcal{V}$ contains proxy nodes, entity nodes, and context nodes as: $\mathcal{V} = \{z_i\}_{i=1}^{n} \cup \{e_i\}_{i=1}^{|e|} \cup \{s_i\}_{i=1}^{|s|}$ with their embeddings $\{\boldsymbol{h}_{z_i}^{(0)}\}_{i=1}^{n} \cup \{\boldsymbol{h}_{e_i}\}_{i=1}^{|e|} \cup \{\boldsymbol{h}_{s_i}\}_{i=1}^{|s|}$. The edge set $\mathcal{E}$ includes three kinds of edges as follows:

Proxy↔Proxy Edge The bidirectional edge between all proxy nodes $\{z_i \rightarrow z_j : 0 < i \leq n, 0 < j \leq n\}$ allows the information exchange between proxy nodes.

Entity→Proxy Edge The directed edge from all entity nodes e to all proxy nodes z as $\{e_j \rightarrow z_i : 0 < i \leq n, 0 < j \leq |e|\}$ provides the entity information for pseudo-events.

Context→Proxy Edge The directed edge from all context node s to all proxy node z as $\{s_j \rightarrow z_i : 0 < i \leq n, 0 < j \leq |s|\}$ provides the contextual information.

In a typical setup for GNN, each node has its embedding updated by aggregating the neighborhood information. The aggregation weight matrix is shared across all nodes. But in our task here, each proxy node is expected to represent a distinct event. As such, we would like to have a unique aggregation function for each proxy node. To this end, we use the Graph Neural Network with Feature-wise Linear Modulation (GNN-FiLM) (Brockschmidt, 2020) to update the proxy node embeddings in $\mathcal{G}$. It introduces Hypernetwork to enable each proxy node to compute a unique aggregation function with different parameters. More concretely, given a node $v \in \mathcal{V}$ at the $(l+1)$-th layer, its hidden representation $\boldsymbol{h}_v^{(l+1)}$ is updated as:

$$\begin{gathered} \boldsymbol{h}_v^{(l+1)} = \sigma\Bigg(\sum_{u \xrightarrow{\varepsilon} v} \boldsymbol{\gamma}_{\varepsilon,v}^{(l)} \odot \boldsymbol{W}_{\varepsilon} \boldsymbol{h}_u^{(l)} + \boldsymbol{\beta}_{\varepsilon,v}^{(l)}\Bigg), \\ \boldsymbol{\gamma}_{\varepsilon,v}^{(l)} = f_{\gamma}(\boldsymbol{h}_v^{(l)}; \boldsymbol{\theta}_{\gamma,\varepsilon}), \quad \boldsymbol{\beta}_{\varepsilon,v}^{(l)} = f_{\beta}(\boldsymbol{h}_v^{(l)}; \boldsymbol{\theta}_{\beta,\varepsilon}), \end{gathered} \tag{3}$$

where $u \xrightarrow{\varepsilon} v$ denotes a neighboring node u connected with node v with the edge type ε. $\boldsymbol{W}_{\varepsilon} \in \mathbb{R}^{d_h \times d_h}$ is a learnable parameter for edge type ε. σ

and $\odot$ denote the activation function and Hadamard product, respectively. $\boldsymbol{\gamma}_{\varepsilon,v}^{(l)}$ and $\boldsymbol{\beta}_{\varepsilon,v}^{(l)}$ define the message-passing function of edge type ε and node v at layer l. They are computed by functions f_γ and f_β given $\boldsymbol{h}_v^{(l)}$ as the input. $\boldsymbol{\theta}_{\gamma,\varepsilon}$ and $\boldsymbol{\theta}_{\beta,\varepsilon}$ are learnable parameters of f_γ and f_β, respectively. To keep it simple, we only use one-layer GNN-FiLM with a single linear layer as the hyper-function in our experiments.

With the above formulation, each proxy node z has its unique message-passing function to aggregate information from entity nodes and context nodes in different ways. In summary, the representations of proxy nodes $\{\widehat{\boldsymbol{h}}_{z_i}\}_{i=1}^n$ are updated through GNN-FiLM learning:

$$\{\widehat{\boldsymbol{h}}_{z_i}\}_{i=1}^n = \text{GNN-FiLM}(\mathcal{V}, \mathcal{E}) \tag{4}$$

where z_i represents a pseudo-event. The training with proxy nodes is challenging, which will be addressed in Section 3.5.

3.4 Event Decoding

In this section, each proxy node representation $\widehat{\boldsymbol{h}}_{z_i}$ is decoded into an event, which is formulated into two parallel sub-tasks: *event type classification* and *event argument classification*.

Event Type Classification The event type of proxy node z_i is inferred from $\widehat{\boldsymbol{h}}_{z_i}$ with MLP as:

$$\boldsymbol{p}_{\hat{c}_i} = \text{softmax}\left(\text{MLP}(\widehat{\boldsymbol{h}}_{z_i})\right), \tag{5}$$

where $\boldsymbol{p}_{\hat{c}_i}$ denotes the event type probability distribution of z_i. Event type labels includes a *null* event type, denoting no correspondence between a proxy node and any events. The number of non-*null* proxy nodes is the number of predicted events.

Event Argument Classification In this task, we need to associate an entity with an event under an event-specific argument type. As the same entity (e.g., a company name) may have multiple mentions in a document, we aggregate their representations by a Multi-Head Attention (MHA) mechanism using a proxy node as the query. More concretely, assuming $\{\boldsymbol{h}_e\}_{e\in\bar{e}_k}$ denotes a set of mentions representations for the same entity $\bar{e}_k$, we use MHA to derive the aggregated entity representation for $\bar{e}_k$. The query, key and value are defined as $\boldsymbol{Q}_{z_i} = \widehat{\boldsymbol{h}}_{z_i}, \boldsymbol{K}_{\bar{e}_k} = \{\boldsymbol{h}_e\}_{e\in\bar{e}_k}, \boldsymbol{V}_{\bar{e}_k} = \{\boldsymbol{h}_e\}_{e\in\bar{e}_k}$. The representation of $\bar{e}_k$ is:

$$\widehat{\boldsymbol{h}}_{z_i,\bar{e}_k} = \text{MHA}(\boldsymbol{Q}_{z_i}, \boldsymbol{K}_{\bar{e}_k}, \boldsymbol{V}_{\bar{e}_k}), \tag{6}$$

where $\widehat{\boldsymbol{h}}_{z_i,\bar{e}_k}$ denotes the aggregated representation for entity $\bar{e}_k$ using the proxy node z_i as the query. Then the probability distribution $\boldsymbol{p}_{\hat{a}_{i,k}}$ of argument types of entity $\bar{e}_k$ with respect to proxy node z_i is:

$$\boldsymbol{p}_{\hat{a}_{i,k}} = \text{softmax}\left(\text{MLP}([\widehat{\boldsymbol{h}}_{z_i}; \widehat{\boldsymbol{h}}_{z_i,\bar{e}_k}])\right), \tag{7}$$

where $[;]$ denotes the concatenation. The argument type set includes a *null* argument type, denoting that entity $\bar{e}_k$ does not relate to proxy node z_i.

The final event type $\hat{c}_i$ for proxy node z_i and argument type for entity $\bar{e}_k$ under the event encoded by proxy node z_i are determined by:

$$\begin{aligned} \hat{c}_i &= \text{argmax}(\boldsymbol{p}_{\hat{c}_i}) \\ \hat{a}_{i,k} &= \text{argmax}(\boldsymbol{p}_{\hat{a}_{i,k}}) \end{aligned} \tag{8}$$

Each event is represented by an event type $\hat{c}_i$ and a list of arguments $\{\hat{a}_{i,k}\}$. Any predicted argument type which is not in the pre-defined schema for its associated event type will be removed. Proxy nodes classified as *null* event or entities classified as *null* arguments will be removed. If there are multiple entities predicted as the same argument, the one with the highest probability will be kept.

3.5 Hausdorff Distance Minimization

In this section, we construct a predicted pseudo-event set $\mathcal{U}_z$ represented by proxy node and a ground-truth event set $\mathcal{U}_y$. We define μ_{z_i} as the i-th pseudo-event, represented by z_i, with $\big(\hat{c}_i, \{(e_k, \hat{a}_{i,k})\}\big)$, and μ_{y_i} denotes the j-th ground-truth event $\big(c_j, \{(e_k, a_{j,k})\}\big)$. We further define the distance $d(\mu_{z_i}, \mu_{y_j})$ between predicted event μ_{z_i} and the ground-truth event μ_{y_i} as:

$$\begin{aligned} d(\mu_{z_i}, \mu_{y_j}) &= \text{CE}(\boldsymbol{p}_{\hat{c}_i}, c_j) \\ &\quad + \frac{1}{|\bar{e}|}\sum_{k=1}^{|e|} \text{CE}(\boldsymbol{p}_{\hat{a}_{i,k}}, a_{j,k}) \end{aligned} \tag{9}$$

where CE(.) is the cross-entropy loss; $|\bar{e}|$ denotes the number of unique entities; k indicates different entities. $d(\mu_z, \mu_y)$ is essentially computed by the total cross-entropy loss of event type classification and argument classification between the i-th proxy node and the j-th ground-truth event.

We aim to minimize the Hausdorff distance between sets $\mathcal{U}_z$ and $\mathcal{U}_y$ to learn the model by considering all events and their arguments simultaneously. As the standard Hausdorff distance is highly sensitive to outliers, we use the average Hausdorff distance (Schütze et al., 2012; Taha and Hanbury, 2015):

$$D_H(\mathcal{U}_z, \mathcal{U}_y) = \frac{1}{|\mathcal{U}_z|} \sum_{\mu_z \in \mathcal{U}_z} \min_{\mu_y \in \mathcal{U}_y} d(\mu_z, \mu_y) + \frac{1}{|\mathcal{U}_y|} \sum_{\mu_y \in \mathcal{U}_y} \min_{\mu_z \in \mathcal{U}_z} d(\mu_z, \mu_y) \tag{10}$$

However, in our task, the average Hausdorff distance could suffer a problem that a predicted event, represented by a proxy node, may be guided to learn towards more than one different t event at the same training iteration when this proxy node is the closest neighbor of multiple ground-truth events.

To address this problem, we add a constraint to the average Hausdorff distance that the distance computation of $d(.)$ should only be performed no more than once on each μ_z and μ_y, and we modify the average Hausdorff distance as:

$$\widehat{D}_H(\mathcal{U}_z, \mathcal{U}_y) = \min \left\{ \sum_{(\mu_z, \mu_p) \in \mathcal{U}_z \times \mathcal{U}_y} d(\mu_z, \mu_y) \right\} \tag{11}$$

For example, if $d(\mu_{z_1}, \mu_{y_1})$ has been computed, then $d(\mu_{z_2}, \mu_{y_1})$ is no longer allowed to perform, as μ_{y_1} has been used in $d(.)$ computation.

To this end, Eq. (11) with the constraint becomes a minimum loss alignment problem. To better solve Eq. (11) under the constraint, we construct an undirected bipartite graph $G = (\mathcal{U}_z, \mathcal{U}_y, \mathcal{T})$, where $\mu_z \in \mathcal{U}_z$ and $\mu_y \in \mathcal{U}_y$ are nodes of two parts representing the predicted events and the ground-truth events, respectively. $t \in \mathcal{T}$ denotes edge, which only exists between μ_z and μ_y. The weight of edge t between nodes μ_z and μ_y is defined as:

$$w(t_{z,y}) = d(\mu_z, \mu_y) \tag{12}$$

The first step is to find an edge set $\mathcal{T}$ that achieves the minimum value in the following equation:

$$\widehat{\mathcal{T}} = \operatorname{argmin} \sum_{t_{z,y} \in \mathcal{T}} w(t_{z,y}), \tag{13}$$

where the edge $t \in \mathcal{T}$ must meet these conditions: (1) each μ_z has exactly one edge connected to it; (2) each μ_y has no more than one edge connected to it. Eq. (13) can be computed efficiently with (Ramakrishnan et al., 1991; Bertsekas, 1981). Then the final distance is computed by combining Eq. (11), (12), and (13) as:

$$\widehat{D}_H(\mathcal{U}_z, \mathcal{U}_y) = \sum_{t_{z,y} \in \widehat{\mathcal{T}}} w(t_{z,y}) \tag{14}$$

Finally, we use $\widehat{D}_H(\mathcal{U}_z, \mathcal{U}_y)$ to approximate average Hausdorff distance $D_H(\mathcal{U}_z, \mathcal{U}_y)$.

As n has been set to be a very large number, if the number of ground-truth events is less than the number of predicted events in a document, pseudo *null* events are added to the ground-truth event set as negative labels to make the number of ground-truth events equals to the number of predicted events.

In summary, $\widehat{D}_H(\mathcal{U}_z, \mathcal{U}_y)$ is the distance between the predicted events set and the ground-truth events set, which considers all events with all of their arguments at the same time, essentially capturing a global alignment.

3.6 Objective Function

The final loss is the sum of approximate Hausdorff distance and entity representation loss:

$$\mathcal{L} = \widehat{D}_H(\mathcal{U}_z, \mathcal{U}_y) + \mathcal{L}_\mathrm{e} \tag{15}$$

4 Experiments

In this section, we present performance and runtime experiments in comparison with state-of-the-art approaches. We also discuss the ablations study. Entity and event visualisation results can be found in Appendix B.

4.1 Experimental Setup

Dataset We evaluate ProCNet on the two document-level multi-event extraction datasets: (1) ChFinAnn dataset[2] (Zheng et al., 2019) consists of 32,040 financial documents, with 25,632, 3,204, and 3,204 in the train, development, and test sets, respectively, and includes five event types. The dataset contains 71% of single-event documents and 29% of multi-event documents. (2) DuEE-Fin dataset[3] (Han et al., 2022) has around 11,900 financial documents and 13 event types. As the dataset has not released the ground truth annotations for the test set, we follow the setting of (Liang et al., 2022) and treat the original development set as the test set. We also set aside 500 documents from the training set as the development set. Our final dataset has 6,515, 500, and 1,171 documents in the train, development, and test set, respectively. There are 67% of single-event documents and 33% of multi-event documents. More details about the event types and their distributions are in Appendix A.1.

[2] https://github.com/dolphin-zs/Doc2EDAG

[3] https://aistudio.baidu.com/aistudio/competition/detail/46/0/task-definition

Model	ChFinAnn					DuEE-Fin				
	P.	**R.**	**F1**	**F1 (S.)**	**F1 (M.)**	**P.**	**R.**	**F1**	**F1 (S.)**	**F1 (M.)**
DCFEE-O	68.0	63.3	65.6	69.9	50.3	59.8	55.5	57.6	62.7	53.3
DCFEE-M	63.0	64.6	63.8	65.5	50.5	50.2	55.5	52.7	57.1	49.5
Greedy-Dec	82.5	53.7	65.1	80.2	36.9	66.0	50.6	57.3	67.8	47.4
Doc2EDAG	82.7	75.2	78.8	83.9	67.3	67.1	60.1	63.4	69.1	58.7
DE-PPN	83.7	76.4	79.9	85.9	68.4	69.0	33.5	45.1	54.2	21.8
PTPCG	83.7	75.4	79.4	88.2	-	71.0	61.7	66.0	-	-
GIT	82.3	78.4	80.3	87.6	72.3	69.8	65.9	67.8	73.7	63.8
ReDEE	83.9	79.9	81.9	88.7	74.1	77.0	72.0	74.4	78.9	70.6
`ProCNet` (Ours)	**84.1**	**81.9**	**83.0**	**89.6**	**75.6**	**78.8**	**72.8**	**75.6**	**80.0**	**72.1**

Table 1: Overall precision (P.), recall (R.), and F1-score (F1) on the ChFinAnn and DuEE-Fin datasets. F1 (S.) and F1 (M.) denote scores under Single-event (S.) and Multi-event (M.) sets.

Evaluation Metrics We follow the same metrics in (Zheng et al., 2019). For a predicted event of a specific event type, the most similar ground-truth event that is of the same event type is selected without replacement. Then the micro-averaged role-level precision, recall, and F1-score are calculated for the predicted event and the selected gold event.

Implementation Detail To keep it simple, we only use one-layer GNN-FiLM (Brockschmidt, 2020) with a single linear layer as the hyper-function. Specifically, we have $f_{\gamma}(\boldsymbol{h}_v^{(l)}; \boldsymbol{\theta}_{\gamma,\varepsilon}) = \boldsymbol{W}_{\gamma,\varepsilon}\boldsymbol{h}_v^{(l)}$ and $f_{\beta}(\boldsymbol{h}_v^{(l)}; \boldsymbol{\theta}_{\beta,\varepsilon}) = \boldsymbol{W}_{\beta,\varepsilon}\boldsymbol{h}_v^{(l)}$ in Eq. (3). The number of proxy nodes n is set to 16. More implementation details are in Appendix A.2

Baselines The baselines that we compare with are as follows: **DCFEE** (Yang et al., 2018) uses an argument-completion strategy in the table-filling task. Two variants of DCFEE are **DCFEE-O** for single-event and **DCFEE-M** for multi-event. **Doc2EDAG** (Zheng et al., 2019) utilizes a path-expansion decoding strategy to extract events like hierarchical clustering. **Greedy-Dec** is a variant of Doc2EDAG that decodes events greedily. **DE-PPN** (Yang et al., 2021) uses Transformer to encode sentences and entities. **GIT** (Xu et al., 2021) uses a Tracker module to track events in the path-expansion decoding. **PTPCG** (Zhu et al., 2022) combines event arguments together in a non-autoregressive decoding approach with pruned complete graphs, aiming to consume lower computational resources. **ReDEE** (Liang et al., 2022) is a Relation-augmented Attention Transformer to cover multi-scale and multi-amount relations.

Model	**EF**	**ER**	**EU**	**EO**	**EP**
DCFEE-O	51.1	83.1	45.3	46.6	63.9
DCFEE-M	45.6	80.8	44.2	44.9	62.9
Greedy-Dec	58.9	78.9	51.2	51.3	62.1
Doc2EDAG	70.2	87.3	71.8	75.0	77.3
DE-PPN	73.5	87.4	74.4	75.8	78.4
GIT	73.4	90.8	74.3	76.3	77.7
ReDEE	74.1	90.7	75.3	**78.1**	80.1
`ProCNet` (Ours)	**75.7**	**93.7**	**76.0**	72.0	**81.3**

Table 2: F1-score of five event types on ChFinAnn.

4.2 Overall Results

Table 1 shows the results on the ChFinAnn and the DuEE-Fin datasets. For ChFinAnn, the baseline results are reported in (Zheng et al., 2019; Yang et al., 2021; Xu et al., 2021; Zhu et al., 2022; Liang et al., 2022). For DuEE-Fin, the baseline results are either taken from (Liang et al., 2022) or by running the published source code of the baselines. We can observe that a simple argument completion strategy (DCFEE-O and DCFEE-M) produces the worst results. Greedy-Dec with the greedy decoding strategy improves upon DCEFF variants, but it reached an F1-score lower than Doc2EDAG by 13.7% on ChFinAnn and 6.3% on DuEE-Fin due to only modeling entity-level representations without a global view. DE-PPN which uses the Transformer to encode sentences and entities performs worse compared to Doc2EDAG which utilizes a path-expansion decoding strategy. Extending DocEDAG with a Track module (GIT) or using a relation-augmented attention transformer (ReDEE) achieves better results compared to earlier approaches. `ProCNet` gives the best overall

Model	WB	FL	BA	BB	CF	CL	SD	SI	SR	RT	PR	PL	EC
DCFEE-O	54.0	65.4	44.0	27.3	58.2	42.0	48.8	53.9	76.7	32.9	63.3	58.3	40.6
DCFEE-M	49.2	68.0	40.4	28.4	51.2	35.1	42.3	45.9	74.0	51.0	55.8	56.4	37.4
Greedy-Dec	53.7	71.8	49.5	41.1	61.3	42.1	49.7	57.4	74.4	29.2	60.8	50.5	39.4
Doc2EDAG	60.0	78.3	50.6	40.1	63.2	51.5	50.7	52.9	83.7	51.2	64.8	61.7	51.2
DE-PPN	50.7	62.7	41.3	21.4	36.3	23.0	32.9	31.3	67.8	25.8	42.1	36.3	23.4
GIT	58.8	77.6	56.6	44.7	68.5	55.1	58.8	**71.2**	86.4	45.0	66.4	71.3	53.8
ReDEE	72.2	81.2	58.9	53.4	76.7	56.7	68.2	56.6	**90.6**	49.9	75.0	**77.8**	56.6
ProCNet (Ours)	**76.0**	**85.0**	**69.8**	**63.5**	**79.0**	**60.5**	**69.3**	68.2	89.2	**50.0**	**77.4**	76.9	**56.9**

Table 3: F1-score on the DuEE-Fin dataset with 13 event types.

F1-score, outperforming the best baseline, ReDEE, by 1.1-1.2%, respectively on ChFinAnn and DuEE-Fin. It can also be observed that all models have better F1-scores for the single-event scenario than the multi-event one, verifying the difficulty of extracting multiple events from a document. When comparing results across the two datasets, we see better results achieved on ChFinAnn, possibly due to its larger training set and smaller set of event types compared to DuEE-Fin.

4.3 Per-Event-Type Results

Table 2 and Table 3 show the evaluation results on the 5 and 13 event types[4] on ChFinAnn and DuEE-Fin, respectively. On ChFinANN, ReDEE outperforms the others on EO. On DuEE-Fin, ReDEE gives the best results on SR and PL, while GIT outperforms the others on SI. Some documents of these event types contain more than 40 sentences. A possible reason for ProCNet not performing well on these event types is its limited capability of capturing long-term dependencies across sentences, since ProCNet does not directly model the relations between sentences. On the contrary, ReDEE and GIT model the inter-relations of sentences directly. Nevertheless, ProCNet achieves superior results on other event types, resulting in overall better performance compared to baselines.

Model	Per Epoch		Convergence	
	Time	Ratio	Time	Ratio
		ChFinANN		
Doc2EDAG	4:40	5.2x	327:09	10.7x
DE-PPN	1:54	2.1x	87:27	2.8x
PTPCG	0:26	0.5x	39:04	1.3x
GIT	4:48	5.3x	317:35	10.3x
ReDEE	8:12	9.1x	525:33	17.1x
ProCNet (Ours)	0:54	1.0x	30:34	1.0x
		DuEE-Fin		
Doc2EDAG	1:53	11.3x	249:35	16.5x
DE-PPN	0:15	1.5x	24:36	1.6x
PTPCG	0:06	0.6x	9:28	0.6x
GIT	1:50	11.0x	178:38	11.8x
ReDEE	7:28	44.8x	687:14	45.4x
ProCNet (Ours)	0:10	1.0x	15:09	1.0x

Table 4: The GPU time (hh:mm) of each epoch and reaching convergence in average.

4.4 Run-Time Comparison

We compare the training time of the five baselines, Doc2EDAG, DE-PPN, PTPCG, GIT, and ReDEE, with ProCNet on a GPU server with NVIDIA Quadro RTX 6000 and the same setting. We record the average per epoch training time and the total time to reach convergence in Table 4. DuEE-Fin contains fewer data than ChFinANN, as such, Doc2EDAGE, GIT, and ProCNet trained faster on DuEE-Fin. However, ReDEE took longer time to converge on DuEE-Fin, because ReDEE models the relations of all argument-argument pairs. As the number of event types and argument types in DuEE-Fin is more than that in ChFinANN, the training time of ReDEE increases exponentially. DE-PPN runs faster than Doc2EDAG, GIT, and ReDEE but slower than ProCNet. In contrast, ProCNet avoids the time-consuming decoding by introducing the proxy nodes and HDM. Besides, ProCNet can run all proxy nodes and their arguments in parallel, which is more GPU-friendly. PTPCG has a shorter per-epoch run time, but took a longer time to converge on ChFinAnn; though it appears to be more run time efficient on DuEE-Fin compared to our approach. In summary, ProCNet is 0.5x-44.8x times faster than baselines per epoch, and is 0.6x-45.4x times faster to reach convergence.

[4] Please refer to Appendix A.1 for event type descriptions.

... [9] Name of shareholder: Guangxin Holding Group Co., Ltd. ... [11] Guangxin Group disclosed its share increase plan on **October 23, 2018**. ... [21] As of **November 19, 2018**, Guangxin Group has accumulated 1653640 shares of the company through centralized bidding through the Shanghai Stock Exchange trading system, accounting for 0.08% of the company's total share capital, with an average increase price of 9.59 yuan per share, the increase amount is 15854061.0 yuan,... [22] On **November 20, 2018**, Guangxin Group increased its holdings of the company's shares by 1788000 shares through centralized bidding through the Shanghai Stock Exchange trading system, accounting for 10% of the company's total share capital. 0.08%, the average increase price is 9.36 yuan per share, and the increase amount is 16740153.0 yuan. ... [24] After the above-mentioned increase in holdings, Guangxin Group directly held **264558774 shares** of the company, accounting for 12.49% of the company's total share capital ...

True Events:
Event #1: Equity Overweight
EquityHolder: Guangxin Holding Group Co., Ltd.
TradedShares: 1653640 shares
StartDate: October 23, 2018
EndDate: November 19, 2018
LaterHoldingShares: null
AveragePrice: 9.59 yuan per share

Event #2: Equity Overweight
EquityHolder: Guangxin Holding Group Co., Ltd.
TradedShares: 1788000 shares
StartDate: November 20, 2018
EndDate: November 20, 2018
LaterHoldingShares: 264558774 shares
AveragePrice: 9.36 yuan per share

Predicted Events:
Event #1: Equity Overweight
EquityHolder: Guangxin Holding Group Co., Ltd.
TradedShares: 1653640 shares
StartDate: **null**
EndDate: **November 20, 2018**
LaterHoldingShares: null
AveragePrice: 9.59 yuan per share

Event #2: Equity Overweight
EquityHolder: Guangxin Holding Group Co., Ltd.
TradedShares: 1788000 shares
StartDate: **null**
EndDate: November 20, 2018
LaterHoldingShares: **null**
AveragePrice: 9.36 yuan per share

Figure 3: Error case study with incorrect arguments colored in red. [.] denotes the sentence numbering.

4.5 Ablation Study

Model	**ChFinANN**			**DuEE-Fin**		
	P.	**R.**	**F1**	**P.**	**R.**	**F1**
ProCNet (Ours)	84.1	81.9	83.0	78.8	72.8	75.6
−Hypernetwork	82.7	81.6	82.1	77.0	72.2	74.5
−Proxy node	41.3	2.3	4.4	21.1	1.0	1.7
−HDM	17.0	19.8	18.3	13.3	8.2	10.1

Table 5: Ablation study on ChFinAnn and DuEE-Fin.

Table 5 shows how different components in ProCNet contribute to performance:

−Hypernetwork Hypernetwork is removed by replacing GNN-FiLM with RGCN (Schlichtkrull et al., 2018), where all proxy nodes in RGCN share the same message-passing function. We see a drop of about 1% in F1 on both datasets, showing the importance of using different entity aggregation functions for different event proxy nodes.

−Proxy Node We replace $\{\boldsymbol{h}_{z_i}\}_{i=1}^{n}$ with $\{\boldsymbol{h}_{z_0}\}_{i=1}^{n}$, where all proxy nodes share the same embedding $\boldsymbol{h}_{z_0}$. In this way, $\boldsymbol{h}_{z_0}$ acts as a common start node as in existing baselines. It can be observed that F1 drops significantly to 4.4% and 1.7%, respectively. The model learns almost nothing, which verifies the importance of the proxy nodes for ProCNet.

−HDM Instead of minimizing the Hausdorff distance between the predicted set and the ground-truth set globally, we randomly initialize the edge set $\widehat{\mathcal{T}}$ without employing Eq. (13), where the minimization is not performed towards the global minimum. We see a drastic decrease in performance. Without HDM, it is difficult for the the model to learn the alignment between a proxy node and a ground-truth event, showing that HDM is an indispensable component of ProCNet.

4.6 Case Study

Figure 3 shows an error case of ProCNet. *Event #1* spans from sentence #9 to sentence #21, and the *StartDate* is too far from the main context of *Event #1*. Moreover, the classification of *LaterHoldingShares* in *Event #2* requires the model to relate the pronoun *above-mentioned* to the *Event #2*. These mistakes show that ProCNetstill faces a difficulty in modeling long-distance dependencies.

5 Conclusion

In this paper, we no longer focus on inter-entities relation modeling and decoding strategy as in previous methods, but directly learns all events globally through the use of event proxy nodes and the minimization of the Hausdorff distance in our proposed ProCNet. In our experiments, ProCNet outperforms state-of-the-art approaches while only requiring a fraction of time for training.

Acknowledgements

This work was supported in part by the UK Engineering and Physical Sciences Research Council (grant no. EP/T017112/2, EP/V048597/1, EP/X019063/1). YH is supported by a Turing AI Fellowship funded by the UK Research and Innovation (grant no. EP/V020579/2).

Limitations

In our proposed model, we introduce a hyper-parameter n as the number of event proxy nodes. The value of n needs to be pre-set. Setting n to a value larger than the actual event number in a document would lead to computational redundancy as more proxy nodes would be mapped to the *null* event. However, setting n to a small value may miss some events in a document. We have experimented with automatically learning the value of n based on an input document in `ProCNet`. But we did not observe improved event extraction performance. As such, we simply set it to 16. In the ChFinAnn dataset, 98% documents have less than 7 events annotated. This results in the learning of many redundant proxy nodes for such documents. It remains an open challenge on automatically learning a varying number of event proxy nodes based on an input document. Reducing the number of redundant proxy nodes can reduce training time further.

Another shortcoming is the limited capability of `ProCNet` in capturing the long-term dependencies of sentences, as have been discussed in the per-event-type results in Section 4.2 and 4.3. We observed a relatively worse performance of `ProCNet` in dealing with long documents with more than 40 sentences as it does not explicitly model the inter-relations of sentences. One possible direction is to explore the use of a heterogeneous graph which additionally models the entity-entity, entity-sentence, and sentence-sentence relations. We will leave it as the future work to study the trade-off between event extraction performance and training efficiency.

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Appendix

A Experimental Setup

A.1 Dataset

Event Type	**Distribution**
Equity **F**reeze	4.2%
Equity **R**epurchase	9.5%
Equity **U**nderweight	16.0%
Equity **O**verweight	18.3%
Equity **P**ledge	52.0%

Table A1: Event type distribution in ChFinAnn.

Event Type	**Distribution**
Win **B**idding	9.5%
Financial **L**oss	11.1%
Business **A**cquisition	9.7%
Business **B**ankruptcy	2.5%
CCorporate **F**inancing	5.5%
Companies **L**isting	5.1%
Shareholders **H**oldings **D**ecrease	9.3%
Shareholders **H**oldings **I**ncrease	3.5%
Share **R**epurchase	14.1%
Regulatory **T**alk	1.8%
Pledge **R**elease	7.7%
Pledge	10.8%
Executive **C**hange	9.4%

Table A2: Event type distribution in DuEE-Fin.

ChFinAnn ChFinAnn dataset contains 32,040 financial documents collected from public reports, with 25,632 in the train set, 3,204 in the development set and 3,204 in the test set. There are 71% of single-event documents and 29% of multi-event documents. It includes five event types. The distribution of event types is shown in Table A1.

DuEE-Fin DuEE-Fin dataset did not release the ground truth publicly available for the test set. We follow the setting of Liang et al. (2022), but additionally split 500 documents from train set as development set and treat the original development set as test set. To this end, there are 6,515, 500, and 1,171 documents in train, development, and test set, respectively. There are 67% of single-event documents and 33% of multi-event documents. The DuEE-Fin dataset contains 13 event types. The distribution of event types is shown in Table A2.

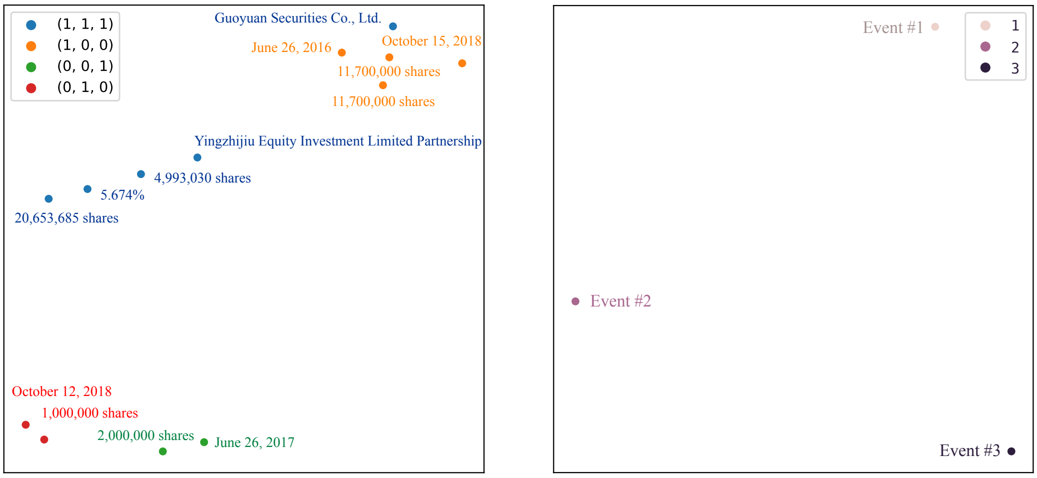
A.2 Implementation Detail

We follow the setting of Liang et al. (2022) using the BERT-base (Devlin et al., 2019) in Roberta setting (Liu et al., 2019) as the sequence labeling model. We use one-layer GNN-FiLM (Brockschmidt, 2020) with a single linear layer as the hyper-function and GELU (Hendrycks and Gimpel, 2016) as the activation function. Specifically, we have $f_\gamma(\boldsymbol{h}_v^{(l)};\boldsymbol{\theta}_{\gamma,\varepsilon}) = \boldsymbol{W}_{\gamma,\varepsilon}\boldsymbol{h}_v^{(l)}$ and $f_\beta(\boldsymbol{h}_v^{(l)};\boldsymbol{\theta}_{\beta,\varepsilon}) = \boldsymbol{W}_{\beta,\varepsilon}\boldsymbol{h}_v^{(l)}$ in Eq. (3), where $\boldsymbol{W}_{\gamma,\varepsilon} \in \mathbb{R}^{d_h \times d_h}$ and $\boldsymbol{W}_{\beta,\varepsilon} \in \mathbb{R}^{d_h \times d_h}$ are learnable parameters. The hidden size is 512. We employ the Adam optimizer (Kingma and Ba, 2015) with a batch size 32, a learning rate $1e$-5 for pretrained parameters, a learning rate $1e$-4 for randomly initialized parameters. We run the model 3 times with a maximal number of epochs 100 selecting the best checkpoint and with one NVIDIA Quadro RTX 6000 GPU.

B Visualisation

We employ t-SNE (van der Maaten and Hinton, 2008) to visualize in Figure A1 the representations of entities and proxy nodes of an example illustrated in Figure A2. The three numbers in Figure A1a denote whether an entity belongs to the three corresponding events. For example, the *(0, 0, 1)* means green entities are arguments of *Event #3*, whereas *(1, 1, 1)* means blue entities are arguments of all three events. Blue entities are also separated from the other three kinds of entities. It is difficult to identify events from the entity-level representations. In contrast, after mapping entities to the event-level metric space, the three points denoting the three proxy nodes are easier to be distinguished as shown in Figure A1b.

Figure A2 shows the example used in Figure A1. The three events correspond to three proxy nodes. The entity *11,700,000 shares* appears two times in the document, so there are two points in Figure A1 representing *11,700,000 shares*.



(a) Entity

(b) Proxy Node

Figure A1: Visualisation of entity and proxy node representations of the example in Figure A2.

... [4] On October 16, 2018, Jinhui Wine Co., Ltd. (hereinafter referred to as the "Company") received the shareholder **Yingzhijiu Equity Investment Limited Partnership** (hereinafter referred to as "Yingzhijiu") to transfer the company it holds ... [6] **On June 27, 2016**, Yingzhijiu pledged **9,000,000 shares** of the company it held to **Guoyuan Securities Co., Ltd.** (hereinafter referred to as "Guoyuan Securities") for processing pledged repurchase transactions. ... [7] On June 6, 2017, the company implemented the 2016 profit distribution plan, that is, every 10 shares will be increased by 3 shares and a cash dividend of 2.4 yuan will be distributed. After the transfer, the above pledged shares increased from 9,000,000 shares to **11,700,000 shares** ... [8] On **October 15, 2018**, Yingzhijiu released all the above-mentioned **11,700,000 shares** from the pledge, ... [12] On **June 26, 2017**, Yingzhijiu pledged **2,000,000 shares** of the company it held to Guoyuan securities. ... [13] On **October 12, 2018**, Yingzhijiu pledged **1,000,000 shares** of the company (accounting for 0.275% of the total share capital of Jinhui Wine) to Guoyuan Securities as a supplementary pledge for the above-mentioned pledged shares, and handled the related procedures. ... [16] As of the date of this announcement, Yingzhijiu held **20,653,685 shares** of the company, accounting for **5.674%** of the company's total share capital, and pledged **4,993,030 shares** in total, accounting for 24.175% of the company's shares and 1.372% of the company's total share capital. . ...

Event #1: Equity Pledge	**Event #2: Equity Pledge**	**Event #3: Equity Pledge**
Pledger: Yingzhijiu Equity Investment Limited Partnership	Pledger: Yingzhijiu Equity Investment Limited Partnership	Pledger: Yingzhijiu Equity Investment Limited Partnership
PledgedShares: 11,700,000 shares	PledgedShares: 1,000,000 shares	PledgedShares: 2,000,000 shares
Pledgee: Guoyuan Securities Co., Ltd.	Pledgee: Guoyuan Securities Co., Ltd.	Pledgee: Guoyuan Securities Co., Ltd.
TotalHoldingShares: 20,653,685 shares	TotalHoldingShares: 20,653,685 shares	TotalHoldingShares: 20,653,685 shares
TotalHoldingRatio: 5.674%	TotalHoldingRatio: 5.674%	TotalHoldingRatio: 5.674%
TotalPledgedShares: 4,993,030 shares	TotalPledgedShares: 4,993,030 shares	TotalPledgedShares: 4,993,030 shares
StartDate: June 26, 2016	StartDate: October 12, 2018	StartDate: June 26, 2017
EndDate: null	EndDate: null	EndDate: null
ReleasedDate: October 15, 2018	ReleasedDate: null	ReleasedDate: null

Figure A2: The example used in Figure A1. Bold words are arguments, and [.] denotes the sentence numbering.

ACL 2023 Responsible NLP Checklist

A For every submission:

☑ A1. Did you describe the limitations of your work?
Limitations

☑ A2. Did you discuss any potential risks of your work?
Limitations

☑ A3. Do the abstract and introduction summarize the paper's main claims?
1

☒ A4. Have you used AI writing assistants when working on this paper?
Left blank.

B ☑ Did you use or create scientific artifacts?

4 A

☑ B1. Did you cite the creators of artifacts you used?
4

☑ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
4 A

☑ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?
4 A

☑ B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?
4 A

☑ B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?
4 A

☑ B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.
4 A

C ☑ Did you run computational experiments?

4 A

☑ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
4

The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.

☑ C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
4 A

☑ C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
4 A

☑ C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
4

D ☒ Did you use human annotators (e.g., crowdworkers) or research with human participants?

Left blank.

□ D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
No response.

□ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?
No response.

□ D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
No response.

□ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
No response.

□ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
No response.