STAGE: Tool for Automated Extraction of Semantic Time Cues to Enrich Neural Temporal Ordering Models

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Abstract

Despite achieving state-of-the-art accuracy on temporal ordering of events, neural models showcase significant gaps in performance. Our work seeks to fill one of these gaps by leveraging an under-explored dimension of textual semantics: rich semantic information provided by explicit textual time cues. We develop STAGE, a system that consists of a novel temporal framework and a parser that can automatically extract time cues and convert them into representations suitable for integration with neural models. We demonstrate the utility of extracted cues by integrating them with an event ordering model using a joint BiLSTM and ILP constraint architecture. We outline the functionality of the 3-part STAGE processing approach, and show two methods of integrating its representations with the BiLSTM-ILP model: (i) incorporating semantic cues as additional features, and (ii) generating new constraints from semantic cues to be enforced in the ILP. We demonstrate promising results on two event ordering datasets, and highlight important issues in semantic cue representation and integration for future research.

1 Introduction

The semantics of time has been of interest for decades among semanticists and computational linguists alike. A challenge in NLP tasks that require reasoning about time is that temporal information is encoded at many levels of linguistic analysis. This spectrum includes lexical cues such as prepositions and discourse markers, syntactic constructions related to tense and aspect, time-related adjective and adverbial expressions, and at the extreme, inferences that require abstract reasoning from indirect references, such as past its prime. Temporal reasoning is difficult for neural models because it requires first understanding the time expression and then understanding the interplay between that meaning and the meaning of the surrounding text. For a model to perform reasoning with time expressions like unit conversion and date-time comparison, we must have a method of formalizing this semantic information in a form that is consumable by a neural model. We address this within our proposed framework, which builds on decades of existing exploration into the semantics of time, with a new framing aimed to effectively support contemporary neural approaches. Further, we exhibit the downstream utility of our framework using temporal ordering of events as a demonstration task.

In particular, we present STAGE (Semantic Temporal Alignment Grammatical Extraction), a system that parses time expressions, extracts the semantic meaning, and converts it into representations that can be integrated with neural models. STAGE follows a 3-step process to identify time expressions and align them along a single standardized timeline. We test the performance of STAGE on time expression identification (Uzzaman et al., 2013a), and observe that its coverage is competitive with state-of-the-art approaches, while providing richer semantic structural information (§5.1).

To demonstrate the utility of richer semantic structural information on the downstream task of temporal ordering, we integrate this information into a state-of-the-art ordering model that uses a joint BiLSTM and ILP constraint architecture. We experiment with two integration strategies: (i) incorporating semantic cues as additional features, and (ii) generating new constraints from semantic cues to be enforced in the ILP. Our initial results on two event ordering datasets (Chambers et al., 2014; Naik et al., 2019) look promising, showing slight gains from incorporating features and constraints. Additionally, our experiments highlight key issues in semantic information representation and integration, providing clear directions for future research in the computational semantics of time.
2 Related Work

Our work bridges the world of formal semantic approaches to analysis of time and computational work on neural event ordering.

2.1 Evolution of Temporal Frameworks

Since the body of formal semantic work on time is vast, we highlight papers most relevant to our proposed framework here. A foundational body of work that informed our approach is the framework by Allen and Hayes (Allen, 1984; Allen and Hayes, 1985; Allen, 1991). Allen and Hayes (1985) present an axiomatic model of time that expresses time spans as intervals or moments, distinguished by whether these time spans can be broken into smaller constituents or not. Most subsequent work on temporal semantics, including our work, maintains this influential distinction. Our framework builds most directly on the OWL-S ontology (Pan and Hobbs, 2004), though it shares similarities with others such as Verhagen et al. (2005). Like Pan and Hobbs (2004), it identifies as possible time expressions instants and intervals, which represent moments along a timeline and spans of time, respectively. It also adds ranges, which cover spans of time like intervals, but reference the outer bounds of when the event takes place.

With advances in statistical learning, the field has been slowly shifting its focus away from formal models of semantics, though there have been periodic resurgences and some continuing work in adjacent fields. Some early contemporary formalizations of time can be found in the TimeML annotation scheme (Pustejovsky et al., 2003a), and the TimeBank dataset (Pustejovsky et al., 2003b). Shared tasks using TimeBank data such as the TempEval 1-3 tasks (Verhagen et al., 2007, 2010; UzZaman et al., 2013b) motivated much recent work on temporal frameworks and taggers, such as HeidelTime (Strötgen and Gertz, 2010) SUTime (Chang and Manning, 2012), and TARSQI, which builds on Verhagen et al. (2005). Finally recent work like the Temporal Event Ontology designed by Li et al. (2020) specifically aimed to resolve complex temporal reasoning in clinical texts.

While constructing the semantic meaning of time expressions from text is interesting, it also has clear applications for downstream NLP tasks requiring temporal reasoning. We are interested in the application of semantic time extraction for temporal ordering of events within a document.

2.2 Temporal Ordering

Temporal ordering of events has been an active area of research in NLP starting from the development of TimeML (Pustejovsky et al., 2003a) and TimeBank (Pustejovsky et al., 2003b). In recent years, several new datasets have been proposed for this task (Pustejovsky et al., 2003b; Bramsen et al., 2006; Kolomiyets et al., 2012; Do et al., 2012; Cassidy et al., 2014; Reimers et al., 2016; Ning et al., 2018b; Naik et al., 2019; Vashishtha et al., 2019). Many datasets use or build upon the scheme proposed by TimeBank, which represents temporal ordering via TLINKs (Setzer, 2002). A TLINK expresses the temporal relationship between two events, e.g., event A occurs after event B. We follow the same scheme in this work, and focus on the task of predicting TLINKs between events.

A variety of models have been developed for TLINK prediction, spurred by the TempEval shared tasks. These systems cover a wide range of modeling approaches, such as rule-based systems, trained classifiers and hybrid approaches (UzZaman and Allen, 2010; Llorens et al., 2010; Strötgen and Gertz, 2010; Chang and Manning, 2012; Chambers, 2013; Bethard, 2013a; Chambers et al., 2014; Mirza and Tonelli, 2016; Cheng and Miyao, 2017; Reimers et al., 2018). Most models were built with a focus on improving performance on TimeBank and/or TimeBank-Dense (Cassidy et al., 2014), which suffer from two key issues: (i) heavy focus on TLINKs between events in the same or adjacent sentences, and (ii) large proportion of TLINKs marked vague due to ambiguity. Additionally, models focused on predicting TLINKs between pairs of events independently. This has led to the development of models which ignore important factors such as document-level consistency, document-level cues such as event coreference, etc. There are some notable exceptions to this general trend, which introduce document-level consistency, coreference and causality via integer linear programming (ILP) constraints (Bramsen et al., 2006; Chambers and Jurafsky, 2008; Denis and Muller, 2011; Do et al., 2012; Llorens et al., 2015; Ning et al., 2017, 2018a).

In our work, we develop a temporal ordering model to address the problem of maintaining document-level consistency. Our model extends the dependency parse-based BiLSTM model of Cheng and Miyao (2017) by introducing transitivity and semantic information extracted by STAGE as ILP.
constraints. The constraints are incorporated during training via a structured support vector machine (SSVM) framework. Our formulation is close to the joint event-temporal model developed by Han et al. (2019), but we do not model event extraction. Instead, we introduce rich semantic information extracted by STAGE.

3 The STAGE System

Our central contribution is the development of a novel semantic framework to represent explicit time cues, and a tool that automatically extracts these cues from raw text. Collectively, this framework and tool make up the STAGE (Semantic Temporal Alignment Grammatical Extraction) system.

3.1 Semantic Framework

Several temporal logic frameworks and tools have been developed that automatically extract temporal information with good reliability and accomplish some level of semantic normalization. However, older ontologies, which are constructed by hand, guided in a top-down fashion by theoretical insights into language, provide limited coverage and do not scale well to current datasets. Conversely, recent approaches perform well on current datasets while sacrificing some rich semantic information that would be valuable in more rigorous temporal reasoning. Our tool is designed to balance both, maintaining a semantically rich, complex representation of time that is yet standardized enough that it can be extracted automatically from explicit textual time cues in large corpora.

In our work, an explicit textual time cue or “time expression” refers to a contiguous string of text that communicates a concept about time. Depending upon its contextualization, an event time expression can be assigned to one (or more) of the three basic categories of time expressions: instant, interval or range, as shown by the examples below:

- “The celebration took place on January 1st, 2001”: instant occurring on 01/01/01.
- “People were waiting from January to June”: interval starting in January and ending in June.
- “The party will happen sometime in December”: range covering the month of December.
- “We should meet for an hour sometime next week”: both an interval lasting one hour and a range covering the next week.

Beyond assignment of expressions to the categories enumerated above, and formalization of the status of temporal expressions not explicitly connected to an event in a discourse, we address the issue of comparison between temporal expressions. The goal is to design our temporal expression ontology such that models can easily learn to make comparisons between time expressions. This approach makes the following specific modifications to the Pan and Hobbs (2004) framework:

1. Lengths of time are represented using a standard unit (hours) in order to facilitate comparison between semantic objects that may have been expressed in different units.
2. Relative expressions (e.g., “three days ago”) are converted to dates based on document date, when known.
3. Intervals/ranges are represented as one (or a combination) of the following properties: starting point, ending point, and length. This better mimics the ways in which humans describe time spans.

| Text                              | Semantic type                                      |
|-----------------------------------|---------------------------------------------------|
| “four hours”                      | A length of time.                                 |
| “in four hours”                   | An instant with a clear position on a timeline.   |
| “for four hours”                  | An interval with clear duration and vague position.|
| “within four hours”               | A range with clear duration and position that an event occurs for some vague duration and position within. |

Table 1: Impact of function words on semantic meaning of time expression.
4. Instead of resolving relationships between time expressions in a rule-based manner as in previous temporal formalisms, we instead represent each temporal expression separately but include representation of associated properties that provide cues for uncovering the relationship between temporal expressions downstream. In this way, individual temporal expressions are somewhat more elaborate than in other recent work (see Table 3) in ways meant to support the event ordering task performed in a subsequent stage.

3.2 Parser

Building on the formalism described in the previous section, STAGE also includes a semantic extraction tool focusing on the identification and arrangement of time expressions along a single standardized timeline. The tool utilizes lexical time cues alongside function words, which were frequently omitted from consideration in published annotation schemes for time expressions (e.g., TempEval-3 Platinum (UzZaman et al., 2013a)). But function words have significant impact on the underlying semantic meaning of a time cue; in Table 1 we show how distinct function words change the properties and even type of our semantic representation. We design a context-free semantic grammar to parse time expressions into representations according to the stable correspondence between function words and temporal concepts, such that the results have utility for downstream temporal processing.

STAGE does its extraction and representation work in three steps, separated into three distinct modules shown in Figure 1. The first module produces all potential parses for a time cue. This module takes a text string as input, identifies the words which belong to STAGE’s temporal vocabulary, and applies the STAGE temporal grammar rules. It uses a binary CKY chart parser to efficiently generate all possible parses for each input string, and outputs the full chart. As an example, Figure 2 shows all parse trees produced for the time cue “three days ago”. The trees that do not span the full time cue often resolve to complete (though less semantically specific) time expressions.

The second module produces a logical representation of a text string’s underlying semantic information using a set of heuristically-determined semantic rules. It takes as input a set of parse trees. In this paper, we choose from the first module’s output the parse tree spanning the largest subsection of the input which also resolves to one of our three “complete” expression types (instant, interval, or range). The nodes of the parse tree instruct the module how to apply the semantic transformations, and the output is a formal semantic representation of the original text string. In the example above, the module behaves as follows:

- **START:** “three days ago” $\rightarrow$ NUM(val=3) UNIT(val=day) ago
- **RULE:** NUM + UNIT = LENGTH $\rightarrow$ NUM(3) + UNIT(day) = LENGTH(num=3, unit=day)
- **RULE:** LENGTH + ago = INSTANT $\rightarrow$ LENGTH(num=3, unit=day) + ago = INSTANT(ANCHOR="present", DIST from anchor=LENGTH(number=3, unit=day))

Our rules allow for complete time expressions to be transformed into other types with infinite recursion. If we change the string to “before three days ago” we would see:

- **RULE:** before + INSTANT = INTERVAL $\rightarrow$ before + INSTANT(ANCHOR=...unit=day) = INTERVAL(START=Unknown, END=INSTANT(ANCHOR=...unit=day), LENGTH=Unknown)

The final module takes this high-level logical representation and converts it to a machine-readable form for downstream tasks. Our work integrates...
semantic information into a neural model, and thus we convert our representation into two different formats: (i) a set of input features, and (ii) constraints dictating the order of certain event-pairs. For our feature set, we identify four key attributes: the time expression’s type, the position on the timeline where it begins, the position where it ends (for an instant, this point is the same as its start), and the expression’s length. We initially render these in a set of 10 features, but based on experimentation, we choose a reduced set of only 4 features, described in Table 2, for the final model presented in this paper. We leave further experimentation to future work. To generate constraints, we examine the start and end points for each event in the pair and heuristically identify pairs for which the relation is certain based on these features alone. The constraint generated pushes the model to prioritize the predicted relation over others for this pair. See example of resulting constraint logic output shown in Figure 3.

As a result of the process, the final output for the example input string “three days ago” will be the feature set (is_point = True, start_is_int = True, end_is_int = True, len_is_int = False). If our dataset included three events, where “three days ago” is linked to event A, and event B takes place “two days ago” while C is “one week ago”, STAGE would also constraints “A before B” and “B after C”.

4 Temporal Ordering System

To test the downstream utility of semantic features and constraints generated by STAGE, we integrate these features/constraints into a state-of-the-art neural model and evaluate it on the task of temporal ordering. The following subsections detail our model architecture and integration strategies.

4.1 Neural Baselines

Figure 4 gives a brief overview of the architecture of our baseline model (BiLSTM), which is a re-implementation of the state-of-the-art dependency parse-based BiLSTM model developed by Cheng and Miyao (2017). For each event pair in a document, we compute dependency paths from source and target events to the sentence root, which are then fed to a BiLSTM. For events in different sentences, source and target event sentences are assumed to be connected to a “common root”. Source and target path representations computed by the BiLSTM are fed to an MLP, followed by a softmax layer which predicts the temporal relation.

We also propose an additional neural model (BiLSTM+ILP), which infuses transitivity into BiLSTM as integer linear programming (ILP) constraints in a structured support vector machine (SSVM) framework. We use a similar ILP formulation as Naik et al. (2019). Let $E$, $R$, and $P$ be sets of events, temporal relations and event pairs respectively($P = \{ (e_i, e_j) \in E \times E | e_i, e_j \in E, i \neq j \}$). We define an array of binary indicator variables $y$, where $y_{<r,i,j>}$ indicates whether the relation $r$ holds between events $e_i$ and $e_j$. Our ILP objective is defined as:

$$\arg \max_y \sum_{<e_i,e_j> \in P} \sum_{r \in R} y_{<r,i,j>^p}$$

subject to the following constraints:

$$y_{<r,i,j>} \in \{0,1\}, \forall (e_i, e_j) \in P, \forall r \in R$$

$$\sum_{r \in R} y_{<r,i,j>} = 1, \forall (e_i, e_j) \in P$$

$$y_{<r_1,i,j>} + y_{<r_2,j,k>} - y_{<r_3,i,k>} \leq 1, \forall (e_i, e_j), (e_j, e_k), (e_i, e_k) \in P, \forall (r_1, r_2, r_3) \in TC$$
where \( p_{<r,i,j>} \) is the probability that event pair \((e_i, e_j)\) has label \( r \). (2) ensures that indicator variables are binary, (3) forces event pairs to be assigned a unique label and (4) imposes transitivity. \( TC \) denotes the set of transitive relation triples.\(^1\) Relation probabilities \( p_{<r,i,j>} \) come from the softmax layer of the BiLSTM. For all event pairs in a document, we use the BiLSTM to compute relation probabilities. Using these scores, we solve the ILP optimization and obtain a set of predictions \( y \). Given gold predictions \( y' \) and BiLSTM predictions \( y \), we compute a structured hinge loss using the following formulation:

\[
L(y, y') = \max(0, \Delta(y, y') + \Psi(y, p) - \Psi(y', p))
\]

Here \( \Delta(y, y') \) is a distance measure between the gold and predicted labels. We use Hamming distance in our formulation. \( \Psi(y, p) \) and \( \Psi(y', p) \) are scoring functions used to compute scores for the gold and predicted labels. We use the same function as the ILP objective for score computation.

The main intuition behind the hinge loss formulation is that if the gold labels \( y' \) are not scored higher than the predicted ones \( y \) (with a margin of \( \Delta(y, y') \)), there will be a non-zero loss. The objective is to minimize this margin loss.

### 4.2 Integrating STAGE

BiLSTM and BiLSTM+ILP form our neural baselines, and we evaluate the effect of incorporating features/constraints from STAGE on these models. We test two integration strategies. In the first (simpler) strategy, the sets of 4 features per event in the pair are concatenated with representations from the BiLSTM before passing them to the MLP.

\(^1\) ("before", "before", "before") form a transitive relation triple as A before B and B before C implies A before C.

In the second strategy, we incorporate STAGE-generated constraints into the ILP formulation. First, we add dummy events representing the time expressions that have been extracted by STAGE to the ILP. Let this set of dummy events be \( E_d \). The ILP now contains new variables for each pair of events \((e_i, e_j)\) where \( e_i, e_j \) or both are dummy events from \( E_d \), and the non-dummy event is from the set \( E \). For each date in \( E_d \), STAGE generates temporal relations between the date and all other events/dates \((\hat{E} = E \setminus E_d)\), following its constraint logic (Figure 3). Empty outputs (i.e., cases where it cannot deduce a relation) from STAGE are ignored. These relations are introduced as ILP constraints in two ways: (i) adding hard constraints, and (ii) adding soft constraints. Adding hard constraints is done by incorporating the following new constraints into the ILP:

\[
\text{Obj}_{\text{new}} = \text{Obj}_{\text{old}} + \alpha \sum_{e_i \in E_d} \sum_{e_j \in \hat{E}} y_{<TP(e_i, e_j),i,j>} + \left( \frac{1 - \alpha}{|R| - 1} \right) \sum_{e_i \in E_d} \sum_{e_j \in \hat{E}} \sum_{r \in \hat{R}} y_{<r,i,j>}
\]

Here \( \hat{R} = R - TP(e_i, e_j) \), which is the set of all relations except for the one predicted by STAGE for pair \((e_i, e_j)\). \( \alpha \) is a constant which indicates how much weight we give to the STAGE’s prediction. We set it to 0.9 in our experiments because STAGE is a high-precision system (§5.1).

### 5 System Evaluation

#### 5.1 Evaluating STAGE

We first evaluate the performance of our STAGE system in isolation on the task of identifying tem-
Table 4: Dataset sizes for TimeBank-Dense and TDDiscourse. Note that we only count event-event TLINKs since our models focus on those.

| Dataset      | Train | Dev  | Test  |
|--------------|-------|------|-------|
| TB-Dense     | 4032  | 629  | 1427  |
| TDD-Man      | 4000  | 650  | 1500  |
| TDD-Auto     | 32609 | 1435 | 4258  |

Table 5: Temporal relation set used in the two datasets. Note that TDDiscourse omits the vague relation.

| Symbol | Relation                                      |
|--------|-----------------------------------------------|
| a      | $e_1$ occurs after $e_2$                     |
| b      | $e_1$ occurs before $e_2$                    |
| s      | $e_1$ and $e_2$ are simultaneous              |
| i      | $e_1$ includes $e_2$                         |
| ii     | $e_1$ is included in $e_2$                   |
| v      | relation of $e_1$ to $e_2$ is ambiguous       |

5.2 Evaluating Temporal Ordering

To demonstrate downstream utility of information extracted by STAGE, we compare the performance of two state-of-the-art neural temporal ordering models (BiLSTM and BiLSTM+ILP), with variants that incorporate features, constraints or both within the neural architecture.

5.2.1 Datasets

To evaluate temporal ordering performance, we use the following datasets:

- **TimeBank-Dense**: 36 English news articles annotated with events and temporal relations using the TimeML annotation scheme (Casidy et al., 2014).
- **TDDiscourse**: Augmentation of TimeBank-Dense, focused on annotating temporal relations between events that are more than one sentence apart (Naik et al., 2019). This dataset is divided into two subsets TDD-Auto and TDD-Man, which contain automatically generated and manually annotated relations respectively.

Table 4 shows the training, development and test set sizes for both datasets and table 5 provides an overview of the temporal relations present.

5.2.2 Results and Discussion

Table 6 shows the performance of all models on TimeBank-Dense and TDDiscourse. From the table, we can see that while the BiLSTM baseline is quite strong, our proposed augmentation of incorporating transitivity as ILP constraints (BiLSTM + ILP) further improves performance by 1-2 F1 points. Among the variants which incorporate features and constraints from STAGE, we observe that incorporating features into BiLSTM+ILP achieves the highest performance on TDD-Man, while incorporating both features and hard constraints achieves...
Table 6: Performance of all baselines and proposed models on TimeBank-Dense and TDDiscourse.

| Model                  | TB-Dense | TDD-Auto | TDD-Man |
|------------------------|----------|----------|---------|
| BiLSTM                 | P        | R        | F1      | P        | R        | F1      | P        | R        | F1      |
| BiLSTM + ILP           | 49.3     | 49.3     | 49.3    | 49.5     | 46.9     | 48.2    | 30.9     | 30        | 30.3    |
| BiLSTM + FEAT          | 47.9     | 47.9     | 47.9    | 48.5     | 45.8     | 47.1    | 29       | 27.8      | 28.4    |
| BiLSTM + ILP + FEAT    | 48.8     | 48.5     | 48.5    | 48.9     | 46       | 47.2    | 29.1     | 27.9      | 28.5    |
| BiLSTM + ILP + HARD    | 48.1     | 48.1     | 48.1    | 48.1     | 45.5     | 46.8    | 31.1     | 29.9      | 30.5    |
| BiLSTM + ILP + SOFT    | 47.9     | 47.9     | 47.9    | 49.5     | 46.8     | 48.1    | 30.8     | 29.6      | 30.2    |
| BiLSTM + ILP + FEAT + HARD | 47       | 47       | 47      | 49.1     | 46.5     | 47.8    | 30.8     | 29.6      | 30.2    |
| BiLSTM + ILP + FEAT + SOFT | 47       | 47       | 47      | 49.1     | 46.5     | 47.8    | 30.8     | 29.6      | 30.2    |

competitive performance on TDD-Auto. However, none of the feature/constraint combinations improve the performance of the augmented BiLSTM + ILP baseline on TimeBank-Dense. Thus despite accurately extracting rich temporal information (§5.1), integrating it with neural models in a way that improves performance on downstream tasks like event ordering is extremely challenging. The encouraging results on TDDiscourse indicate that the extracted temporal semantic information is valuable, but we believe that the following directions must be explored further to make more significant advances:

#### Exploring Representation Schemes:
Currently, we only incorporate a restricted set of coarse boolean features produced by STAGE. However, STAGE is also capable of generating fine-grained features such as normalized start and end points and length values for temporal expressions. This fine-grained information anchors events on a timeline, and is thus informative for temporal ordering. But our initial experiments on incorporating these values into the feature space caused F1 scores to drop, particularly for models that contain the ILP module. We speculate that adding these features as integers skews neural model probabilities (i.e., produces overconfident predictions), which harms the ILP. Building a temporal mathematics module which produces boolean comparison features using start, end and length values for events in a pair and adding these features into the neural models is an interesting direction to explore. Additionally, our integration strategies so far have not explored the possibility of representing temporal semantic information using the parses produced by STAGE during the first phase. While these parses are less fine-grained, we are interested in studying whether this allows neural models more flexibility in learning when to rely on the semantic framework.

#### Dynamic Neural/Semantic Integration:
Our current strategies for integrating STAGE into neural models are static, i.e., they combine the neural and STAGE-produced features in the same manner for all event pairs. Studying whether the neural models and STAGE have different strengths and weaknesses on various categories of event pairs can help in designing a smarter ensembling strategy that learns to modify its reliance on neural/STAGE features depending on event pair type. While there are several avenues to explore to further improve performance, our results show promise and highlight important issues that arise when integrating neural models with semantic representations, which must be addressed in future work.

#### 6 Conclusion

Temporal reasoning is a challenging task due to the presence of temporal information at various linguistic layers in text. This poses a challenge in building temporal models that extract rich semantic information, which being efficient and high-coverage enough to tackle large corpora. Much of the community has moved away from semantics-driven models, which often involve a lot of domain knowledge and complex inefficient execution pipelines. Our work demonstrates that a tightly-focused, structured semantic framework (STAGE) can be used to identify and extract relevant semantic information with high accuracy. This information can also be integrated with state-of-the-art neural models to improve performance on complex downstream tasks such as temporal ordering. Our initial results show promising improvements, and outline challenges in semantic representation and integration which must be addressed by the community to make further progress on temporal reasoning.
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