Extracting Temporal Event Relation with Syntactic-Guided Temporal Graph Transformer

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Abstract

Extracting temporal relations (e.g., before, after, concurrent) among events is crucial to natural language understanding. Previous studies mainly rely on neural networks to learn effective features or manualcrafted linguistic features for temporal relation extraction, which usually fail when the context between two events is complex or wide. Inspired by the examination of available temporal relation annotations and human-like cognitive procedures, we propose a new Temporal Graph Transformer network to (1) explicitly find the connection between two events from a syntactic graph constructed from one or two continuous sentences, and (2) automatically locate the most indicative temporal cues from the path of the two event mentions as well as their surrounding concepts in the syntactic graph with a new temporal-oriented attention mechanism. Experiments on MATRES and TB-Dense datasets show that our approach significantly outperforms previous state-of-the-art methods on both end-to-end temporal relation extraction and temporal relation classification.

1 Introduction

Understanding events and bringing order to chaos are fundamental human activities. Temporal relations, such as Before, After, Concurrent, Include, allow us to quickly understand the process of a complex event, and reason across multiple sub-events, which further support and benefit many downstream applications, such as summarization (Jiang et al., 2011; Ng et al., 2014), dialog understanding and generation (Ritter et al., 2010; Zhai and Williams, 2014; Shi et al., 2019), reading comprehension (Harabagiu and Bejan, 2005; Sun et al., 2018; Ning et al., 2020) and so on. Progress in natural language processing, especially information extraction (Lin et al., 2020; Huang and Ji, 2020), has helped automate the identification of each single event separately, however, how to organize them into an event network is still a challenge.

Recent studies (Han et al., 2019b; Ning et al., 2019a; Vashishtha et al., 2019; Wang et al., 2020a) that leverage pre-training language models, such as BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019), have shown prominent performance gain over the previous approaches (Mani et al., 2006b; Verhagen et al., 2007; Chambers et al., 2007; Bethard and Martin, 2008), by benefiting from the better contextual representations yielded by the state-of-the-art Transformer (Vaswani et al., 2017) encoder. However, different from other natural language understanding tasks, temporal relation prediction requires more accurate characterization of the connection between two event mentions and the cues indicating their temporal relationship, especially when the context is wide and complicated. By manually examining 100 examples of human annotated temporal relations from MATRES (Ning et al., 2018) dataset, we observe that about 55% of the temporal cues come from the connection between two event mentions (e.g., S1 in Figure 1), while 35% come from their surrounding contexts.
(e.g., S2 in Figure 1) and the remaining 10% comes from others, e.g., event co-reference or subordinate clause structures (e.g., S3 in Figure 1).

In this paper, we propose to explicitly find the connection between two event mentions from the syntactic parsing graph constructed from one or two continuous sentences, and automatically capture the indicative temporal cues with a new Temporal Graph Transformer network, which integrates both the multi-head self-attention and a new temporal oriented attention mechanism to capture temporal cues from the connection between two event mentions as well as their surrounding context within the graph. Experiments on two public benchmarks, MATRES (Ning et al., 2018) and TB-Dense (Cassidy et al., 2014a), demonstrate the effectiveness of our new Temporal Graph Transformer over the previous state-of-the-art approaches.

In summary, we make the following contributions:

- We investigate the available temporal relation annotations and categorize the main sources of temporal cues.
- We design a new Temporal Graph Transformer network by combining the traditional multi-head self-attention with a new temporal oriented attention to effective capture the temporal cues.
- We demonstrate the effectiveness of our new approach and establish a new state-of-the-art on two public benchmarks.

2 Related Work

Early studies on temporal relation extraction mainly model it as a pairwise classification problem (Mani et al., 2006a; Verhagen et al., 2007; Verhagen and Pustejovsky, 2008; Verhagen et al., 2010; Bethard et al., 2016; MacAvaney et al., 2017) and use statistical machine learning techniques with hand-crafted features and carefully designed rules, such as temporal links (Verhagen and Pustejovsky, 2008), verb-clauses (Bethard et al., 2007) to extract temporal relations between two events. Recently, deep neural networks (Dligach et al., 2017; Tourille et al., 2017) and large-scale pre-training language models (Han et al., 2019a, 2020; Wang et al., 2020a; Zhou et al., 2020) are further employed and show state-of-the-art performance on temporal relation extraction.

Similar to our approach, several studies (Ling and Weld, 2010; Nikfarjam et al., 2013; Mirza and Tonelli, 2016; Meng et al., 2017; Cheng and Miyao, 2017) explored syntactic features, e.g., Part-of-Speech tags, preposition, etc., and syntactic path between two events for temporal relation extraction. Different from previous studies, our approach takes account of three important factors: local context information, denoting the neighbors of each node within the syntactic graph; connection of two event mentions, which is based on the shortest dependency path between two mention mentions; and rich semantics of nodes and dependency relations, e.g., the dependency relation nmod usually indicates a Before relationship between two events. All these indicative information are automatically selected and aggregated with the multi-head self-attention and our new temporal oriented attention mechanism.

A lot of temporal relation extraction benchmarks have been developed over the past years (Pustejovsky et al., 2003; UzZaman et al., 2013; Cassidy et al., 2014b; Ning et al., 2018; Vashishth et al., 2019; Ning et al., 2020), among which, MATRES and TimeBank-Dense(TB-Dense) are the two largest manually annotated temporal relation datasets, which only annotate the temporal relation of two event mentions from one or two continuous sentences. MATRES is a multi-axis modeling which tries to capture the temporal structure of events by anchoring events to different semantic axes and only comparing events in the same axis. In MATRES, only verbs are considered as events and 4 relation types, including Before, After, Simultaneous and Vague are annotated while TB-Dense adopts a denser annotation scheme with 2 additional types comparing with MATRES: Includes and Is Included.

Our work is also related to the variants of Graph Neural Networks (GNN) (Kipf and Welling, 2016; Veličković et al., 2017; Zhou et al., 2018), especially Graph Transformers (Yun et al., 2019; Chen et al., 2019; Hu et al., 2020; Wang et al., 2020b). Different from previous GNNs which aim to capture the context from neighbors of each node within the graph, in our task, we aim to select and capture the most meaningful temporal cues for two specific event mentions from their connections within the graph as well as their surrounding contexts.
3 Approach

Figure 2 shows the overview of our approach. Given an input sentence $S = [w_1, w_2, ..., w_n]$ which consists of $n$ tokens, we aim to detect a set of event mentions $E = \{e_1, e_2, ...\}$ where each event mention $e_i$ may contain one or multiple tokens by leveraging the contextual representations learned from a pre-trained BERT (Devlin et al., 2018) encoder. Then, following previous studies (Ning et al., 2019b,a; Han et al., 2019b; Wang et al., 2020a), we consider each pair of event mentions that are detected from one or two continuous sentences, and predict their temporal relationship.

To effectively capture the underlying connection of two event mentions, we build a syntactic graph from the one or two input sentences and design a new Temporal Graph Transformer network to automatically learn a new contextual representation for each event mention by considering the triples that they are locally involved as well as the triples along the connection path of the two event mentions within the syntactic graph. Finally, the two event mention representations are concatenated to predict their relationship.

3.1 Sequence Encoder

Given an input sentence $S = [w_1, w_2, ..., w_n]$, we apply the same tokenizer as BERT (Devlin et al., 2018) to get all the subtokens. If a token $w_i$ is split into multiple subtokens, we only keep the first one. Then, we feed the sequence of subtokens as input to a pre-trained BERT model to get a contextual representation for each token $w_i$. To enrich the contextualized representations, each token is initialized with a one-hot Part-of-Speech (POS) tag vector and concatenate it with BERT contextualized embeddings. In this way, we obtain the final representation $c_i$ for $w_i$.

To detect event mentions from the sentence, we take the contextual representation of each word as input to a binary linear classifier to determine whether it’s an event mention or not, which is optimized by minimizing the binary cross-entropy loss:

$$\tilde{y}_i = \text{softmax}(W_{\text{eve}} \cdot c_i + b_{\text{eve}})$$

$$L_e = -\sum_{i=1}^{N} \sum_{j=1}^{|S_i|} \sum_{l \in \{0, 1\}} w_l \cdot y_{i,l,j} \cdot \log(\tilde{y}_{i,j})$$

where $L_e$ denotes the cross entropy loss for event
As the example sentences shown in Section 1, the set of neighbor triples characterizing the indicative temporal cues from the connection path between event mentions mainly come from their surrounding contexts as well as their underlying connections. However, the sequence encoder is not capable of accurately capturing such information, thus we design a new Temporal Graph Transformer (TGT) network.

Given two event mentions with a source event $e_s$ and a target event $e_t$ detected from one or two continuous sentences, we apply a public dependency parsing tool to parse each sentence into a syntactic graph, and connect the graphs of the two continuous sentences with an arbitrary cross-sentence edge pointing from the preceding sentence to the following one, and obtain the graph $G = (V,E)$, where $e_s$ and $e_t$ correspond to $v_s$ and $v_t$ respectively in $G$. For each node $v_i$, we use $N_{in}^i = \{(v_i,r_k,v_k) | v_k \in V\}$ and $N_{out}^i = \{(v_k,r_k,v_i) | v_k \in V\}$ to denote all the neighbor triples of $v_i$ with in-going and out-going edges respectively, and use $P_{ij} = \{(v_i,r_k,v_j),\ldots,(v_r,q,v_j)\}$ as the triple set along the shortest path from $v_i$ to $v_j$ in $G$.

**Node Representation Initialization** For each node $v_i$ in the graph $G$, we map it to a particular token $w_{v_i}$ from the original sentences and obtain the contextual representation from the BERT based sequence encoder.

$$h_i^0 = W_e \cdot c_{v_i} + b_e$$

$c_{v_i}$ is the contextual vector obtained from the BERT sequence encoder for $v_i$, $W_e$ and $b_e$ are learnable parameters.

**Graph Multi-head Self-attention** Following transformer model (Vaswani et al., 2017), we adapt the multi-head self-attention to learn a contextual embedding of each node in the graph $G$.

Each node $v_i$ in the graph $G$ is associated with a set of neighbor triples $N_{in}^{\text{in},\text{out}}_{i} \in \mathcal{P}_{st}$ and a node representation $h_i^{l-1}$. To perform self-attention, we first apply linear projections to obtain the query, key and value vectors where the query vector is obtained from a particular node and both key and value vectors are from the neighbor triples:

$$q_i^l = W_q^x \cdot h_i^{l-1}$$
$$k_i^l_{ij} = W_k^x \cdot r_i^{l-1}$$
$$v_i^l_{ij} = W_v^x \cdot r_i^{l-1}$$
$$r_i^{l}_{ij} = W_r \cdot (h_i^{l-1})^T \left\| c_{ij} \right\| h_i^{l-1} + b_r$$

where $x$ denotes the index of a particular head, $l$ denotes the index of layer, $i,j$ denotes the head and tail node of a particular relation triple and $c_{ij}$ denotes their dependency relation. Each triple $(v_i,r_{ij},v_j)$ is represented as $r_{ij}, W_q^x, W_r, W_v^x$ and $W_k^x$ are learnable parameters. For each node $v_i$, we then perform self-attention over all the neighbor triples that it's involved, and compute a new context representation:

$$g_i^l = \sum_{x \in \{(v_i,r_{ij},v_j)\in N_{in}^{\text{in},\text{out}}_{i} \cup P_{ij}\}} W_O \cdot \alpha_{ij}^x \cdot v_i^l_{ij}$$
$$\alpha_{ij}^x = \frac{\exp(\frac{q_i^{l-1}(k_{ij})^T}{\sqrt{d_k}})}{\sum_{(v_i,r_{ij},v_j)\in N_{in}^{\text{in},\text{out}}_{i} \cup P_{ij}} \exp(\frac{q_i^{l-1}(k_{ij})^T}{\sqrt{d_k}})}$$

where $\|\|$ denotes the concatenation operation. $g_i^l$ is the aggregated representation computed over all neighbor triples of node $v_i$ with $X$ attention heads at $l$-th layer. $\alpha_{ij}^x$ is the attention score of node $v_i$ over a particular neighbor triple $(v_i,r_{ij},v_j)$. $\sqrt{d_k}$ is the scaling factor denoting the dimension size of each key vector. $W_O$ is a learnable parameter.

**Temporal Oriented Attention** To automatically characterize the indicative temporal cues from the connection path between event mentions $v_j$ and $v_t$ as well as their surrounding contexts, we design a new temporal oriented attention.

For a particular event node $e_s$ or $e_t$, we first extract the set of nodes from the shortest dependency path between $e_s$ and $e_t$ (including $e_s$ and $e_t$), which is denoted as $\Theta_{st}$, and then get all the triples from the dependency path between $e_s$ and $e_t$ as well as the triples that any node from $\Theta_{st}$ is involved, which are denoted as $\Phi_{st} = \cup \{N_{in}^{\text{in},\text{out}}_{i} \in \Theta_{st} \cup N_{out}^{\text{out}}_{i} \in \Theta_{st} \} \cup \mathcal{P}_{st}$. In order to compute the temporal oriented attention over all the triples.

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2https://spacy.io/
from $\Phi_{st}$, we apply linear projections to get the query, key and value vectors where the query is obtained from the representations of the two event mentions, and key and value vectors are computed from the triples in $\Phi_{st}$:

$$g^l_{st} = \tilde{W}_g \cdot (h^{l-1}_{st} || h^{l-1}_t)^x$$

$$\tilde{h}^{l}_{ij} = \tilde{W}_h \cdot r^{l-1}_{ij}$$

$$\tilde{v}^{l}_{ij} = \tilde{W}_v \cdot r^{l-1}_{ij}$$

$$r^{l}_{ij} = \tilde{W}_r \cdot (h^{l-1}_i || h^{l-1}_j)^x + \tilde{b}_r$$

where $x$ is the index of a particular head, $s$ and $t$ represents the source and target event nodes, $l$ is the index of layer, $i, j$ denotes the head and tail node of a particular triple from $\Phi_{st}$. $\tilde{W}_q, \tilde{W}_r, \tilde{W}_k$ and $\tilde{W}_v$ are learnable parameters.

Given the query vector, we then compute the attention distribution over all triples from $\Phi_{st}$ and get an aggregated representation to denote the meaningful temporal features captured from the connection between two event mentions as well as their surrounding contexts.

$$\tilde{g}^l_{st} = \prod_{x (v_i, r_{ij}, v_j) \in \Phi_{st}} \tilde{W}_P \cdot \tilde{\alpha}^{x}_{ij} \cdot \tilde{v}^{l}_{ij}$$

$$\tilde{\alpha}^{x}_{ij} = \exp\left(\frac{\tilde{g}^{l-1}_{ij} (k^{l}_{ij})^T}{\sqrt{d_k}}\right)$$

$$\sum_{(v_i, r_{ij}, v_j) \in \Phi_{st}} \exp\left(\frac{\tilde{g}^{l-1}_{ij} (k^{l}_{ij})^T}{\sqrt{d_k}}\right)$$

where $\tilde{g}^l_{st}$ is the aggregated temporal related information from all the triples in $\Phi_{st}$ based on the temporal orientated attention at $l$-th layer. $\tilde{\alpha}^{x}_{ij}$ is the attention score of the event pair over a particular triple $(v_i, r_{ij}, v_j)$. $W_P$ is a learnable parameter.

**Node Representation Fusion** Each event node will receive two representations learned from the multi-head self-attention and the temporal oriented attention respectively, thus we further fuse the two representations for both the source event $e_s$ and the target event $e_t$:

$$\tilde{h}^{l}_{s} = \tilde{W}_f \cdot (g^{l-1}_{s} || \tilde{g}^l_{st})$$

$$\tilde{h}^{l}_{t} = \tilde{W}_f \cdot (g^{l-1}_{t} || \tilde{g}^l_{st})$$

where $g^l_{s}$ and $g^l_{t}$ denote the context representations learned from the multi-head self-attention for $e_s$ and $e_t$. $\tilde{g}^l_{st}$ denotes the representation learned from the triples along the connection path of $e_s$ and $e_t$ as well as their surrounding triples using temporal oriented attention. $h^{l}_s$ and $h^{l}_t$ are the fused representations of $e_s$ and $e_t$, respectively. $W_f$ is a learnable parameter.

For each non-event node $v_i$, we apply a linear projection to transform its contextual representation $g^l_{i}$ obtained from multi-head self-attention, and get a new node representation:

$$h^l_i = W_t \cdot g^l_i$$

where $W_t$ is a learning parameter.

Our Temporal Graph Transformer encoder is composed of a stack of multiple layers, while each layer consists of the two attention mechanisms and the fusion sub-layer. We use residual connection followed by LayerNorm for each layer to get the final representations of all the nodes:

$$H^l = \text{LayerNorm}(H^l + H^{l-1})$$

### 3.3 Temporal Relation Prediction

To predict the temporal relation between two event mentions $e_s$ and $e_t$, we concatenate the final hidden states of $v_s$ and $v_t$ obtained from the Temporal Graph Transformer network, and apply a Feedforward Neural Network (FNN) to predict their relationship.

$$r_{st} = W_r \cdot (h^L_s || h^L_t)$$

$$\tilde{y}_{st} = \text{softmax}(W_r \cdot r_{st} + b_r)$$

where $\tilde{y}_{st}$ denotes the probabilities over all possible temporal relations between event mentions $e_s$ and $e_t$. The training objective is to minimize the following cross-entropy loss function:

$$L_r = - \sum_{i} \sum_{l} w_l \cdot y_{l,i} \cdot \log(\tilde{y}_{st,i})$$

where $N$ denotes the total number of event pairs for temporal relation prediction and $M$ denotes the total number of classes. $y_{l,i}$ is a binary indicator (0 or 1) if the class label $l$ is correct or not based on $\tilde{y}_{st,i}$. In addition to the loss of each class, we assign a weight for each class to mitigate the label imbalance issue.
4 Experiment

4.1 Dataset and Experimental Setup

We perform experiments on two public benchmarks for temporal relation extraction: (1) MATRES (Ning et al., 2018) annotates verb event mentions along with 4 types of temporal relations: Before, After, Simultaneous and Vague. Following previous studies, we divide MATRES into three subsets: TB (TimeBank) and AQ (AQUAINT) as the training set, TCR as the validation set and PT (Platinum) as the test set. (2) TB-Dense (Cassidy et al., 2014b) is a densely annotated dataset for temporal relation extraction and contains 6 types of relations: Before, After, Simultaneous, Includes, Is included and Vague. We also use the same train/dev/test splits as previous studies (Ning et al., 2019b,a; Han et al., 2019a,b). Table 1 shows the statistics of the two datasets and Table 2 shows the label distribution. Note that, for evaluation, following previous studies, we disregard the Vague relation from both datasets.

| Corpora | Train | Dev | Test |
|---------|-------|-----|------|
| TB-Dense | # Documents | # Relation Pairs |       |       |
| MATRES  | # Documents | # Relation Pairs |       |       |

Table 1: Data statistics for TB-Dense and MATRES

| Labels     | TBDense | MATRES |
|------------|---------|--------|
| Before     | 384     | 417    |
| After      | 274     | 266    |
| Includes   | 56      | -      |
| Is Included| 53      | -      |
| Simultaneous| 22   | 31     |
| Vague      | 638     | 133    |

Table 2: Label distribution for MATRES and TB-Dense. For each dataset, the first column shows the number of instances of each relation type while the second shows the percentage.

For fair comparison with previous baseline approaches, we use the pre-trained bert-large-cased4 model for fine-tuning and optimize our model with BertAdam. We optimize the parameters with grid search: training epoch 10, learning rate $\in \{3e6, 1e5\}$, training batch size $\in \{16, 32\}$, encoder layer size $\in \{4, 12\}$, number of heads $\in \{1, 8\}$. During training, we first optimize the event extraction module for 5 epochs, and then jointly optimize both event extraction and temporal relation extraction modules.

4.2 Evaluation Results

We conduct experiments to compare our approach with various baseline methods on the two public benchmarks under two settings: (1) joint event and relation extraction, where we jointly optimize the event extraction and temporal relation extraction modules and report performance on the two sub-tasks respectively; (2) temporal relation classification, where all the approaches take in the gold event mentions as input and just predict the temporal relation.

Table 3 shows the experimental results for joint event detection and temporal relation extraction. We can see that: (1) Our approach significantly outperforms all previous baselines on event detection and relation extraction with up to 2.7% F-score gain. (2) Our approach achieves better performance on event detection than previous baselines though they are based on the same BERT encoder. There are two possible reasons: one is that by leveraging the syntactic graph, our approach can better identify verbs given the surrounding contexts as well as syntactic relations; the other reason is that we carefully tune a weight for the two labels (0 or 1) of event detection in the loss function, which is proved to be beneficial, especially when the label distributions are not balanced. (3) Table 4 shows the results on temporal relation classification which are based on gold event mentions. Unlike other models which are based on larger contextualized embeddings such as RoBERTa, our baseline model which uses BERT base achieves comparable performance, and further surpasses the state-of-the-art baseline methods using BERT large embeddings, which demonstrate the effectiveness of our Temporal Graph Transformer network. (4) Several previous studies focus on resolving the inconsistency in terms of the symmetry and transitivity properties among the temporal relation predictions of two or three events, e.g., if event A and event B are predicted as Before, event B and event C are predicted as Before, then if event A and event C are predicted as Vague or After, it will be considered as an inconsistent case. However, our approach shows consistent predictions with few inconsistent cases when Simultaneous relation is involved. This analysis also demonstrates that our approach can correctly capture the temporal cues between event
**Table 3:** Comparison of various approaches on joint event detection and relation extraction. F-score (%)

| Dataset          | Model                        | Pretrained Model | Event Detection | Relation Extraction(E) |
|------------------|------------------------------|------------------|-----------------|-------------------------|
| MATRES           | Siamese (Ning et al., 2019b) | BERT Base        | 83.5            | 87.0                    | 85.2 | 48.4 | 58  | 52.8 |
|                  | Joint Structured (Han et al., 2019b) | BERT Base        | 87.1            | 88.5                    | 87.8 | 59.0 | 60.2 | 59.6 |
|                  | Our Approach                 | BERT Base        | -              | -                       | 90.5 | 56.3 | 69.9 | 62.3 |

**Table 4:** Comparison of various approaches on temporal relation classification where all approaches take gold event mentions as input. F-score (%)

| Dataset          | Model                        | Pretrained Model | Relation Classification |
|------------------|------------------------------|------------------|-------------------------|
| TB-Dense         | Joint structured (Han et al., 2019b) | BERT Base | 64.5 |
|                  | PSL (Zhou et al., 2020)       | RoBERTa Large    | 65.2 |
|                  | DEER (Han et al., 2020)       | RoBERTa Large    | 66.8 |
|                  | Our Approach                  | BERT Base        | 66.7 |
| MATRES           | Siamese (Ning et al., 2019b)  | BERT Base        | 65.9 |
|                  | Joint Structured (Han et al., 2019b) | BERT Base | 75.5 |
|                  | Our Approach                  | BERT Base        | 79.3 |
|                  | Joint Constrained (Wang et al., 2020a) | RoBERTa Large | 78.8 |
|                  | DEER (Han et al., 2020)       | RoBERTa Large    | 79.3 |
|                  | Our Approach                  | BERT Large       | 80.3 |

**Ablation Study** We further conduct ablation studies on temporal relation classification to examine the impact of each component of our model. We compare the performance of our approach with two baseline methods: (1) BERT (Devlin et al., 2018), which uses the same pre-trained language model to encode the sentence and predict the temporal relationship of two event mentions based on their contextual representations; (2) BERT with Graph Transformer (BERT+GT), which is similar to our approach and use Graph Transformer (Wang et al., 2020b) with only multi-head self-attention to obtain graph-based contextual representations of two event mentions and then predict their temporal relation.

From Table 5, we can see that by adding Graph Transformer to capture the syntactic-based context, BERT+GT achieves 2.65% performance improvement over the BERT baseline model, which demonstrates the benefit of syntactic-based context to temporal relation prediction. By adding our new temporal oriented attention to explicitly capture the temporal cues from the connection of two event mentions as well as their surrounding contexts, our approach further provides 2.38% F-score gain over BERT+GT, which demonstrates the effectiveness of our new Temporal Graph Transformer and testify the importance of capturing temporal cues from the connection of two event mentions as well as their surround contexts.

**Table 5:** Ablation study on MATRES. We use BERT base as our comparison basis.

| Model                        | F-score (%) | Gain (%) |
|------------------------------|-------------|----------|
| BERT (Devlin et al., 2018)   | 75.5        | -        |
| BERT+GT (Wang et al., 2020b) | 77.5        | +2.65    |
| BERT+TGT (Our Approach)      | 79.3        | +5.03    |

As qualitative analysis, we use two examples to compare the temporal relation classification results between our approach and the BERT and BERT+GT baselines. As Figure 3 shows, for the first example, BERT mistakenly predicts the temporal relation as *Before* as it’s confused by context word *Before*, which is also the most indicative temporal cue from the sentence. However, by incorporating the syntactic graph structures, especially the triples \{*worked*, *prep*, *Before*\}, \{*Before*, *pcomp*, *retiring*\} and the path between the two event mentions, *worked*→*prep*→*Before*→*pcomp*→*retiring*, both BERT+GT and our approach correctly determine the relation as *After*. For the second example, both BERT and BERT+GT mistakenly predict the temporal relation as *Before* as the context between the two event mentions is very wide and complicated, and these two nodes are not close within the syntactic graph. However, by explicitly considering and understanding the connection path between the two event mentions, *sought*$_{e1}$→*on*→*Marmara*→*was*→*part*→*Flotilla*→*sought*$_{e2}$, our approach correctly predicts the
temporal relation between the two event mentions.

We further illustrate the impact of context width between two event mentions to the models. We divide the context width into three categories: < 10, 10 – 20, and > 20. Figure 4 shows the total number of event pairs that fall into each category, and the classification performance of BERT baseline method and our approach for each category. We can see that as the context width increases from 10 to 20, the performance of BERT baseline drops a lot while our approach provides consistently better performance than BERT. This comparison demonstrates the capability of our approach on modeling distant event pairs and the effectiveness of our Temporal Graph Transformer network.

4.3 Impact of Wide Context

![Figure 4: Context width analysis on TB-Dense](image)

Figure 3: A comparison of samples which are predicted by BERT+GT and BERT+TGT but not BERT and which are predicted by BERT+TGT but not by others. Bolded tokens are our event mentions and highlighted tokens are the tokens with the highest attention score.

We randomly sample 100 classification errors from the output of approach and categorize the errors into three categories. Figure 5 shows an example of each error category. The first category is due to the lack of sufficient annotation. We observe that none of the Simultaneous relation can be correctly predicted for MATRES dataset as the percentage of Simultaneous (3.7%) is much lower than other relation types. In TB-Dense dataset, labels are even more imbalanced as the Vague relation is over 50% while the percentage of Includes, Is Included and Simultaneous are all less than 4%. The second category error is due to the complicated subordinate clause structure, especially the clauses related to quoted or reported speech, e.g., S2 in Figure 5. The third error category is that our approach cannot correctly differentiate the actual events from the hypothetical and intentional events, while in most cases, the temporal relation among hypothetical and intentional events is annotated as Vague.

5 Conclusion

We investigate the main challenges of temporal relation extraction task and design a novel Temporal Graph Transformer which integrates both traditional multi-head self-attention and a new temporal oriented attention mechanism. Experiments on both MATRES and TB-Dense datasets show that our approach significantly outperforms previous state-of-the-art methods on both end-to-end event detection and temporal relation extraction as well as the temporal relation classification tasks. In the future, we will extend our approach to predict the temporal relation of two events from different documents.

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| Error Category          | Example                                                                                                                                  | Temporal Relation |
|------------------------|------------------------------------------------------------------------------------------------------------------------------------------|-------------------|
| Imbalanced Label       | **S1:** "This is not a Lehman, " he (e1: said), (e2: referring) to the disastrous chain reaction touched off by the collapse of Lehman brothers in 2008. | Simultaneous      |
| Subordinate Clause     | **S2:** "We were pleased that England and New Zealand knew about it, and we (e1: thought) that's where it would stop. " He also (e2: talked) about his "second job" as the group's cameraman, and having to wear four pairs of gloves to work the clockwork camera. | After             |
| Hypothetical Events    | **S3:** Mr. Netanyahu had previously only (e1: expressed) regret for the deaths. The deal was (e2: brokered) by US president Barack Obama during a visit to Israel. | Vague             |

Figure 5: Types of remaining errors

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