A Multi-Axis Annotation Scheme for Event Temporal Relations

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Abstract

Existing temporal relation (TempRel) annotation schemes often have low inter-annotator agreements (IAA) even between experts, suggesting that the current annotation task needs a better definition. This paper proposes a new multi-axis modeling to better capture the temporal structure of events. In addition, we identify that event end-points are a major source of confusion in annotation, so we also propose to annotate TempReles based on start-points only. A pilot expert annotation effort using the proposed scheme shows significant improvement in IAA from the conventional 60’s to 80’s (Cohen’s Kappa). This better-defined annotation scheme further enables the use of crowdsourcing to alleviate the labor intensity for each annotator. We hope that this work can foster more interesting studies towards event understanding.1

1 Introduction

Temporal relation (TempRel) extraction is an important task for event understanding, and it has drawn much attention in the natural language processing (NLP) community recently (UzZaman et al., 2013; Chambers et al., 2014; Llorens et al., 2015; Minard et al., 2015; Bethard et al., 2015, 2016, 2017; Leeuwenberg and Moens, 2017; Ning et al., 2017, 2018a,b).

Initiated by TimeBank (TB) (Pustejovsky et al., 2003b), a number of TempRel datasets have been collected, including but not limited to the verb-clause augmentation to TB (Bethard et al., 2007), TempEval1-3 (Verhagen et al., 2007, 2010; UzZaman et al., 2013), TimeBank-Dense (TB-Dense) (Cassidy et al., 2014), EventTimeCorpus (Reimers et al., 2016), and datasets with both temporal and other types of relations (e.g., coreference and causality) such as CaTeRs (Mostafazadeh et al., 2016) and RED (O’Gorman et al., 2016). These datasets were annotated by experts, but most still suffered from low inter-annotator agreements (IAA). For instance, the IAAs of TB-Dense, RED and THYME-TimeML (Styler IV et al., 2014) were only below or near 60% (given that events are already annotated). Since a low IAA usually indicates that the task is difficult even for humans (see Examples 1-3), the community has been looking into ways to simplify the task, by reducing the label set, and by breaking up the overall, complex task into subtasks (e.g., getting agreement on which event pairs should have a relation, and then what that relation should be) (Mostafazadeh et al., 2016; O’Gorman et al., 2016). In contrast to other existing datasets, Bethard et al. (2007) achieved an agreement as high as 90%, but the scope of its annotation was narrowed down to a very special verb-clause structure.

| Example 1: | Serbian police tried to eliminate the pro-independence Kosovo Liberation Army and (e1:restore) order. At least 51 people were (e2:killed) in clashes between Serb police and ethnic Albanians in the troubled region. |
| Example 2: | Service industries (e3:showed) solid job gains, as did manufacturers, two areas expected to be hardest (e4:hit) when the effects of the Asian crisis hit the American economy. |
| Example 3: | We will act again if we have evidence he is (e5:rebuilding) his weapons of mass destruction capabilities, senior officials say. In a bit of television diplomacy, Iraq’s deputy foreign minister (e6:responded) from Baghdad in less than one hour, saying that … |

1The dataset is publicly available at https://cogcomp.org/page/publication_view/834.

This paper proposes a new approach to handling
these issues in TempRel annotation. **First**, we introduce multi-axis modeling to represent the temporal structure of events, based on which we anchor events to different semantic axes; only events from the same axis will then be temporally compared (Sec. 2). As explained later, those event pairs in Examples 1-3 are difficult because they represent different semantic phenomena and belong to different axes. **Second**, while we represent an event pair using two time intervals (say, $[t^1_{\text{start}}, t^1_{\text{end}}]$ and $[t^2_{\text{start}}, t^2_{\text{end}}]$), we suggest that comparisons involving end-points (e.g., $t^1_{\text{end}}$ vs. $t^2_{\text{end}}$) are typically more difficult than comparing start-points (i.e., $t^1_{\text{start}}$ vs. $t^2_{\text{start}}$); we attribute this to the ambiguity of expressing and perceiving durations of events ([Coll-Florit and Gennari, 2011](#)).

We believe that this is an important consideration, and we propose in Sec. 3 that TempRel annotation should focus on start-points. Using the proposed annotation scheme, a pilot study done by experts achieved a high IAA of .84 (Cohen’s Kappa) on a subset of TB-Dense, in contrast to the conventional 60’s.

In addition to the low IAA issue, TempRel annotation is also known to be labor intensive. Our **third contribution** is that we facilitate, for the first time, the use of crowdsourcing to collect a new, high quality (under multiple metrics explained later) TempRel dataset. We explain how the crowdsourcing quality was controlled and how vague relations were handled in Sec. 4, and present some statistics and the quality of the new dataset in Sec. 5. A baseline system is also shown to achieve much better performance on the new dataset, when compared with system performance in the literature (Sec. 6). The paper’s results are very encouraging and hopefully, this work would significantly benefit research in this area.

## 2 Temporal Structure of Events

Given a set of events, one important question in designing the TempRel annotation task is: which pairs of events should have a relation? The answer to it depends on the modeling of the overall temporal structure of events.

### 2.1 Motivation

TimeBank ([Pustejovsky et al., 2003b](#)) laid the foundation for many later TempRel corpora, e.g., ([Bethard et al., 2007](#); [UzZaman et al., 2013](#); [Cassidy et al., 2014](#)). In TimeBank, the annotators were allowed to label TempRels between any pairs of events. This setup models the overall structure of events using a general graph, which made annotators inadvertently overlook some pairs, resulting in low IAA’s and many false negatives.

| Example 4: Dense Annotation Scheme. |
|-------------------------------------|
| Serbian police (**e1**:tried) to (**e8**:eliminate) the pro-independence Kosovo Liberation Army and (**e1**:restore) order. At least 51 people were (**e2**:killed) in clashes between Serb police and ethnic Albanians in the troubled region. |
| **Given 4 NON GENERIC events above, the dense scheme presents 6 pairs to annotators one by one:** (**e7**, **e8**, (**e7**, **e1**), (**e7**, **e2**), (**e8**, **e1**), (**e8**, **e2**), and (**e1**, **e2**). Apparently, not all pairs are well-defined, e.g., (**e8**, **e2**) and (**e1**, **e2**), but annotators are forced to label all of them. |

To address this issue, [Cassidy et al. (2014)](#) proposed a dense annotation scheme, TB-Dense, which annotates all event pairs within a sliding, two-sentence window (see Example 4). It requires all TempRels between GENERIC and NON GENERIC events to be labeled as vague, which conceptually models the overall structure by two disjoint time-axes: one for the NON GENERIC and the other one for the GENERIC.

However, as shown by Examples 1-3 in which the highlighted events are NON GENERIC, the TempRels may still be ill-defined: In Example 1, Serbian police tried to restore order but ended up with conflicts. It is reasonable to argue that the attempt to **e1**:restore order happened **before** the conflict where 51 people were **e2**:killed; or, 51 people had been **killed** but order had not been **restored** yet, so **e1**:restore is **after** **e2**:killed. Similarly, in Example 2, service industries and manufacturers were originally expected to be hardest **e4**:hit but actually **e3**:showed gains, so **e4**:hit is **before** **e3**:showed; however, one can also argue that the two areas had **showed** gains but had not been **hit**, so **e4**:hit is **after** **e3**:showed. Again, **e5**:rebuilding is a hypothetical event: “we will act if **rebuilding** is true”. Readers do not know for sure if “he is already rebuilding weapons but we have no evidence”, or “he will be building weapons in the future”, so annotators may disagree on the relation between **e5**:rebuilding and **e6**:responded. Despite, importantly, minimizing missing annotation.

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2 EventTimeCorpus ([Reimers et al., 2016](#)) is based on TimeBank, but aims at anchoring events onto explicit time expressions in each document rather than annotating TempRels between events, which can be a good complementary to other TempRel datasets.

3 For example, **lions eat meat** is GENERIC.
tions, the current dense scheme forces annotators to label many such ill-defined pairs, resulting in low IAA.

2.2 Multi-Axis Modeling

Arguably, an ideal annotator may figure out the above ambiguity by him/herself and mark them as vague, but it is not a feasible requirement for all annotators to stay clear-headed for hours; let alone crowdsourcers. What makes things worse is that, after annotators spend a long time figuring out these difficult cases, whether they disagree with each other or agree on the vagueness, the final decisions for such cases will still be vague.

As another way to handle this dilemma, TB-Dense resorted to a 80% confidence rule: annotators were allowed to choose a label if one is 80% sure that it was the writer’s intent. However, as pointed out by TB-Dense, annotators are likely to have rather different understandings of 80% confidence and it will still end up with disagreements.

In contrast to these annotation difficulties, humans can easily grasp the meaning of news articles, implying a potential gap between the difficulty of the annotation task and the one of understanding the actual meaning of the text. In Examples 1-3, the writers did not intend to explain the TempRels between those pairs, and the original annotators of TimeBank did not label relations between those pairs either, which indicates that both writers and readers did not think the TempRels between these pairs were crucial. Instead, what is crucial in these examples is that “Serbian police tried to restore order but killed 51 people”, that “two areas were expected to be hit but showed gains”, and that “if he rebuilds weapons then we will act.” To “restore order”, to be “hardest hit”, and if he was rebuilding were only the intention of police, the opinion of economists, and the condition to act, respectively, and whether or not they actually happen is not the focus of those writers.

This discussion suggests that a single axis is too restrictive to represent the complex structure of NON-GENERIC events. Instead, we need a modeling which is more restrictive than a general graph so that annotators can focus on relation annotation (rather than looking for pairs first), but also more flexible than a single axis so that ill-defined relations are not forcibly annotated. Specifically, we need axes for intentions, opinions, hypotheses, etc. in addition to the main axis of an article. We thus argue for multi-axis modeling, as defined in Table 1. Following the proposed modeling, Examples 1-3 can be represented as in Fig. 1. This modeling aims at capturing what the author has explicitly expressed and it only asks annotators to look at comparable pairs, rather than forcing them to make decisions on often vaguely defined pairs.

In practice, we annotate one axis at a time: we first classify if an event is anchorable onto a given axis (this is also called the anchorability annotation step); then we annotate every pair of anchorable events (i.e., the relation annotation step); finally, we can move to another axis and repeat the two steps above. Note that ruling out cross-axis relations is only a strategy we adopt in this paper to separate well-defined relations from ill-defined relations. We do not claim that cross-axis relations are unimportant; instead, as shown in Fig. 2, we think that cross-axis relations are a different semantic phenomenon that requires additional investigation.

| Event Type               | Category                      |
|--------------------------|-------------------------------|
| INTENTION, OPINION       | On an orthogonal axis         |
| HYPOTHESIS, GENERIC      | On a parallel axis            |
| NEGATION                 | Not on any axis               |
| STATIC, RECURRENT        | Other                         |

Table 1: The interpretation of various event types that are not on the main axis in the proposed multi-axis modeling. The names are rather straightforward; see examples for each in Appendix A.

Figure 1: A multi-axis view of Examples 1-3. Only events on the same axis are compared.

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4Recall that they were given the entire article and only salient relations would be annotated.
2.3 Comparisons with Existing Work
There have been other proposals of temporal structure modelings (Bramsen et al., 2006; Bethard et al., 2012), but in general, the semantic phenomena handled in our work are very different and complementary to them. (Bramsen et al., 2006) introduces “temporal segments” (a fragment of text that does not exhibit abrupt changes) in the medical domain. Similarly, their temporal segments can also be considered as a special temporal structure modeling. But a key difference is that (Bramsen et al., 2006) only annotates inter-segment relations, ignoring intra-segment ones. Since those segments are usually large chunks of text, the semantics handled in (Bramsen et al., 2006) is in a very coarse granularity (as pointed out by (Bramsen et al., 2006)) and is thus different from ours.

(Bethard et al., 2012) proposes a tree structure for children’s stories, which “typically have simpler temporal structures”, as they pointed out. Moreover, in their annotation, an event can only be linked to a single nearby event, even if multiple nearby events may exist, whereas we do not have such restrictions.

In addition, some of the semantic phenomena in Table 1 have been discussed in existing work. Here we compare with them for a better positioning of the proposed scheme.

2.3.1 Axis Projection
TB-Dense handled the incomparability between main-axis events and HYPOTHESIS/NEGATION by treating an event as having occurred if the event is HYPOTHESIS/NEGATION. In our multi-axis modeling, the strategy adopted by TB-Dense falls into a more general approach, “axis projection”. That is, projecting events across different axes to handle the incomparability between any two axes (not limited to HYPOTHESIS/NEGATION). Axis projection works well for certain event pairs like Asian crisis and e4:highest hit in Example 2: as in Fig. 1, Asian crisis is before expected, which is again before e4:highest hit, so Asian crisis is before e4:highest hit.

Generally, however, since there is no direct evidence that can guide the projection, annotators may have different projections (imagine projecting e5:rebuilding onto the main axis: is it in the past or in the future?). As a result, axis projec-

2.3.2 Introduction of the Orthogonal Axes
Another prominent difference to earlier work is the introduction of orthogonal axes, which has not been used in any existing work as we know. A special property is that the intersection event of two axes can be compared to events from both, which can sometimes bridge events, e.g., in Fig. 1. Asian crisis is seemingly before highest hit due to their connections to expected. Since Asian crisis is on the main axis, it seems that e4:highest hit is on the main axis as well. However, the “highest hit” in “Asian crisis before highest hit” is only a projection of the original e4:highest hit onto the real axis and is valid only when this OPINION is true.

Nevertheless, OPINIONS are not always true and INTENTIONS are not always fulfilled. In Example 5, e9:sponsoring and e10:resolve are the opinions of the West and the speaker, respectively: whether or not they are true depends on the au-
thors’ implications or the readers’ understandings, which is often beyond the scope of TempRel annotation. Example 6 demonstrates a similar situation for INTENTIONS: when reading the sentence of e11: report, people are inclined to believe that it is fulfilled. But if we read the sentence of e12: report, we have reason to believe that it is not. When it comes to e13: tell, it is unclear if everyone told the truth. The existence of such examples indicates that orthogonal axes are a better modeling for INTENTIONS and OPINIONS.

Example 5: Opinion events may not always be true.
He is ostracized by the West for (e9: sponsoring) terrorism.
We need to (e10: resolve) the deep-seated causes that have resulted in these problems.

Example 6: Intentions may not always be fulfilled.
A passerby called the police to (e11: report) the body. Unfortunately, the line was busy.
I asked everyone to (e13: tell) the truth.

2.3.3 Differences from Factuality
Event modality have been discussed in many existing event annotation schemes, e.g., Event Nugget (Mitamura et al., 2015), Rich ERE (Song et al., 2015), and RED. Generally, an event is classified as Actual or Non-Actual, a.k.a. factuality (Saurí and Pustejovsky, 2009; Lee et al., 2015).

The main-axis events defined in this paper seem to be very similar to Actual events, but with several important differences: First, future events are Non-Actual because they indeed have not happened, but they may be on the main axis. Second, events that are not on the main axis can also be Actual events, e.g., intentions that are fulfilled, or opinions that are true. Third, as demonstrated by Examples 5-6, identifying anchorability as defined in Table 1 is relatively easy, but judging if an event actually happened is often a high-level understanding task that requires an understanding of the entire document or external knowledge.

Interested readers are referred to Appendix B for a detailed analysis of the difference between Anchorable (onto the main axis) and Actual on a subset of RED.

3 Interval Splitting
All existing annotation schemes adopt the interval representation of events (Allen, 1984) and there are 13 relations between two intervals (for readers who are not familiar with it, please see Fig. 4 in the appendix). To reduce the burden of annotators, existing schemes often resort to a reduced set of the 13 relations. For instance, Verhagen et al. (2007) merged all the overlap relations into a single relation, overlap. Bethard et al. (2007); Do et al. (2012); O’Gorman et al. (2016) all adopted this strategy. In Cassidy et al. (2014), they further split overlap into includes, included and equal.

Let $[t^1_{start}, t^1_{end}]$ and $[t^2_{start}, t^2_{end}]$ be the time intervals of two events (with the implicit assumption that $t_{start} \leq t_{end}$). Instead of reducing the relations between two intervals, we try to explicitly compare the time points (see Fig. 3). In this way, the label set is simply before, after and equal, while the expressivity remains the same. This interval splitting technique has also been used in (Raghavan et al., 2012).

In addition to same expressivity, interval splitting can provide even more information when the relation between two events is vague. In the conventional setting, imagine that the annotators find that the relation between two events can be either before or before and overlap. Then the resulting annotation will have to be vague, although the annotators actually agree on the relation between $t^1_{start}$ and $t^2_{start}$. Using interval splitting, however, such information can be preserved.

An obvious downside of interval splitting is the increased number of annotations needed (4 point comparisons vs. 1 interval comparison). In practice, however, it is usually much fewer than 4 comparisons. For example, when we see $t^1_{end} < t^2_{start}$ (as in Fig. 3), the other three can be skipped because they can all be inferred. Moreover, although the number of annotations is increased, the work load for human annotators may still be the same, because even in the conventional scheme, they still need to think of the relations between start- and

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6For instance, there is undoubtedly a causal link between e9: sponsoring and ostracized.

7We will discuss vague in Sec. 4.
end-points before they can make a decision.

### 3.1 Ambiguity of End-Points

During our pilot annotation, the annotation quality dropped significantly when the annotators needed to reason about relations involving end-points of events. Table 2 shows four metrics of task difficulty when only $t_{\text{start}}^1$ vs. $t_{\text{start}}^2$ or $t_{\text{end}}^1$ vs. $t_{\text{end}}^2$ are annotated. Non-chorable events were removed for both jobs. The first two metrics, qualifying pass rate and survival rate are related to the two quality control protocols (see Sec. 4.1 for details). We can see that when annotating the relations between end-points, only one out of ten crowdsourcers (11%) could successfully pass our qualifying test; and even if they had passed it, half of them (56%) would have been kicked out in the middle of the task. The third line is the overall accuracy on gold set from all crowdsourcers (excluding those who did not pass the qualifying test), which drops from 67% to 37% when annotating end-end relations. The last line is the average response time per annotation and we can see that it takes much longer to label an end-end TempRel (52s) than a start-start TempRel (33s). This important discovery indicates that the TempRels between end-points is probably governed by a different linguistic phenomenon.

| Metric                  | $t_{\text{start}}^1$ vs. $t_{\text{start}}^2$ | $t_{\text{end}}^1$ vs. $t_{\text{end}}^2$ |
|-------------------------|-----------------------------------------------|-----------------------------------------------|
| Qualification pass rate | 50%                                           | 11%                                           |
| Survival rate           | 74%                                           | 56%                                           |
| Accuracy on gold        | 67%                                           | 37%                                           |
| Avg. response time      | 33s                                           | 52s                                           |

Table 2: Annotations involving the end-points of events are found to be much harder than only comparing the start-points.

We hypothesize that the difficulty is a mixture of how durative events are expressed (by authors) and perceived (by readers) in natural language. In cognitive psychology, Coll-Florit and Gennari (2011) discovered that human readers take longer to perceive durative events than punctual events, e.g., *owe 50 bucks* vs. *lost 50 bucks*. From the writer’s standpoint, durations are usually fuzzy (Schockaert and De Cock, 2008), or assumed to be a prior knowledge of readers (e.g., college takes 4 years and watching an NBA game takes a few hours), and thus not always written explicitly. Given all these reasons, we ignore the comparison of end-points in this work, although event duration is indeed, another important task.

### 4 Annotation Scheme Design

To summarize, with the proposed multi-axis modeling (Sec. 2) and interval splitting (Sec. 3), our annotation scheme is two-step. First, we mark every event candidate as being temporally anchorable or not (based on the time axis we are working on). Second, we adopt the dense annotation scheme to label TempRels only between anchorable events. Note that we only work on verb events in this paper, so non-verb event candidates are also deleted in a preprocessing step. We design crowdsourcing tasks for both steps and as we show later, high crowdsourcing quality was achieved on both tasks. In this section, we will discuss some practical issues.

#### 4.1 Quality Control for Crowdsourcing

We take advantage of the quality control feature in CrowdFlower in our crowdsourcing jobs. For any job, a set of examples are annotated by experts beforehand, which is considered gold and will serve two purposes. (i) Qualifying test: Any crowdsourcer who wants to work on this job has to pass with 70% accuracy on 10 questions randomly selected from the gold set. (ii) Surviving test: During the annotation process, questions from the gold set will be randomly given to crowdsourcers without notice, and one has to maintain 70% accuracy on the gold set till the end of the annotation; otherwise, he or she will be forbidden from working on this job anymore and all his/her annotations will be discarded. At least 5 different annotators are required for every judgement and by default, the majority vote will be the final decision.

#### 4.2 Vague Relations

How to handle vague relations is another issue in temporal annotation. In non-dense schemes, annotators usually skip the annotation of a vague pair. In dense schemes, a majority agreement rule is applied as a postprocessing step to back off a decision to vague when annotators cannot pass a majority vote (Cassidy et al., 2014), which reminds us that annotators often label a vague relation as non-vague due to lack of thinking.

We decide to proactively reduce the possibility of such situations. As mentioned earlier, our label set for $t_{\text{start}}^1$ vs. $t_{\text{start}}^2$ is *before, after, equal* and *vague*. We ask two questions: Q1=Is it possible that $t_{\text{start}}^1$ is before $t_{\text{start}}^2$? Q2=Is it possible that $t_{\text{start}}^2$ is before $t_{\text{start}}^1$? Let the an-
swers be A1 and A2. Then we have a one-
to-one mapping as follows: A1=A2=yes→vague,
A1=A2=no→equal, A1=yes, A2=no→before, and
A1=no, A2=yes→after. An advantage is that one
will be prompted to think about all possibilities,
thus reducing the chance of overlook.

Finally, the annotation interface we used is shown in Appendix C.

5 Corpus Statistics and Quality

In this section, we first focus on annotations on
the main axis, which is usually the primary story-
line and thus has most events. Before launching
the crowdsourcing tasks, we checked the IAA be-
tween two experts on a subset of TB-Dense (about
100 events and 400 relations). A Cohen’s Kappa
of .85 was achieved in the first step: anchorabil-
ity annotation. Only those events that both ex-
erts labeled Anchorable were kept before they
moved onto the second step: relation annotation,
for which the Cohen’s Kappa was .90 for Q1 and
.87 for Q2. Table 3 furthermore shows the dis-
bution, Cohen’s Kappa, and F1 of each label. We
can see the Kappa and F1 of vague (κ=.75, F1=.81)
are generally lower than those of the other labels,
confirming that temporal vagueness is a more dif-
ficult semantic phenomenon. Nevertheless, the
overall IAA shown in Table 3 is a significant im-
provement compared to existing datasets.

| Metric       | Q1  | Q2  | All |
|--------------|-----|-----|-----|
| Accuracy on Gold | .89 | .85 | .88 |
| WAWA          | .82 | .81 | .81 |

Table 4: Quality analysis of the relation annotation step of MATRES. “Q1” and “Q2” refer to the two questions crowdsourcers were asked (see Sec. 4.2 for details). Line 1 measures the level of consistency between crowdsourcers and the authors and line 2 measures the level of consistency among the crowdsourcers themselves.

With the improved IAA confirmed by experts,
we sequentially launched the two-step crowd-
sourcing tasks through CrowdFlower on top of
the same 36 documents of TB-Dense. To evaluate
how well the crowdsourcers performed on our
task, we calculate two quality metrics: accuracy
on the gold set and the Worker Agreement with
Aggregate (WAWA). WAWA indicates the average
number of crowdsourcers’ responses agreed with
the aggregate answer (we used majority aggrega-
tion for each question). For example, if N indi-
vidual responses were obtained in total, and n of them
were correct when compared to the aggregate an-
swer, then WAWA is simply n/N. In the first step,
crowdsourcers labeled 28% of the events as Non-
Anchorable to the main axis, with an accuracy on
the gold of .86 and a WAWA of .79.

With Non-Anchorable events filtered, the rela-
tion annotation step was launched as another
crowdsourcing task. The label distribution is
b=.50, a=.28, c=.03, and v=.19 (consistent with
Table 3). In Table 4, we show the annotation qual-
ity of this step using accuracy on the gold set
and WAWA. We can see that the crowdsourcers
achieved a very good performance on the gold set,
indicating that they are consistent with the authors
who created the gold set; these crowdsourcers also
achieved a high-level agreement under the WAWA
metric, indicating that they are consistent among
themselves. These two metrics indicate that the
annotation task is now well-defined and easy to
understand even by non-experts.

We continued to annotate INTENTION and
OPINION which create orthogonal branches on
the main axis. In the first step, crowdsourcers
achieved an accuracy on gold of .82 and a WAWA
of .89. Since only 16% of the events are in this cat-
egory and these axes are usually very short (e.g.,
allocate funds to build a museum.), the annotation
task is relatively small and two experts took the
second step and achieved an agreement of .86 (F1).

We name our new dataset MATRES for Multi-
Axis Temporal RElations for Start-points. Each
individual judgement cost us $0.01 and MATRES
in total cost about $400 for 36 documents.

5.1 Comparison to TB-Dense

To get another checkpoint of the quality of the new
dataset, we compare with the annotations of TB-
Dense. TB-Dense has 1.1K verb events, between
which 3.4K event-event (EE) relations are anno-
tated. In the new dataset, 72% of the events (0.8K)
are anchored onto the main axis, resulting in 1.6K
EE relations, and 16% (0.2K) are anchored onto
orthogonal axes, resulting in 0.2K EE relations.
The following comparison is based on the 1.8K EE relations in common. Moreover, since TB-Dense annotations are for intervals instead of start-points only, we converted TB-Dense’s interval relations to start-point relations (e.g., if \(A\) includes \(B\), then \(t_{\text{start}}^A\) is before \(t_{\text{start}}^B\)).

|   | b  | a  | c  | v  | All |
|---|----|----|----|----|-----|
| b | 455| 11 | 5  | 42 | 513 |
| a | 45 | 309| 16 | 68 | 438 |
| c | 13 | 7  | 2  | 10 | 32  |
| v | 450| 138| 20 | 192| 800 |
| All | 963| 465| 43 | 312| 1783|

Table 5: An evaluation of MATRES against TB-Dense. Horizontal: MATRES, Vertical: TB-Dense (with interval relations mapped to start-point relations). Please see explanation of these numbers in text.

The confusion matrix is shown in Table 5. A few remarks about how to understand it:

First, when TB-Dense labels before or after, MATRES also has a high-probability of having the same label (\(b=455/513=.89, a=309/438=.71\)); when MATRES labels vague, TB-Dense is also very likely to label vague (\(v=192/312=.62\)). This indicates the high agreement level between the two datasets if the interval- or point-based annotation difference is ruled out. Second, many vague relations in TB-Dense are labeled as before, after or equal in MATRES. This is expected because TB-Dense annotates relations between intervals, while MATRES annotates start-points. When durative events are involved, the problem usually becomes more difficult and interval-based annotation is more likely to label vague (see earlier discussions in Sec. 3). Example 7 shows three typical cases, where \(e14: \text{became}\), \(e17: \text{backed}\), \(e18: \text{rose}\) and \(e19: \text{extending}\) can be considered durative. If only their start-points are considered, the crowd-sourcers were correct in labeling \(e14\) before \(e15\), \(e16\) after \(e17\), and \(e18\) equal to \(e19\), although TB-Dense says vague for all of them. Third, equal seems to be the relation that the two dataset mostly disagree on, which is probably due to crowd-sourcers’ lack of understanding in time granularity and event coreference. Although equal relations only constitutes a small portion in all relations, it needs further investigation.

6 Baseline System

We develop a baseline system for TempRel extraction on MATRES, assuming that all the events and axes are given. The following commonly-used features for each event pair are used: (i) The part-of-speech (POS) tags of each individual event and of its neighboring three words. (ii) The sentence and token distance between the two events. (iii) The appearance of any modal verb between the two event mentions in text (i.e., will, would, can, could, may and might). (iv) The appearance of any temporal connectives between the two event mentions (e.g., before, after and since). (v) Whether the two verbs have a common synonym from their synsets in WordNet (Fellbaum, 1998). (vi) Whether the input event mentions have a common derivational form derived from WordNet. (vii) The head words of the preposition phrases that cover each event, respectively. And (viii) event properties such as Aspect, Modality, and Polarity that come with the TimeBank dataset and are commonly used as features.

The proposed baseline system uses the averaged perceptron algorithm to classify the relation between each event pair into one of the four relation types. We adopted the same train/dev/test split of TB-Dense, where there are 22 documents in train, 5 in dev, and 9 in test. Parameters were tuned on the train-set to maximize its F1 on the dev-set, after which the classifier was retrained on the union of train and dev. A detailed analysis of the baseline system is provided in Table 6. The performance on equal and vague is lower than on before and after, probably due to shortage in these labels in the training data and the inherent difficulty in event coreference and temporal vagueness. We can see, though, that the overall performance on MATRES is much better than those in the literature for TempRel extraction, which used to be in the low 50’s (Chambers et al., 2014; Ning et al., 2017). The same system was also retrained
and tested on the original annotations of TB-Dense (Line “Original”), which confirms the significant improvement if the proposed annotation scheme is used. Note that we do not mean to say that the proposed baseline system itself is better than other existing algorithms, but rather that the proposed annotation scheme and the resulting dataset lead to better defined machine learning tasks. In the future, more data can be collected and used with advanced techniques such as ILP (Do et al., 2012), structured learning (Ning et al., 2017) or multi-sieve (Chambers et al., 2014).

|                  | Training |          | Testing |          |
|------------------|----------|----------|---------|----------|
|                  | P    | R    | F1   | P    | R    | F1   |
| Before           | .74  | .91  | .82  | .71  | .80  | .79  |
| After            | .73  | .77  | .75  | .55  | .64  | .59  |
| Equal            | 1    | .05  | .09  | -    | -    | -    |
| Vague            | .75  | .28  | .41  | .29  | .13  | .18  |
| Overall          | .73  | .81  | .77  | .66  | .72  | .69  |
| Original         | .44  | .67  | .53  | .40  | .60  | .48  |

Table 6: Performance of the proposed baseline system on MATRES. Line “Original” is the same system retrained on the original TB-Dense and tested on the same subset of event pairs. Due to the limited number of equal examples, the system did not make any equal predictions on the testset.

7 Conclusion

This paper proposes a new scheme for TempRel annotation between events, simplifying the task by focusing on a single time axis at a time. We have also identified that end-points of events is a major source of confusion during annotation due to reasons beyond the scope of TempRel annotation, and proposed to focus on start-points only and handle the end-points issue in further investigation (e.g., in event duration annotation tasks). Pilot study by expert annotators shows significant IAA improvements compared to literature values, indicating a better task definition under the proposed scheme. This further enables the usage of crowdsourcing to collect a new dataset, MATRES, at a lower time cost. Analysis shows that MATRES, albeit crowdsourced, has achieved a reasonably good agreement level, as confirmed by its performance on the gold set (agreement with the authors), the WAWA metric (agreement with the crowdsourcers themselves), and consistency with TB-Dense (agreement with an existing dataset). Given the fact that existing schemes suffer from low IAAAs and lack of data, we hope that the findings in this work would provide a good start towards understanding more sophisticated semantic phenomena in this area.

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