Predicting Event Time by Classifying Sub-Level Temporal Relations Induced from a Unified Representation of Time Anchors

Fei Cheng
Department of Intelligence
Science and Technology
Graduate School of Informatics
Kyoto University
feicheng@i.kyoto-u.ac.jp

Yusuke Miyao
Department of Computer Science
Graduate School of Information Science and Technology
University of Tokyo
yusuke@is.s.u-tokyo.ac.jp

Abstract

Extracting event time from news articles is a challenging but attractive task. In contrast to the most existing pair-wised temporal link annotation, Reimers et al. (2016) proposed to annotate the time anchor (a.k.a. the exact time) of each event. Their work represents time anchors with discrete representations of Single-Day/Multi-Day and Certain/Uncertain. This increases the complexity of modeling the temporal relations between two time anchors, which cannot be categorized into the relations of Allen’s interval algebra (Allen, 1990).

In this paper, we propose an effective method to decompose such complex temporal relations into sub-level relations by introducing a unified quadruple representation for both Single-Day/Multi-Day and Certain/Uncertain time anchors. The temporal relation classifiers are trained in a multi-label classification manner. The system structure of our approach is much simpler than the existing decision tree model (Reimers et al., 2018), which is composed by a dozen of node classifiers. Another contribution of this work is to construct a larger event time corpus (256 news documents) with a reasonable Inter-Annotator Agreement (IAA), for the purpose of overcoming the data shortage of the existing event time corpus (36 news documents). The empirical results show our approach outperforms the state-of-the-art decision tree model and the increase of data size obtained a significant improvement of performance.

1 Introduction

Along with TimeBank (Pustejovsky et al., 2003) (TB) and other temporal corpora, a series of competitions on temporal information extraction (TempEval-1,2,3) (Verhagen et al., 2009, 2010; Uz-Zaman et al., 2012) are attracting growing research efforts. Predicting the exact time when an event occurred can effectively contribute various time-aware tasks, such as timeline (Minard et al., 2015), temporal question answering (Llorens et al., 2015; Meng et al., 2017), knowledge base population, etc. For instance, given a hot topic (event, person, product, company, etc.), we can first gather its related news articles, extract events, and predict event time from them. An event timeline can be automatically generated by ordering events on a time axis according to their occurring time. Such timeline representations can be extremely helpful for readers to comprehend new topics efficiently.

TimeBank-EventTime (TBET) is a new temporal information corpus based on TB. Instead of using the majority of a pair-wise Temporal Link (TLINK) (Setzer, 2002) to model a relation between two mentions (i.e. event, time expression and document creation time), TBET annotates the occurring time of each individual event. Their annotation schema first distinguishes between Single-Day/Multi-Day and Certain/Uncertain events as following:

- **Single-Day** denotes an event occurs in a single day. A Single-day event can be further categorized into two types as follows:
  - **Certain** day, e.g. '1998-02-06'
  - **Uncertain** day, e.g. 'before1998-01-31', 'after1998-01-01' or 'after1998-01-01, before1998-02-06'.

- **Multi-Day** event time can be seen as a tuple of two Single-Day (begin, end).

For predicting Single-Day event time, Cheng and Miyao (2018) induced 6-label temporal relations induced from TBET to train two classifiers of Event-to-DCT and Event-to-Timex mention pairs.

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In this paper, ‘Timex’ denotes time expression and ‘DCT’ denotes document creation time.
A major difficulty preventing them from extending this approach to the Multi-Day events is the complexity of inducing relations with Uncertain information. Manually extending the existing temporal relation types (Allen (1990)’s interval algebra) will be hard.

Another approach (Reimers et al., 2018) of predicting both Single-Day and Multi-Day event time trains a series of classifiers to make tree-structure decisions starting from the root decision of whether an event is Single-Day or Multi-Day. The Single-Day branch determines the temporal clues from relevant time expressions. While, the Multi-Day branch will further determine begin and end points separately. However, such decision tree of classifiers is less generalized for only fitting this event time definition and training a series of classifiers is complex and time-consuming.

In this work, we propose a simple method to predict both Single-Day and Multi-Day event time effectively. We introduce a quadruple expression with 4-date values, i.e. (begin_earliest, begin_latest, end_earliest and end_latest), which is capable of unifying the representation of Single/Multi-Day and Certain/Uncertain event time (Section 3.1). This expression enables us to decompose a complex temporal relation into four simple sub-level temporal relations (Section 3.2). In Section 4, we perform classifications in a multi-label fashion. In the inference step, we gather all the relevant time clues of an event to infer the time. Another contribution (Section 5) is that we constructed a larger event time corpus with 256 news articles, compared to the existing TBET with 36 articles. In Section 6.1, we show the experiments of increasing the training data and being evaluated in two different test data. The results show that the large data size significantly improves classification results in the large test data: TE3-Test. The comparison to the SOTA decision tree model shows our sub-level temporal relation model with attention significantly outperforms their model in the TBET data (Section 6.4).

2 Background

2.1 Event Time Annotation

Most existing temporal corpora adopted a pair-wise schema (i.e. TLINK) to encode temporal relations between mentions. A major drawback is that the potential pair candidates are quadratic to the number of mentions. This resulted in the sparsity of TLINKs in the original TimeBank. The later TimeBank-Dense (Cassidy et al., 2014) achieved denser TLINKs by forcing the annotators labeling all the possible pairs in any two adjacent sentences. However, the dense annotation is time-consuming and performed on a subset of Timebank with only 36 documents.

Reimers et al. (2016) proposed an event time schema to annotate the TBET corpus with a linear annotation effort, in which annotators infer the exact time of each individual event. The main limitation is that the new schema requires events to be capable of being anchored on exact time. In this paper our main target is processing news articles, in which time expressions and document creation time provide rich exact time information. Therefore, this limitation will affect less.

2.2 Existing Event Time Prediction Systems

The proposal of TBET raised a new task of predicting the exact time of events. Intuitively, knowing when an event occurred is an attractive target to achieve many practical applications. For instance, ordering events according to their occurring time can naturally generate an event timeline in a cross-document scenario.

Reimers et al. (2016) released a baseline for event time prediction based on CAEVO (Chambers et al., 2014), which is trained on TimeBank-Dense. This baseline can only predict Single-Day Events, because the Timebank-Dense TLINKs adopted a limited 6-label set without providing the necessary begin or end information to predict Multi-Day Events.

Cheng and Miyao (2018) proposed an approach to induce similar 6-label relations based on the event time annotation. Their temporal relation classifiers are fully trained on the new TBET corpus and achieve better performance on predicting Single-Day event time.

Reimers et al. (2018) included the Multi-Day Events prediction into their target. They designed a series of individual classifiers to make hierarchical decisions of whether an event is Single-Day or Multi-Day, the temporal relation from the begin day of an event to a time expression, etc. The drawback is that training a decision tree of individual classifiers is complicated and the data of some leaf classifiers become very sparse.
### Table 1: The comparison of the time anchor and quadruple examples. "˜" denotes the blank information in some *Uncertain* cases.

| Single/Multi | Certainty | Type               | Representation                        |
|-------------|-----------|--------------------|---------------------------------------|
| Single-Day  | Certain   | Time anchor        | 1998-01-26                           |
|             |           | Quadruple          | (((1998-01-26, 1998-01-26), (1998-01-26, 1998-01-26)) |
| Single-Day  | Uncertain | Time anchor        | after1998-01-26 before1998-02-06     |
|             |           | Quadruple          | (((1998-01-26, 1998-02-06), (1998-01-26, 1998-02-06)) |
| Multi-Day   | Certain   | Time anchor        | begin:1998-01-01, end:1998-01-31     |
|             |           | Quadruple          | (((1998-01-01, 1998-01-01), (1998-01-31, 1998-01-31)) |
| Multi-Day   | Uncertain | Time anchor        | begin:1998-01-01, end:after1998-02-06|
|             |           | Quadruple          | (((1998-01-01, 1998-01-01), (1998-02-06, ˜)) |

#### 2.3 Neural Temporal Relation Classifier

Temporal relation classification can be categorized as a variation of a more general Relation Classification (RC) task, in which the models are required to detect a semantic relation between two nominals in a sentence. Zeng et al. (2014) proposed a Convolutional Neural Network (CNN) model with the relevant distances from each word to the two nominals as the additional features to achieve state-of-the-art performance. From 2016, researchers started to introduce the attention mechanism into RC to push the scores higher. Zhou et al. (2016) proposed an attention-based RNN model to obtain normalized scores along the time steps for calculating a weighted representation of an sentence.

The step of applying neural networks into Temporal Relation Classification started from the work of (Cheng and Miyao, 2017; Meng et al., 2017). These two works feed the shortest dependency path (SDP) between two mentions into recurrent neural networks (RNNs). Reimers et al. (2018) adopted Zeng et al. (2014)’s model to train a series classifiers to make hierarchical decisions.

In this work, we proposed a mention-wised attention LSTM (Hochreiter and Schmidhuber, 1997) classifier, which emphasized the interaction between words and the given mentions to obtain the weighted context information of an sentence.

#### 3 Representing Time Anchors and Sub-level Temporal Relations

There are two obstacles to prevent us from achieving a more effective way to predict event time. First, the discrete annotation of the *Single/Multi-day* and *Certain/Uncertain* information in TBET forced Reimers et al. (2018) to make hierarchical decisions from the top question whether the given event is *Single-Day* or *Multi-Day* to the leaf temporal relation classifiers. It raised the complexity of their system and accumulated errors from early classifiers. The second question is that extending the definition of temporal relation is hard but necessary in order to represent the relation with *Uncertain* time.

#### 3.1 A Unified Quadruple Representation of Time Anchors

In this work, we adopt a quadruple representation (Berberich et al., 2010) for consistently representing the *Single/Multi-Day* and *Uncertainty* information of a time anchor.

\[ T = ((begin_e, begin_i), (end_e, end_i)) \]

\((begin_e, begin_i)\) stand for the earliest and latest possible days of the beginning point. Analogously, \((end_e, end_i)\) are its earliest and latest possible days of the end point.

This representation is naturally designed for representing *Multi-Day* and *Uncertain* information. We adopt an inclusive rule, which includes *Single-Day* into our representation by making beginning and end annotation to the same. A *Certain* day has the same earliest and latest days. To make it clear, we list several examples in Table 1 with both TBET and our quadruple representations for comparison.

#### 3.2 Decomposing temporal relations into sub-level

Most existing temporal relation annotation adopted Allen (1990)’s algebra, which defined 13 relations between two *Certain* time intervals. Many of the following works attempted to reduce the sparsity of relations by merging some relations to a coarse relation. The *Uncertainty* information in TBET even
aggravates the complexity of modeling temporal relations between two time anchors.

In this work, we decompose a temporal relation into a group of sub-level relations for avoiding laboriously extending the relation definition. Let \( (\text{begin}_e, \text{begin}_l) \) and \( (\text{end}_e, \text{end}_l) \) stand for two time anchors: \( T_e \) of an event and \( T_t \) of a DCT or Timex. We explicitly compare four sub-level relations (SR) \( \{ \text{SR}_1, \text{SR}_2, \text{SR}_3, \text{SR}_4 \} \) as follows:

- \( \text{SR}_1\): \( (\text{begin}_e, \text{begin}_l) \) to \( (\text{begin}_e, \text{begin}_l) \)
- \( \text{SR}_2\): \( (\text{begin}_e, \text{begin}_l) \) to \( (\text{end}_e, \text{end}_l) \)
- \( \text{SR}_3\): \( (\text{end}_e, \text{end}_l) \) to \( (\text{begin}_e, \text{begin}_l) \)
- \( \text{SR}_4\): \( (\text{end}_e, \text{end}_l) \) to \( (\text{end}_e, \text{end}_l) \)

Figure 2 is an example of the sub-level relations between \( T_e \) and \( T_t \). This example can not be categorized into any existing relation types defined in Allen’s algebra due to the Uncertainty of whether the end point of \( T_e \) is \( \text{after} \), \( \text{before} \) or \( \text{equal} \) to the end point of \( T_t \). However, our proposal can encode the sub-level information \( \{ \text{equal, before, after, vague} \} \) indicating that \( T_e \) and \( T_t \) holds the same begin points, but the temporal relation between the end points is \( \text{vague} \).

Each sub-level relation is naturally defined with a simple label set \( \{ \text{equal, after, before, vague} \} \) as shown in Table 2. Any relation between two time anchors can be represented as the combination of four sub-level relations. This approach effectively avoids an exhaustive expansion of Allen’s algebra in order to include the Uncertain information of time anchors.

### 4 Event Time Prediction System

Once we have the unified representation of time anchors and sub-level relations (SR), we can directly classify SRs between a given event to DCT or any other Timex in the text, instead of constructing a complex tree structure of node classifiers. The overall system architecture is shown in Figure 1. Given a target event, our SR classifiers first predict four SRs to each time expression in the context. Then, the quadruple values of the given event are inferred by a strategy based on the SR inputs.

#### 4.1 Mention-wise Attention Classifiers

Based on the link types (Event-to-DCT and Event-to-Timex), temporal relation classifiers take different input information. For instance, Event-to-DCT (E-D) has only one event information, while Event-
We use the pre-trained word embedding Glove\(^2\) presented by Pennington et al. (2014). The input words are mapped into their embedding vectors by the embedding layer of our model. We use the 200-dimension Glove in our model.

In TRC, the given information of a data sample includes a sentence and mentions (event or Timex) inside it. An important feature is to distinguish between the mention words and other words inside the sentence. A popular method is called position embedding, which represents the relative distance from a word to the mention word. For instance, an event the \(k\)-th word (from left to right) in a sentence, a word \(i\) has a relative distance \(i - k\) to the event. We embed this number into a random initialized vector and the dimension of the vector is a hyper-parameter.

### 4.3 Multi-label Loss

Based on our definition in Section 3.2, each E-D or E-T link consists of 4 SRs and each SR adopts a 4-label set \{\textit{equal}, \textit{after}, \textit{before}, \textit{vague}\}. In this paper, we formulate the SR classification as a multi-label multi-class problem. We fixed the dimension number of the output layer to 16 (4 SRs \(\times\) 4 Labels) and calculate the Softmax distribution for each SR. We define the multi-label loss as the sum of the negative log-likelihood of each SR.

\[
L = -\sum_i \sum_j g_{ij} \log p_{ij} \tag{3}
\]

In Eq 3, \(i, j\) denote the SR, label. \(g, p\) denote the gold label, predicted Softmax probability.

### 4.4 Inference Strategy

Once a target event given the predicted 4-SR to a Timex, the SRs naturally indicate the action of operating the normalized value of the Timex to infer the time of the event. For instance, if \(SR_1\) is \textit{equal} to a Timex, our inference strategy will update \((\text{begin}_e, \text{begin}_t)\) as the same as \((\text{begin}_e, \text{begin}_t)\). If \(SR_1\) is \textit{after}, the strategy will update \(\text{begin}_e\) to the same as \(\text{begin}_t\).

We infer the time of the target event along the SRs to DCT, Timex-0 (the same sentence), Timex-1 (the adjacent sentences), etc. An exception is that if an Event-to-DCT \(SR_t\) is predicted as \textit{equal}, the following \(SR_t\) of Event-to-Timex will not effect anymore. The reason is that Event-to-DCT usually provides a majority of time information to predict event time in this task. We give it higher priority than Event-to-Timex to avoid wrong prediction of Event-to-Timex.


Table 3: The corpus statistics of our annotation data. ‘TB’ stands for 147 articles of the original TimeBank excluding 36 TBET articles.

| Corpus | Article | Event | IAA   |
|--------|---------|-------|-------|
| TBET   | 36      | 1.5K  | 0.580 |
| AQ     | 73      | 4.4K  | 0.567 |
| TB     | 147     | 5.2K  | 0.552 |

6 Experiments

6.1 The Effect of Larger Training Data

The TempEval-2013\(^4\) data consists of two training corpora (TB, AQ) and one test data TE3-Test. As TBET is based on a subset (36 articles) of TimeBank (183 articles), ‘TB’ stands for the other 147 articles in TB excluding TBET. We treat TBET as the baseline and gradually add AQ, TB and AQ + TB into the train data. The increase of the training data is expected to effectively improve the performance of the SR classifiers. We separately evaluate the classification results on TBET-Test (9 articles), TE3-Test (20 articles). In the experiments on TBET-Test, we use the same data split as the previous work\(^5\). In the experiments on TE3-Test, we randomly split 20% training data as the validation set. The validation set is used to optimize the hyper-parameters and perform early stopping.

Figure 4 shows the classification performance against different training data size. We find TBET performs surprisingly well on TBET-Test. The increase of other corpora even reduces the classification performance. It’s possibly because the 36 documents of TBET was manually selected with the close published dates and share some overlapped information between the train and test split. However, in the evaluation on the larger TE3-Test, TBET obtains the lowest scores. As the training data size increases, the classification performance is significantly improved. We believe TE3-Test can more correctly reflect the generalization ability of the classification, because the article topics are less dependent to the training data and test data.

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\(^3\)https://github.com/rcfsd/LETC

\(^4\)https://www.cs.york.ac.uk/semeval-2013/task1/index.php?Fid=data.html

\(^5\)https://github.com/nchambers/caevo/blob/master/src/main/java/caevo/Evaluate.java
## 6.2 Oracle Test with Gold SRs

SRs between an event and a Timex are computed based on the two quadruple vectors. This method has the capability of inducing SRs between an event and a Timex with long distance, which means our system can collect the Event-to-Timex information as much as we want. However, in reality, the overall performance will be a trade-off between the amount of Event-to-Timex information and the classification accuracy. More SRs will bring more errors produced by the Event-to-Timex classifier.

We perform the oracle tests in two test data, which let our system accept gold SRs with different distance settings between events to Timex. It helps us to select a reasonable sentence window. Table 5 shows that the Event-to-Timex information in the adjacent sentences can achieve 70.98% (TE3-Test) and 77.81% (TBET-Test) upper-bound accuracy and larger sentence window will significantly increase the number of E-T links. Our SR classifiers are set to provide the information of Event-to-DCT and Event-to-Timex in two adjacent sentences for the inference strategy.

Table 5 also reveals that Event-to-DCT in TE3-Test contributes approximately 16% less than TBET-Test to the event time prediction. Considering the relatively lower classification scores of TE3-Test in Figure 4, we can expect that the event time prediction scores of TE3-Test will certainly lower than TBET-Test a lot. And of course, the classification and event time prediction performance of two test data are not comparable.

## 6.3 Event Time Prediction in LETC

We perform the experiment of training the SR classifiers with the LETC (TBET + AQ + TB) corpus and evaluate the performance in TE3-Test.

We first report the classification performance of each SR and 'complete match' in Table 6. The Event-to-DCT results show very similar scores between SR1 and SR3, SR2 and SR4. This is because DCT is always a Single-Day and Certain time anchor. It’s quadruple vector has the same begin and end points.

In Table 4, we report the performance of predicting event time. We separately feed the predicted SRs (E-D, E-T) into the inference strategy. The last column shows the ‘complete match’ accuracy of event time prediction. We provide a baseline model for observing the effect of the attention, which feeds the word and position embeddings into a Bidirectional LSTM model and feed the last
hidden state into the Softmax layer. Event-to-DCT contributes to the main performance for predicting event time, which is matching the observation from the oracle test (Table 5). Our mention-wised attention model significantly outperforms the baseline, which used the same word and position embedding inputs.

6.4 Comparing the SR classifier to SOTA

We compare our model to the SOTA decision tree model trained on the re-annotated TBET. The experiment follows the exactly same data split as the previous work: 22/5/9 articles as the train/dev/test data. Table 7 shows that our mention-wise attention classifier outperforms the decision tree model trained on the same data. The performance of the w/o attention model slightly lower than the decision tree model.

Our system is relatively lightweight compared to the decision tree model, in which each decision node relies on a classifier, while our system consists of only two classifiers: Event-to-DCT and Event-to-Timex.

7 Conclusion

In this paper, we proposed a simple but effective approach to address the event time prediction task. The existing model was hampered by the discrete time anchor representations and Uncertain information, which increased the complexity of requiring the model to make hierarchical decisions. We first proposed a unified quadruple representation of time anchors. For preventing explicitly extending new temporal relation types to include the Uncertain information, we proposed an idea of decomposing a temporal relation into four sub-level relations (SRs). Any complex relation can be derived as a combination of SRs. In the second step, we proposed a simple event time prediction system, which is composed of two mention-wised attention LSTM classifiers and an inference strategy. Our third contribution is the construction of a larger event time corpus of 256 news articles, compared to the existing 36 TBET corpus. The empirical results showed our proposed method outperformed the decision tree model with a more lightweight structure. Other experiments show that as the increase of training data size, the classification performance is significantly improved in a public test data: TE3-Test.

This work leaves the space of improvement from several aspects. For instance, the current SRs adopt a coarse definition as the relation between the begin/end points between two time anchors. A fine-grained sub-level relation could be defined as a relation between one of the quadruple values, which will raise the number of SRs to 16 ($4 \times 4$). It can possibly encode more accurate temporal information. Also this work follows the traditional temporal relation classification setting, which trained the Event-to-DCT and Event-to-Timex classifiers independently. Intuitively, Event-to-DCT and Event-to-Timex share the common useful information to be trained jointly or be optimized globally based on the event time prediction score.

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