RSGT: Relational Structure Guided Temporal Relation Extraction

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Abstract
Temporal relation extraction aims to extract temporal relations between event pairs, which is crucial for natural language understanding. Few efforts have been devoted to capturing the global features. In this paper, we propose RSGT: Relational Structure Guided Temporal Relation Extraction to extract the relational structure features that can fit for both inter-sentence and intra-sentence relations. Specifically, we construct a syntactic-and-semantic-based graph to extract relational structures. Then we present a graph neural network based model to learn the representation of this graph. After that, an auxiliary temporal neighbor prediction task is used to fine-tune the encoder to get more comprehensive node representations. Finally, we apply a conflict detection and correction algorithm to adjust the wrongly predicted labels. Experiments on two well-known datasets, MATRES and TB-Dense, demonstrate the superiority of our method (2.3% F1 improvement on MATRES, 3.5% F1 improvement on TB-Dense).

1 Introduction
Temporal relation extraction (TRE) is crucial for natural language understanding and can facilitate various downstream applications such as summarization (Zhou et al., 2010), question answering (Yu et al., 2017), and clinical diagnosis (Zhou et al., 2021). As shown in Figure 1, the goal of TRE is to determine the temporal order between an event pair (BEFORE, AFTER, etc.).

Most early methods were based on statistical machine learning (Mani et al., 2006; Chambers, 2013). In recent years, neural network based methods and large-scale pre-trained language models such as BERT (Devlin et al., 2018) have contributed to a substantial increase in the performance of TRE task (Ning et al., 2019; Wang et al., 2020).

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S1: Former President Nicolas Sarkozy was (e1,informed) Thursday that he would face a formal investigation into whether he (e2,abused) the frailty of Liliane Bettencourt, to get funds for his 2007 presidential campaign.
S2: Mr. Sarkozy has (e3,denied) accepting illegal campaign funds from Ms. Bettencourt, either personally or through his party treasurer at the time, Eric Woerth, as (e4,alleged) by her former butler.

Figure 1: An example of temporal relation extraction. There are four events in these sentences. The graph below shows the pair-wise event temporal relationships.

However, these methods may ignore the global structure features which carry non-consecutive and long-distance semantics (Peng et al., 2018). This shortcoming is obvious in dealing with an event pair that the two events belong to different sentences (inter-sentences event pair), such as < e1, e4 > in Figure 1. Few previous works differentiate inter-sentence event pairs from intra-sentence ones (where the two events appear in the same sentence). Thus, the performance may be impacted. For example, we test that there is a 5 accuracy points gap between intra-sentences and inter-sentence event pairs with the recent state-of-the-art method (Wen and Ji, 2021a).

To fill this gap, we aim to develop a structural features method that captures temporal semantic relations for both the inter-sentence and intra-sentence event pairs. Specifically, we adopt graph neural networks (GNNs), which have been proved to be effective in preserving global structure information of a graph in graph embeddings (Yao et al., 2019), to bridge the temporal relations.

Based on the above analysis, we present RSGT: Relational Structure Guided Temporal Relation Extraction. To enable our model to learn more ef-
fective representation for relational structures, we take the following strategies: First, to obtain more relational information, we create different types of connections for the graph nodes based on their syntactic and semantic information. Such connections are combined together to generate a rich relational graph. In particular, the node embeddings are obtained with the GGNN algorithm (Li et al., 2016). To avoid graph over-smoothing, RoBERTa (Liu et al., 2019) embeddings are concatenated with GGNN embeddings to make the final prediction.

Second, unlike most previous graph-based models which directly use the pre-trained language model as the node encoder, we present a task called temporal event neighbor prediction to fine-tune the encoder. This task aims to predict the neighbor node of event mentions from the relational graph. The fine-tuned encoder can help RSGT better understand the correlation between the relational structure and raw text. Ablation studies demonstrate that it can significantly boost efficiency.

Finally, we present a conflict detection and correction algorithm based on the transitivity rule of temporal relations to promote performance.

Experiments on two popular benchmarks, MATRES (Ning et al., 2018) and TB-Dense (Cassidy et al., 2014), show that RSGT outperforms the state-of-the-art methods (2.3% F1 points improvement on MATRES, 3.5% F1 points improvement on TB-Dense). Meanwhile, we improve the accuracy of inter-sentence relations to the same level as intra-sentence relations.

2 Method

We formulate the TRE problem as a multi-class classification task. For a document \( D \) with \( n \) sentences \( (S_1, S_2, ..., S_n) \), it can have multiple event mentions \( E = (e_1, e_2, ..., e_m) \). The goal of TRE is to predict the temporal relation type between event pairs. For an event pair \(< e_i, e_j >\), the input of our model is the sentence they belong to. In particular, if two events belong to different sentences (we call it inter-sentence event pair), two sentences \(< S_i, S_j >\) are concatenated together as the input.

Our work RSGT involves five major parts: (i) Structure Generation to generate a relational-guided graph based on syntactic-and-semantic information, (ii) Temporal Event Neighbor Prediction to transform words into embedding vectors, (iii) Relational-guided Graph Model to predict temporal relations, (iv) Conflict Detect and Correct algorithm to revise temporal errors.

2.1 Structure Generation

Building graphs is a feature selection process that can facilitate representation learning for the TRE problem. Given an input sentence \( S \), our goal is to generate a relational graph \( G = \{\mathcal{N}, \mathcal{E}\} \) as the input of our graph neural network. Our relational graph is based on syntactic and semantic information extracted from \( S \). The node set \( \mathcal{N} \) and edge set \( \mathcal{E} \) in \( G \) are constructed as follows strategies.

2.1.1 Nodes

The node set \( \mathcal{N} \) should capture all objects related to temporal events. We take two types of nodes to make up the node set. The first type is from the original words \( w_i \in S \). The second type is the event arguments extracted by the Semantic Role Labeling (SRL) model, which we will introduce in the semantic-guided edges section. Formally, let \( W = \{w_1, w_2, ..., w_{|W|}\} \), \( \mathcal{Arg} = \{a_1, a_2, ..., a_{|\mathcal{Arg}|}\} \) be the set of words and event arguments, respectively. Then the node set of the input sentence should consist of two parts: \( \mathcal{N} = \{W \cup \mathcal{Arg}\} \). After the generation of \( G \), nodes with no edges pointing to other nodes are removed from \( \mathcal{N} \).

2.1.2 Syntactic-guided Edges

Dependency Parsing (DP) can examine the dependencies between the phrases of a sentence to determine its syntactic structure. As such, we apply the dependency parsing tree of the input sentence
to build syntactic-guided edges $E_d$. For the dependency tree consisting of multiple head-dependent arcs, the arcs whose head is event mention are converted to edges $E_{d, along}$ as the solid black arcs in Figure 2. In addition, we assume that information flows not only along the syntactic dependency arcs, so we create edges $E_{d, rev}$ in the opposite direction as well (i.e., from dependents to heads). Following Kipf and Welling (2016), we also add self-edges for each nodes as $E_{d, loop}$. Therefore, syntactic-guided edges $E_d$ contains three kinds of edges $E_{d, along}$, $E_{d, rev}$ and $E_{d, loop}$.

2.1.3 Semantic-guided Edges

We design semantic-guided edges $E_t$ to fetch semantic information related to a temporal event. Specifically, we want to import an event extraction model that can extract event arguments based on event mentions. SRL-BERT (Shi and Lin, 2019) becomes our final choice because it not only meets our above requirements but also marks out the argument’s types. As shown in the Figure 2’s red arcs, arguments are connected to the event mentions as $E_t$. SRL task assumes event mentions trigger the arguments, so we only consider unidirectional edges from event nodes. Some particular argument types, such as Temporal and Discourse, which can probably provide extra information to understand the temporal relation, are assigned to different edge types with higher weight.

2.2 Temporal Event Neighbor Prediction

In the graph model, we need to apply an encoder to transform each word $w_l \in S$ into a contextual represented vector for nodes. Most previous studies directly use pre-trained language models as the encoder. However, Chien et al. (2021) argues that these pre-trained language models ignore the correlations between graph topology and raw text features. Inspired by this work, we propose a task called Temporal Event Neighbor Prediction. Given a syntactic-guided graph $G_d$ we construct, this task aims to distinguish whether a node is the neighbor of the event mention’s node or not. We pick $k$ words before and after per event mention respectively in the sentence, and they can form node pairs with its event mention.

Take the sentence in 2 as an example. Suppose we are using $k = 2$, so for the first event mentions $w_4$, we pick 4 words before and after $w_4$, which are $\{w_2, w_3, w_5, w_6\}$. Node pairs $<w_4, w_3>$, $<w_4, w_6>$ are neighbors, so their labels are 1. $<w_4, w_5>$ are not neighbors and their labels are 0. The second event mentions $w_6$ can be treated in the same way. The input of this task is each event-neighbor pair $<w_e, w_{nbr}>$ and its raw sentence.

To handle this task, we first apply RoBERTa to encode the sentences and extract the nodes’ embeddings of $<w_e, w_{nbr}>$. The represented vector of two nodes then passes through a Feed-Forward Network (FFN) layer with a $tanh$ activation function, respectively. For the output of FFN layer $h_e$ and $h_{nbr}$, we concatenate them together and apply Batch Normalization as the representation of node pair. Then a FFN layer with softmax is added for prediction. The model can be formalized as:

$$
\begin{align*}
\phi &= tanh(FFN_1(\phi(w_e))) \\
\phi_{nbr} &= tanh(FFN_2(\phi(w_{nbr}))) \\
y_{nbr} &= softmax(FFN_3(BN[h_{nbr}; h_e]))
\end{align*}
$$

where BN denotes Batch Normalization, and $\phi$ is the encoder that maps $w$ to feature vectors. We adjust $k$ to ensure that the distribution of labels is balanced. To make sure RoBERTa can maintain more topology information from the relational graph, the learning rate of RoBERTa is larger than other layers.

This task allows the encoder to understand not only the contextual information from the raw text but also the topology information from our relational graph $G$. We select the model with the best accuracy in the validation set as the encoder. Then we apply this fine-tuned encoder to represent the node set $N$. This task can be further extended to other graph-related models as an efficient way for the encoder’s fine-tuning.

2.3 Relational-guided Graph Model

We have already generated a relational graph $G$ and the represented vector $x$ for each node. We apply Gated Graph Sequence Neural Networks (GGNN) to handle our relational graph. GGNN employs a gated recurrent unit (GRU) as a recurrent function, reducing the recurrence to a fixed number of steps. The advantage is that it no longer needs to constrain parameters to ensure convergence. We parse each sentence into the relational graph and use GGNN to digest this structural information. The forward process of GGNN is:
\[ x_u = \phi(w_u) \]
\[ h_u^0 = |x_u||0| \]
\[ a_u = \sum_{v \in \mathcal{N}(u)} W_{uv} h_v^t \]
\[ h_u^{t+1} = \text{GRU}(a_u^t; h_u^t) \]

where \( u \) denotes the current node and \( v \) denotes the neighbor node of \( u \). \( \phi \) is the fine-tuned encoder, and \( h_u^t \) denotes the \( t \) step hidden states of \( u \).

As discussed in Chen et al. (2020), over-smoothing is a common issue faced by GNNs, which means that the representations of the graph nodes of different classes would become indistinguishable when stacking multiple layers. To avoid over-smoothing problems, the embeddings \( < x_i, x_j > \) from fine-tuned RoBERTa are passed through a fully connected layer parallel with GGNN. For event pair \( < x_i, x_j > \), the representation \( H_F \) from the fully connected layer is then concatenated with GGNN’s final hidden states \( H_G \). Concatenation may help us maintain some contextual information from RoBERTa encoder and increase the differentiation of event representations. In the end, we apply a two-layer FFN as classifier \( f \) and a BatchNorm layer for the final temporal prediction. The final output of event pair \( < e_i, e_j > \) is:

\[ \hat{y}_{ij} = f(\text{BN}[H_G; H_G; H_F; H_F]) \quad (3) \]

The overall loss function to train our model is:

\[ L = -\sum_{i,j} \hat{y}_{ij}^\ast \log(\hat{y}_{ij}) + \gamma L_{reg} \quad (4) \]

where \( \hat{y}_{ij}^\ast \) is the gold labels of temporal relations and \( \gamma \) is a trade-off parameter for regularization techniques.

### 2.4 Conflict Detect and Correct

There exists a transitivity rule in temporal relationships. Take the events depicted in Figure 1 as an example. We consider the intra-sentence and inter-sentence event pairs relationships together and build the temporal diagram on the left side of the Figure 3. A transitivity rule could be explained as “\( e_2 \) happens before \( e_1 \), \( e_1 \) and \( e_4 \) occur simultaneously, then \( e_1 \) should happen after \( e_2 \)”. On the right side of Figure 3 is a counterexample. The red arrows can form a cycle, which indicates that at least one temporal relation edge violates the transitivity rule.

To take full advantage of this rule, we design an algorithm to find potential conflicts. From the output of the classifier \( f \), we obtain a temporal relationship prediction \( \hat{y}_{ij} \) for the event pair \( < e_i, e_j > \). We can build a document-level temporal relational graph by collecting temporal relation predictions as edges and events as nodes from document \( D \). For “BEFORE” relation of \( < e_i, e_j > \), we add an edge from \( e_i \) to \( e_j \). On the contrary, we add an edge from \( e_j \) to \( e_i \) for “AFTER”. We treat “EQUAL” as a bidirectional edge. Other temporal relations are ignored (e.g. “VAGUE”). Obviously, this graph should be a Directed Acyclic Graph (DAG). So our goal is to find the conflict cycles and correct them.

We re-implement the Johnson cycle algorithm (Johnson, 1975) as our temporal event conflict detection algorithm. It was presented to find all the elementary cycles of a directed graph, which time bounded by \( O((n + e)(c + 1)) \) for \( n \) nodes, \( e \) edges and \( c \) elementary cycles.

Then we use algorithm 1 to detect and correct conflict. Basically, we:

1. Apply conflict Detect algorithm to find elementary cycles in the edges.
2. Pick the longest cycle from step 1 and initialize variables cycle_n as cycle’s length, m_logit, m_edge as the smallest logit and its edge (lines 5-7).
3. Traverse all nodes in the cycle and find the smallest logit (lowest probability of confidence edge_logit). Store the start and end node of m_edge(lines 8-20).
4. Reverse the edge found in step 3 to solve the conflicts. Remove m_edge from the graph if it has been corrected twice. Go back to step 1 and repeat until the graph is a directed acyclic graph (lines 21-26).

Figure 3: The example of transitivity rule in temporal relationship. Unidirectional arrows represent “BEFORE”, like \( e_2 \rightarrow e_1 \) refers to \( e_2 \) happens before \( e_1 \). Bidirectional arrows represent two events occurring simultaneously.
Algorithm 1: Correct Algorithm

Input : edges
Output : Corrected edges

1. revised = []
2. while True do
3. cycles = conflict_detect(edges);
4. if no cycles then break;
5. cycle ← longest(cycles);
6. cycle_n ← length(cycle);
7. m_logit, m_edge ← −1, (−1, −1);
8. for i in range(1, cycle_n) do
9. if i ≠ cycle_n then
10. j = i+1;
11. else
12. j = 1;
13. end
14. fr ← cycle[i];
15. to ← cycle[j];
16. edge_logit = edges[now][to];
17. if m_logit ≤ edge_logit then
18. m_logit = edge_logit;
19. m_edge = (fr, to)
20. end
21. fr, to ← m_edge;
22. if fr, to in revised then
23. remove edge(fr, to)
24. revised.add(m_edge);
25. reverse edge(to, fr);
26. cycles ← collision detection(adj)
27. end

This algorithm is concise and efficient, and it can be well adapted to the correction work of various datasets without training.

3 Experiments

3.1 Datasets

We conduct our experiments on two well-known benchmarks for the TRE task, MATRES(Ning et al., 2018) and TB-Dense(Cassidy et al., 2014). MATRES contains refined annotations on TimeBank(Pustejovsky et al., 2003), AQUAINT and Platinum documents. It contains four types of temporal labels: BEFORE, AFTER, EQUAL, VAGUE. TB-Dense is a densely annotated dataset from TimeBank and TempEval(UzZaman et al., 2013). This dataset contains six label types. In addition to the four label types from MATRES, it has two more label types: INCLUDES and IS_INCLUDED. For compatible comparison, we apply the same data splits as in prior work for the considered datasets. The detailed statistics can be found in Table 1.

3.2 Evaluation Metrics

We adopt micro averaged precision, recall, and F1 scores as evaluation metrics following the previous works(Ning et al., 2018; Wen and Ji, 2021a; Cao et al., 2021). For the MATRES, VAGUE is considered to be non-temporal information and is excluded from the F1 calculation. For the TB-Dense, VAGUE is taken into consideration (i.e., all label types are seen as positive classes) so the metric should share the same precision, recall, and F1 value. We follow these different settings for our experiments to ensure fair comparisons.

| Dataset  | Train | Validation | Test | Labels          |
|----------|-------|------------|------|-----------------|
| MATRES   | 10888 | 1852       | 837  | a,b,e,v         |
| TB-Dense | 4032  | 629        | 1427 | a,b,s,v,i,ii    |

Table 1: Data splits and relation pairs statistics. a: AFTER, b: BEFORE, e: EQUAL, s: SIMULTANEOUS, v: VAGUE, i: INCLUDES, ii: IS_INCLUDED.

3.3 Implement Details

The hyperparameters used in the experiment are listed. Neighbor Prediction: RoBERTa-large is adopted to encode the sentence. The learning rate for RoBERTa and FFN are 1e-5, 1e-4, respectively. Syntactic Information: We apply SpaCy toolkit to build dependency trees based on input sentences. Semantic Information: The event arguments corresponding to each event mention are extracted from SRL-BERT. Graphs Training: AdamW with learning rate of 5e-6, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and weight decay of 0.01 is used for optimization. We set the training epochs and batch size to 40 and 32, respectively. Besides, we exploit a dropout with a rate of 0.5 on the concatenated feature representations.

3.4 Baselines

We conduct experiments to compare our approach RSGT with the state-of-the-art models for TRE in each benchmark dataset as follows. Note that MATRES is a relatively new dataset, so we can hardly find more baselines that perform well on both MATRES and TB-Dense.

https://spacy.io/
| Dataset   | Models          | P   | R   | F1  |
|-----------|-----------------|-----|-----|-----|
| MATRES    | Siamese         | 66.6| 60.8| 63.0|
|           | Constrained     | 72.1| 80.8| 76.2|
|           | UAST            | 76.6| 84.9| 80.5|
|           | SMTL            | -   | -   | 81.6|
|           | Stack-Propagation | 78.4| 85.2| 81.7|
|           | RSGT            | 82.2| 85.8| 84.0|
| TB-Dense  | Timelines       | 56.6| 56.6| 56.6|
|           | UAST            | 64.3| 64.3| 64.3|
|           | CTRL-PG         | 65.2| 65.2| 65.2|
|           | RSGT            | 68.7| 68.7| 68.7|

Table 2: Model performance on MATRES and TB-Dense. The performance improvement of RSGT over the baselines is significant with $p < 0.01$.

**MATRES** For this dataset, the following baselines are chosen for comparison. (i) **Siamese** (Ning et al., 2019): A Siamese encoder of a temporal commonsense knowledge base, and global inference via integer linear programming (ILP). (ii) **Constrained** (Wang et al., 2020): A framework bridges temporal and subevent relation extraction tasks with a comprehensive set of logical constraints. (iii) **SMTL** (Ballesteros et al., 2020): A model relies on multi-task learning and self-training techniques. (iv) **Stack-Propagation** (Wen and Ji, 2021a): A Stack-Propagation framework to further incorporate predicted timestamp explicit for relation classification.

**TB-Dense** We use the following baselines for comparison. (i) **Timelines** (Vashishtha et al., 2019) A semantic framework for modeling fine-grained temporal relations and event duration that maps pairs of events to real-valued scales and constructs document-level event timelines. (ii) **UAST** (Cao et al., 2021) An uncertainty-aware self-training framework to quantify the model uncertainty. (iii) **CTRL-PG** (Zhou et al., 2021) A method with probabilistic soft logic Regularization and global inference at the document-level.

### 3.5 Overall Performance

The most important observation from Table 2 is that model **RSGT** has significantly outperformed all the baseline systems on both MATRES and TB-Dense. Thus evidently indicating the effectiveness of the proposed RSGT model for the TRE task. Compared with the previous SOTA method Stack-Propagation, which also uses RoBERTa, our RSGT has 2.3% F1 improvement on the MATRES dataset.

For the more complex dataset TB-sense with six temporal relation types, RSGT also has a 2.6% F1 improvement over the previous SOTA method CTRL-PG. Overall, our method RSGT establishes a new state-of-the-art on two popular datasets of the TRE task.

### 3.6 Intra- and Inter-sentence

Inter-sentence event pairs make up a considerable proportion of the MATRES dataset (69.53% in the train set and 69.77% in the test set). Consequently, the performance on inter-sentence event pairs can significantly influence the overall performance. To explicitly demonstrate the effect of RSGT on the extraction of intra- and inter-sentence event pairs, we conduct a contrast experiment on the MATRES dataset. We attach a learnable fully-connected layer after RoBERTa as the baseline **RoBERTa-F**. The performance on the intra- and inter-sentences is shown in Figure 3. The previous SOTA method, Stack-Propagation, has a clear 4.3% gap in precision value between intra- and inter-sentences. As a comparison, we can observe an absolute F1 gain from RSGT, 2.7% and 4.9% on the intra-sentences and inter-sentences, respectively. Importantly, we successfully fill the performance gap between intra- and inter-sentence event pairs and improve their F1 result to the same level. These experiments show that the introduction of relational structure is of great help for inter-sentence temporal relations extraction.

### 3.7 Ablation Study

To illustrate the impact of each component in RSGT, we further conduct ablation studies with different configurations. Note that MATRES is a relatively new dataset, so we can hardly find more baselines that perform well both on MATRES and TB-Dense.

#### 3.7.1 Effect of Neighbor Prediction

We propose the Neighbor Prediction task so that the encoder can learn the correlation between the relational graph’s topology and raw text. In the
Table 4: Performance of different models on MATRES

| Model                          | P     | R     | F1   |
|-------------------------------|-------|-------|------|
| RSGT -w/o neighbor prediction | 79.7  | 82.7  | 81.2 |
| RSGT -w event prediction      | 69.7  | 79.2  | 74.1 |
| RoBERTa                       | 78.4  | 80.0  | 79.1 |
| RSGT -w/o $E_d$               | 80.5  | 84.7  | 82.5 |
| RSGT -w/o $E_t$               | 81.7  | 85.5  | 83.6 |
| RSGT independent              | 81.0  | 84.8  | 82.8 |
| RSGT                          | 82.2  | 85.8  | 84.0 |

The bottom half of Table 4 shows the performance of the above ablated models. We can observe that all the components can contribute to the proposed model RSGT as eliminating any of them degrades the performance in the F1 score. Apparently, the worse performance of RSGT - $E_d$ model illustrates that syntactic information contributes a major improvement on TRE. And the RSGT - $E_t$ model that removes semantic information slightly loses the performance of 0.4% F1. This is because the syntactic information contains more knowledge about the current event pair, and syntactic information may contain semantic information (event arguments) in some cases. Compared with RSGT independent, the independent graphs lack the interaction of all relational structure information. Instead, syntactic and semantic guided information should work together to form an interactive graph to enrich the relational structure obtained from RSGT.

3.7.2 Effect of Relational Structure Features

We examine the following ablated models to evaluate the effectiveness of different relational structure features in RSGT on the TRE task. (i) RoBERTa is a baseline with RoBERTa model and a fully-connected layer. (ii) RSGT -w/o $E_d$ excludes the syntactic-guided edges. (iii) RSGT -w/o $E_t$ excludes the semantic-guided edges. (iv) RSGT independent apply syntactic and semantics information to construct two independent graphs, respectively. At last, we average the embeddings of the two graphs.

3.7.3 Effect of Conflict Detect and Correct

This algorithm is training-free and the time complexity is $O(n)$. Limited by the test set size, the improvement is slight (about 0.1%) on both MATRES and TB-dense datasets. Notes that the performance improvement from conflict detection gradually decreases with the training process. For example, it can bring a 4.3% average improvement in the first epoch, which means conflict detection can bring huge performance improvements in the early stage. We believe that it will play a more critical role in larger-scale datasets or real-world cases.

3.8 Case Study and Error Analysis

To promote a better understanding of our RSGT and guide potential research direction, we analyze three concrete examples in Figure 4. Each case has a pair of events, and the study results can be categorized into different types that are described...
Case 1. Sentence S1 contains a conversation event mentions “spoken” and a discussion event mentions “discussed”. RSGT correctly predicts the temporal relations while Stack-Propagation fails. RSGT successfully extracts two temporal arguments from S1, enhancing the model’s inference ability by providing the time of occurrence. Obviously, “over the past two years” has happened “this week”. The previous model does not utilize semantic information, which leads to misclassification.

Case 2. The small proportion of EQUAL (about 3.6% in MATRES) makes temporal relationship prediction more challenging, as it can be easily confused with more common labels like BEFORE and AFTER. Sentence S3 contains two events, “allowing” and “serve”. It seems like a simple task for a human. However, Stack-Propagation relies only on two event words and fails to recognize their interaction. We highlight some syntactic information extracted by RSGT. “allow someone to do something” is a typical relational structure that happens simultaneously. As a result, this relational structure makes the prediction much easier for RSGT.

Case 3. S3 and S4 show one intra-sentence and two inter-sentence event temporal relations. Our RSGT correctly classifies <trying, sought>, <sought, said> event pairs. For an inter-sentence event pair like <trying, said>, which is so hard that RSGT fails to predict its temporal relation initially, the conflict detect and correct algorithm can utilize the relationships between the other two event pairs to correct the result. In the directed graph built from the predictions, we obtain three edges (trying → sought), (trying ← said), (sought → said). Obviously, this graph does not meet the DAG definition, and our algorithm reverses the edge with a minimum confidence score (trying ← said) to correct it.

4 Related Work

Earlier efforts on TRE (temporal relation extraction) use statistical machine learning techniques (Support Vector Machine, Max entropy) and hand-craft features (e.g Verhagen and Pustejovsky (2008) and Chambers (2013)). Recently, neural methods and large-scale pre-training language models have also achieved promising improvement (Nguyen and Grishman, 2015; Nguyen et al., 2016; Wang et al., 2020; Mathur et al., 2021). The early feature-based methods for TRE have explored different features and resources to improve the performance, including syntactic patterns and lexical features (Cheng and Miyao, 2017; Mirza and Tonelli, 2016). Unlike previous works, our approach RSGT takes account of relational structure features to induce more accurate representations.

A wave of research at the intersection of deep learning on graphs has influenced a variety of NLP tasks, including event extraction (Xu et al., 2021; Yan et al., 2019), relation extraction (Tran Phu and Nguyen, 2021; Su et al., 2022) and event argument extraction (Pouran Ben Veyseh et al., 2020). These graph-structured data can encode complicated relations between event pairs to infer temporal order. Our model is different from such related works in that we designed a relational structure guided graphs that are tailored to our TRE task. In addition, we introduce a novel Temporal Event Neighbor Prediction task for the fine-tuning of the node encoder.

5 Conclusion

This paper proposes RSGT to capture relational structure information for the temporal relation extraction task. The experimental results well demonstrate our model’s effectiveness and superiority in both the overall datasets and the inter-sentence event pairs. Ablation experiments show that the relational graph model and Temporal Event Neighbor Prediction contribute greatly to RSGT’s performance.

Our future work will focus on how to apply Temporal Event Neighbor Prediction, and Conflict Detect and Correct Algorithm to other tasks with rich relations such as Casual Relations (Caselli and Vossen, 2017). We believe these methods are promising in processing relational structure information from other relational extraction tasks.

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