
tieval: AN EVALUATION FRAMEWORK FOR TEMPORAL INFORMATION EXTRACTION SYSTEMS

Hugo Sousa ^{1,2}, Alípio Jorge ^{1,2}, and Ricardo Campos ^{1,3,4}

¹INESC TEC, Portugal

²University of Porto, Portugal

³Polytechnic Institute of Tomar, Portugal

⁴Ci2 - Smart Cities Research Center, Portugal

{hugo.o.sousa, alipio.jorge, ricardo.campos}@inesctec.pt

January 12, 2023

ABSTRACT

Temporal information extraction (TIE) has attracted a great deal of interest over the last two decades, leading to the development of a significant number of datasets. Despite its benefits, having access to a large volume of corpora makes it difficult when it comes to benchmark TIE systems. On the one hand, different datasets have different annotation schemes, thus hindering the comparison between competitors across different corpora. On the other hand, the fact that each corpus is commonly disseminated in a different format requires a considerable engineering effort for a researcher/practitioner to develop parsers for all of them. This constraint forces researchers to select a limited amount of datasets to evaluate their systems which consequently limits the comparability of the systems. Yet another obstacle that hinders the comparability of the TIE systems is the evaluation metric employed. While most research works adopt traditional metrics such as precision, recall, and F_1 , a few others prefer temporal awareness – a metric tailored to be more comprehensive on the evaluation of temporal systems. Although the reason for the absence of temporal awareness in the evaluation of most systems is not clear, one of the factors that certainly weights this decision is the necessity to implement the temporal closure algorithm in order to compute temporal awareness, which is not straightforward to implement neither is currently easily available. All in all, these problems have limited the fair comparison between approaches and consequently, the development of temporal extraction systems. To mitigate these problems, we have developed *tieval*, a Python library that provides a concise interface for importing different corpora and is equipped with domain-specific operations that facilitate system evaluation. In this paper, we present the first public release of *tieval* and highlight its most relevant features. The library is available as open source, under MIT License, at PyPI¹ and GitHub².



Figure 1: tieval logo.

¹<https://pypi.org/project/tieval/>

²<https://github.com/LIAAD/tieval>

1 Introduction

Understanding the temporal order of events is essential to human communication. We, humans, can easily understand the relative order of events in a conversation or when reading a news article. However, many challenges are raised when we try to automate such tasks with a computer program. The first difficulty that emerges is how to represent temporal information. Since in most cases we do not explicitly specify the start and end time of each event, temporal information, such as order and time span, ends up being inferred from the events themselves. To this regard, computer algorithms can make use of temporal clues in the text, and of external sources, such as knowledge-bases, to anchor events on a timeline. For instance, in the sentence “We went to dinner after the game.”, two events, “dinner” and “game”, can be automatically identified and used, despite the lack of explicit temporal information, to recreate a timeline of events (see Figure 2) supported on the word “after”. The ordering of events and the knowledge about them, can be further expanded if used together with appropriate external sources. For instance, the event “game” can be contextualized and anchored on the timeline by searching for information on a knowledge-base. However, in the case of the “dinner” event, it turns out impossible to know the exact time of occurrence unless it is specified in the text. This shows that representing temporal information is not a trivial task, since there are several borderline cases for which no standard approach has been established.

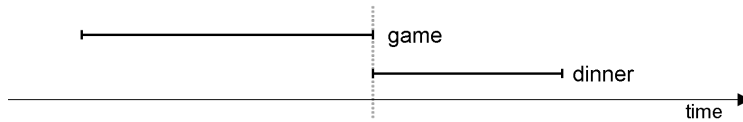


Figure 2: Relative timeline of events that can be inferred from the running example.

Over the years, and particularly in the last two decades, this problem has been highly studied, leading to several proposals from the research community Campos et al. [2014], Leeuwenberg and Moens [2019]. Most of the proposals were in the origin of the emergence of different annotation schemes and the various corpora that we have today at our disposal Naik et al. [2019], Ning et al. [2018a], UzZaman et al. [2013]. Although these efforts have been essential to mature temporal information extraction and its subtasks – such as temporal expression identification or temporal relation classification – they also pose some problems upon the process of benchmarking different methods. One of the problems has its roots in the fact that evaluating the methods, often requires reading multiple corpora, each of which has a different perspective on temporal representation, ultimately preventing comparability among the different methods and corpora. This is compounded by the fact that corpora are stored in a variety of formats (e.g., XML, TimeML, or table), which requires a considerable engineering effort to load them all.

Another issue that limits the comparison between systems is the lack of standardization in the metrics used in the evaluation process. This is a particular problem of temporal relation extraction – a subtask of TIE, which deals with the identification and classification of the temporal relations between entities – where different metrics are often employed during the evaluation process. While initially systems were evaluated and compared using standard metrics, such as recall, precision, and F-score Verhagen et al. [2007, 2010], more recently, metrics such as temporal awareness UzZaman and Allen [2011] have proven to be more reliable in the evaluation of temporal relation extraction methods. The reasoning behind this is that, while traditional metrics focus on the local effectiveness of the model, temporal awareness better understands the relative order of events by considering the global temporal structure of the predictions. This is accomplished by taking into account the temporal relations that can be inferred from the established ones (a process typically referred to as temporal closure), making this a more comprehensive metric for evaluating temporal systems. Despite the emergence of this temporal awareness, many studies still rely solely on traditional metrics to evaluate their system. We speculate that this is due to the fact that temporal awareness requires domain-specific operations such as temporal closure – which are not (yet) readily available in every framework and therefore require individual implementation by each research group. In addition, temporal awareness requires the implementation of a strategy to deal with inconsistent predictions of the system, which is generally not explored in recent studies.

To mitigate the above issues, we developed `tieval`, a Python library that enables the development and evaluation of TIE systems. This framework provides a simple interface to download and read TIE corpora in various formats. It currently covers well-known corpus – such as TempEval-3 UzZaman et al. [2013], TDDiscourse Naik et al. [2019], and MeanTime Minard et al. [2016] – however, it lays the foundations for others to be included by providing base classes for the construction of the corpus. It also provides domain-specific operations – such as temporal closure and simple translation of intervals into point relations – that can be used to develop TIE systems. In addition to this, it includes an evaluation infrastructure for a comprehensive assessment of the effectiveness of the different models being evaluated. Because `tieval` supports the entire development pipeline of TIE, it can also be used to ensure reproducibility and fair benchmarking of future research. The main contributions of `tieval` are the following:

1. it gathers the multiple corpora for the development of TIE systems, making it easy to access with just a few lines of code;
2. it facilitates access to domain-specific operations, such as interval to point relation and temporal closure, as well as metrics such as temporal awareness;
3. it provides a standard framework, thus making it easy for new methods to be compared against previous ones.

The remaining of the paper is organized as follows: The next section, provides an overview of recent work in TIE and some of its software. We then proceed to present the `tieval` package in section 3. We start with a general introduction and then go into some of its most relevant features. Section 5 serves to present our thoughts on what we strive to be next steps in the development of the framework.

2 Related Work

Extracting temporal information from documents written in natural language in an inter-operable format has long been an interest of the artificial intelligence community Ling and Weld [2010], Derczynski et al. [2015]. Since the introduction of the Time Markup Language (TimeML) Pustejovsky et al. [2003a], in 2003, the temporal graph has become the de-facto standard to represent temporal information. In this graph, the nodes are temporal entities and the edges are the temporal relation that hold between them. The temporal entities can take two forms: event expressions, which are defined as situations that happened (e.g., “went” or “bought”); and temporal expressions (timex), which can convey temporal information explicitly (e.g., “October 27, 199”) or implicitly (e.g., “a few years ago”) Campos et al. [2017]. The temporal relations are held in the form of temporal links (tlink) that contain temporal relations between pairs of events (E-E relations), events and time expressions (E-T relations), and events and document creation time (E-DCT relations), where DCT is a special timex that stores document creation time. Overall, these temporal relations can take thirteen types, which is the number of relations that can exist between two time intervals Allen [1983].

The first corpus that was annotated with this scheme was TimeBank Pustejovsky et al. [2003b]. The release of this corpus, dated from 2003, sparked a wave of research in the field later on also used on the TempEval shared tasks UzZaman et al. [2013], Verhagen et al. [2007, 2010]. These tasks end up segmenting TIE into a set of sub-problems that can be conceptually defined as temporal entity identification, tlink identification, and tlink classification. Although some works developed systems for more than one of these sub-tasks, most of the systems are concerned with only one of them. Furthermore, temporal entity identification systems are traditionally partitioned into subsystems for the several classes of temporal entities. For example, for the TimeBank corpus, one system is usually trained to identify events and another to identify timexs. The `tieval` architecture follows this natural decomposition of the TIE.

The TimeBank corpus, and more abstractly, the TimeML annotation scheme was widely studied by the community. Such scrutiny lead to the emergence of several new corpora. Some used the TimeML annotation scheme to create new corpora, such as AQUAINT Graff [2002] and the Platinum corpus UzZaman et al. [2013], while others were concerned in extending the annotation scheme to other languages. The most remarkable effort on this domain was the TempEval-2 shared task Verhagen et al. [2010] that produced corpora for Chinese Li et al. [2014], French Bittar et al. [2011], Italian Caselli et al. [2011], and the Spanish Nieto and Saurí [2012] language. Another noteworthy effort is the MeanTime corpus Minard et al. [2016] in which the authors annotated 120 news articles written in English from Wikinews³, and translated the texts into Italian, Spanish, and Dutch. Costa and Branco Costa and Branco [2012] followed a similar process to construct TimeBankPT, translating the original TimeBank to Portuguese and adapting the annotations when needed. Apart from the extensions to other languages, the TimeML annotation scheme was also extended to other domains. A concrete example is the case of the clinical domain for which two corpora have been produced, the i2b2 Sun et al. [2013] and THYME Styler IV et al. [2014]⁴. Further significant contributions were the proposals that explored ways to mitigate some of the issues found on the TimeBank annotation effort, such as: sparse annotation – TimeBank-Dense Cassidy et al. [2014] and TDDiscourse Naik et al. [2019]; improve inter-annotator agreement – MATRES Ning et al. [2018a]; and include other sources of knowledge – TCR Ning et al. [2018b] and RED O’Gorman et al. [2016].

Aside from the TimeML, and related approaches, there have also been other proposals that were explored by the research community. One of them is absolute timeline placement, in which the temporal entities are directly anchored on a timeline by labeling each entity with the time (or time span) of occurrence. The most remarkable efforts in this direction were produced by Reimers et al. Reimers et al. [2016] – which produced the EventTime corpus by annotating the events in TimeBank with a specific day, or span of days – and Leeuwenberg and Moens Leeuwenberg and Moens

³<https://en.wikinews.org/>

⁴These corpora are not available for open access and, as a consequence, we were not able to include them on the framework.

[2020] – which annotated 169 clinical records from the i2b2 corpus with the most likely start and end time of each event along with a lower and upper bound.

This shows that several corpora have been introduced for the TIE task. However, the fact that they were released in different formats makes it hard to leverage their power, which is one of the issues mitigated by tieval.

To the best of our knowledge, the only framework that made available TIE operations – including temporal closure and temporal awareness – is the Anafora Tools project⁵ which was built to work with files stored in the Anafora XML format Chen and Styler [2013], used to annotate the THYME corpus Styler IV et al. [2014]. The framework presented in this paper aims to be a more general tool, unifying all corpora in a single format.

3 tieval

Our vision for tieval was to build a framework that would support and facilitate the evaluation of TIE systems. With the development of libraries such as Numpy, TensorFlow, and PyTorch, Python has established itself as the programming language of choice within the machine learning community. For that reason, we built tieval in Python. To facilitate the installation we made it available on Python Package Index (PyPI)⁶. Thus, the toolkit can be easily installed through pip, as follows:

```
$ pip install tieval==0.0.6
```

In this paper, we will use version 0.0.6, which is the first and the most recent version of the package. However, the reader is advised to install the newest release at the time of reading the paper and refer to the project repository for up-to-date documentation. Furthermore, for users that might be interested in contributing to tieval, we encourage forking the source repository and making a pull request.

tieval contains three modules that represent the three cornerstones of any machine learning project: datasets, models, and evaluation. The datasets module is responsible for downloading and reading the corpora available for TIE, the models module is responsible for the construction of the models, and the evaluation module has methods to make a proper evaluation for each of the TIE tasks. In the following sections, we will present the inner workings of the framework with scripts to exemplify the usability of the framework.

3.1 Datasets

With tieval, we wanted to mitigate the issues referred above by making it easy for the user to work with several corpora with a few lines of code. To that end, we developed an architecture that would unify the different annotations and storing formats of the corpus. This architecture is composed of several objects which are depicted in Figure 3.

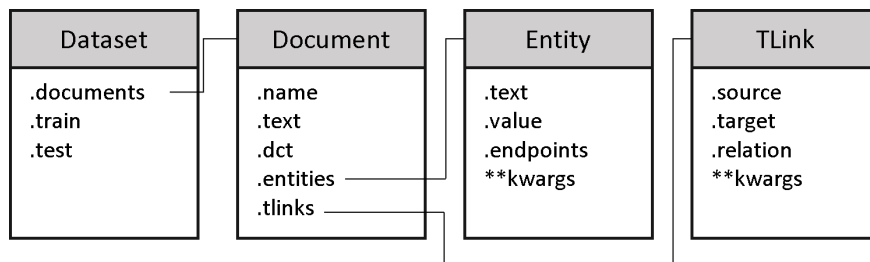


Figure 3: Objects used to represent a dataset on tieval. The arrow represent a relation of “Iterable”.

The Dataset object is the final representation of each corpus. It compiles the set of all the documents in the corpus on the documents attribute which is segmented into the train and test attributes whenever provided in the original paper⁷. Each document is then stored as an instance of the Document class (see the Document grey box in Figure 3), which contains all the information necessary for TIE, more specifically:

name a string that contains the name of the document (e.g. “wsj_0026.tml”);

⁵<https://github.com/bethard/anaforatools>

⁶<https://pypi.org/project/tieval/>

⁷When no standard train/test split is provided by the authors all the documents are placed on the train attribute.

text a string with the raw text of the document;

dct is a Timex that contains the document creation time (e.g. `Timex("12-10-2004")`);

entities is the set of Entities – either a Timex or Event – that are annotated on the corpus. Each Entity is, at its core, a data class made to store all the info provided on the annotation. Therefore, it has to be flexible to accommodate for the different types of information provided in different corpus. For instances, the GraphEve corpus provides the lemma for each event while TempEval-2 does not;

tlinks a set of TLink’s that stores the temporal relations annotated on the document. Each TLink contains a source and target entity as well as the temporal relation between them – on the relation attribute.

A special remark needs to be made about the `relation` attribute of the TLink object. When initiating a TLink instance one needs to pass the temporal relation that holds between the two temporal entities (the source and the target). In most of the corpora this is one of the thirteen temporal relations Allen [1983] that can hold between two time intervals, however, there are corpora where the annotators were more flexible on the type of relations. Examples of this are the TempEval-2 and the MATRES corpus. On TempEval-2 the annotators were allowed to give more ambiguous relations as “BEFORE-OR-OVERLAP” and “OVERLAP-OR-AFTER”. In MATRES the annotators were asked to provide the temporal relation between the start points of the temporal entities. In order to accommodate the several types of annotations, we build TemporalRelation object, which handles the relation that was annotated. Inside this object, every relation is represented in point relations – instead of the traditional interval relations. Figure 4 shows how to represent the interval relation “BEFORE” into a point relation. A relative relation is also included in the figure for illustrative purposes.

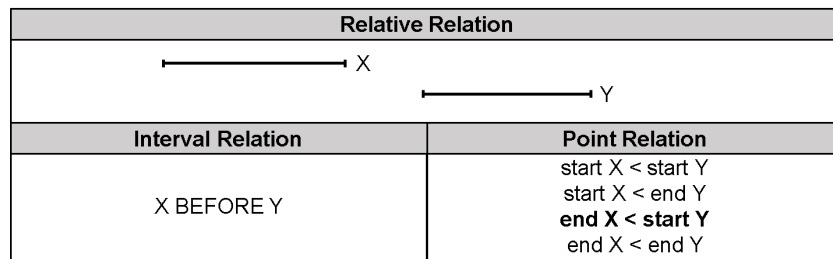


Figure 4: Relative timeline of events that can be inferred from the running example.

Note that the “BEFORE-OR-OVERLAP” relation on TempEval-2 represents an uncertainty of the annotator between the end time of the source entity and the start time of the target entity, however, the annotator is certain about the remaining point relations. Further note that, although we explicitly state four-point relations in Figure 4, upon the adaptation of the current datasets into tieval format, three of them are redundant, as the point relation “end A < start B” completely defines the remaining point relations. Therefore, on tieval, whenever there is a new dataset to include, the user can provide the relation in the way that is most appropriate, as shown in Listing 1.

Listing 1: Different ways to pass the temporal relation to the TLink object. The first argument (X) is the source entity, the second (Y) is the target entity, and the third is the temporal relation between them. This can be passed as an interval relation, “before”, or as a point relation, in the form of a dictionary structure. On the latter, the interpretation for the expected keys is the following: “x” and “y” stands for the source and target entity, respectively; while the “s” and “e” stand for “start” and “end”. As an example, “xe_ys” is the point relation between the source end and the target start.

```

from tieval.links import TLink
t11 = TLink("X", "Y", "before")
t12 = TLink("X", "Y", {"xe_ys": "<"})
t13 = TLink("X", "Y", {"xs_ys": "<", "xs_ys": "<", "xe_ys": "<", "xe_ys": "<"})
    
```

In order to reach a standardized representation for the different corpora, we developed a reader for each of the corpus. Each dataset reader has inherited from an abstract base class, named BaseDocumentReader, which requires the implementation of five methods named after the five attributes used to create an instance of a Document: name, text, dct, entities, and tlinks. To extract this information, the base class contains three attributes: the path for the document being read; the content of the dictionary produced by parsing the document with the `xmltodict`⁸ library; and the `xml` attribute that results from parsing the file with the `xml`⁹ library. Note that, while json is nowadays the standard format for the

⁸<https://pypi.org/project/xmltodict/>

⁹<https://docs.python.org/3/library/xml.etree.elementtree.html>

exchange of the information, we had to resort to xml as most datasets were stored in that format. The script presented in Listing 2 illustrates how to read a document from the TempEval-3 corpus with the TempEval3DocumentReader.

Listing 2: Read a document of the TempEval-3 corpus.

```
from tieval import datasets
path = "tempeval-3/wsj_0026.tml"
reader = datasets.TempEval3DocumentReader(path)
doc = reader.read()
```

To fully integrate a new corpus on the library – and automatically read the entire corpus – the user just needs to add an entry on the DATASETS_METADATA dictionary with the metadata necessary to read the document. This information will be used on the read function of the datasets module, which only requires the name of the corpus to produce an instance of the Dataset object with all the annotations provided in there. The script in Listing 3 presents how to perform such operation.

Listing 3: Read the TempEval-3 corpus.

```
from tieval import datasets
te3 = datasets.read("TempEval-3")
```

The current version of tieval natively supports the download and reading of an extensive list of corpora for TIE. A complete list of the corpora considered is provided in Table 1. In order to ensure long-term support for these corpora, we created a repository with them. Besides that, it also has the advantage that we can standardize the structure of the folders and add useful information to the raw datasets (for instance, the spans of the temporal entities identified on the text) and fix errors on the original annotation¹⁰. For that reason, we were careful to verify the license for each of the corpora and publish only the ones that allowed for redistribution or did not provide any license.

Table 1: The corpora currently supported on tieval.

	Language	# Docs	# Events	# Timexs	# Tlinks
AncientTimes	Arabic	5	0	106	0
	Dutch	5	0	130	0
	English	5	0	311	0
	French	5	0	290	0
	German	5	0	196	0
	Italian	5	0	234	0
	Spanish	5	0	217	0
	Vietnamese	4	0	120	0
Aquaint	English	72	4,351	639	5,832
EventTime	English	36	1,498	0	0
GraphEVE	English	103	4,298	0	18,204
KRAUTS	German	192	0	1,282	0
MATRES	English	274	6,065	0	13,504
MeanTime	English	120	1,882	349	1,753
	Spanish	120	2,000	344	1,975
	Dutch	120	1,346	346	1,487
	Italian	120	1,980	338	1,675
Narrative Container	English	63	3,559	439	737

Continued on next page

¹⁰The changes made on the original corpus are detailed on the file logbook.rst in the docs folder of the project repository.

Table 1: The corpora currently supported on tieval. (Continued)

Professor Heideltime	English	24,642	0	254,803	0
	French	27,154	0	83,431	0
	German	19,095	0	194,043	0
	Italian	9,619	0	58,823	0
	Portuguese	24,293	0	111,810	0
	Spanish	33,266	0	348,011	0
Platinum (TempEval-3)	English	20	748	158	929
TimeBank	Spanish	210	12,384	1,532	21,107
	French	108	2,115	533	2,303
	Portuguese	182	7,887	1,409	6,538
	English	183	6,681	1,426	5,120
TimeBank 1.2	English	183	7,940	1,414	6,413
TCR	English	25	1,134	242	3,515
TDDiscourse	English	34	1,101	0	6,150
TempEval 2	Chinese	52	4,783	946	7,802
	English	182	6,656	1,390	5,945
	French	83	1,301	367	372
	Italian	64	5,377	653	6,884
	Korean	18	2,583	317	0
	Spanish	210	12,384	1,502	13,304
	English	275	11,780	2,223	11,881
TimeBank Dense	English	36	1,712	289	12,715
TrainT3 (TempEval-3)	Spanish	175	10,686	1,269	17,283
Wikiwars	English	22	0	2,662	0
	German	22	0	2,239	0

3.2 Models

The current version of tieval has four built-in models, namely: a baseline for timex identification; the HeidelTime model Strötgen et al. [2013] for timex identification and classification; a baseline for event identification; and the CogCompTime 2.0 model Ning et al. [2019] for tlink classification. The availability of these four models is intended for practitioners that may want to experiment using any layer of temporal information in their specific application. Apart from that, it also provide researchers the implementation of baseline models for reference in their work.

For the baseline models, we provide pre-trained weights, however, the user can also train the model from scratch. A description of each of the models is provided below:

TimexIdentificationBaseline For this baseline we trained – from scratch – the spaCy¹¹ named entity recognition model to identify the timexs on the TempEval-3 corpus.

EventIdentificationBaseline This model has the same architecture of the TimexIdentificationBaseline but was trained to identify events rather than timexs on the TempEval-3 corpus.

HeidelTime This model is a widely recognized multilingual temporal tagger which was original written in Java¹². However there have been efforts to build python wrappers. In tieval we used the py_heideltime wrapper which is available on GitHub¹³.

¹¹<https://spacy.io/>

¹²<https://github.com/HeidelTime/heideltime>

¹³https://github.com/hmosousa/py_heideltime

CogCompTime2 This model leverages the ELMo Peters et al. [2018] word embeddings and the TempProb Ning et al. [2018c] knowledge base to classify the temporal relation between a pair of temporal entities Ning et al. [2019]. Our implementation was adapted from the repository made available¹⁴ by the authors.

Listing 4 presents a script that would download the baseline model for temporal expression identification (TimexIdentificationBaseline), train the model on the TempEval-3 train set, and produce predictions for the TempEval-3 test set.

Listing 4: How to download, train, and predict with for the temporal identification task.

```
from tieval import models
model = model.TimexIdentificationBaseline()
model.fit(te3.train)
predictions = model.predict(te3.test)
```

A user interested in releasing his/her model in tieval can do it by creating a subclass of one of our base classes for models. There are two base classes: a BaseModel which just requires the implementation of the predict method which is intended for models that are available in other repositories – for instance, the HeidelTime model – and a BaseTrainableModel which, besides the predict, requires the implementation of the fit method, which implements the training loop for the model.

3.3 Evaluation

tieval provides an evaluation function for four subtasks of TIE, more specifically: timex identification, event identification, tlink identification, and tlink classification.

Table 2: The results obtained by evaluating the four models integrated in tieval on the Platinum (TempEval-3 test set), TCR, and MeanTime (the English version) corpus. P stands for precision, R for recall, F1 is the F1-score, and TF1 is the temporal awareness. All the results in the table are micro metrics.

	Platinum			TCR			MeanTime		
	<i>P</i>	<i>R</i>	<i>F</i> ₁ (<i>TF</i> ₁)	<i>P</i>	<i>R</i>	<i>F</i> ₁ (<i>TF</i> ₁)	<i>P</i>	<i>R</i>	<i>F</i> ₁ (<i>TF</i> ₁)
TimexBaseline	88.1	75.4	81.2	75.4	82.0	78.6	23.7	57.1	33.5
HeidelTime	84.0	79.4	81.8	70.6	80.6	75.3	26.5	65.8	37.8
EventBaseline	74.6	80.5	77.5	48.3	92.6	63.5	25.8	54.1	34.9
CogCompTime2	39.7	39.7	39.7 (39.3)	75.4	75.4	75.4 (69.3)	30.7	28.6	29.6 (28.9)

The input is standard for all the evaluation functions: annotations, a dictionary with the name of the documents as keys and the annotations as values; predictions, follows the same structure of the annotations but for each document key contains the predictions made by a model. The output of the functions is dependent on the task being evaluated. For the identification tasks (timex, event, and tlink) the function produces the standard macro and micro metrics for precision, recall, and f1-score. Listing 5 presents a script that evaluates the predictions made by the event baseline model in the TempEval-3 test set.

Listing 5: Evaluate event baseline model on the TempEval-3 test set.

```
from tieval import evaluate
annotations = {doc.name: doc.events for doc in te3.test}
result = evaluate.event_identification(annotations, predictions)
```

Table 2 depicts the results obtained by the implemented on benchmark corpora. Note that TF1 is the temporal awareness metric and is only computed for CogCompTime2 (the only tlink classification system). Another interesting remark is the fact that the TimexBaseline achieves effectiveness comparable to HeidelTime despite its simplicity.

The tlink classification is the most elaborate evaluator as it also computes the temporal awareness metric UzZaman and Allen [2011]. The complexity of the calculation of temporal awareness lies in the computation of temporal closure. With temporal_closure the closure operation can be easily performed on the document level, with the closure method of

¹⁴<https://github.com/qiangning/NeuralTemporalRelation-EMNLP19>

the Document object, or applied to a set of tlink’s with the temporal_closure function available on the library. The script in Listing 6 illustrates how to perform such operations.

Listing 6: How to compute the temporal closure with a Document object and with a set of TLink’s.

```

from tieval import temporal_closure
doc = te3["wsj_0026.tml"]
closure_tlinks = doc.closure
closure_tlinks = temporal_closure(doc.tlinks)

```

For the temporal closure to be efficiently performed, on the back-end, the closure operation is executed with a point-based reasoner which was inspired by the work of Gerevini et al. [1993]. As stated above, each TLink instance contains an attribute named relation which is an instance of the TemporalRelation object. Within the TemporalRelation all temporal relations are represented as the point relations by the means of a PointRelation instance. In the point representation there are only four types of temporal relations, namely before (<), after (>), equal (=), and not defined (None). With this point relation one can build a directed graph (henceforth referred as timegraph) where the nodes are the entities endpoints (start and end of the entity) and the edges represent the before (<) relation. This is accomplished by reflecting the after (>) relations and aggregating the equal (=) relations in a single node.

In the timegraph, inferring temporal relations is reduced to the problem of finding if two entities endpoints are connected, i.e., they are in the same subgraph (by subgraph we mean a fully connected graph of the timegraph). If that is the case, one can retrieve the endpoints on the entity pair and validate if the order of the entity endpoints is a valid temporal relation. To clarify this concept, Figure 5 presents the timegraph built for a scenario where two tlinks were provided: X MEETS Y and Y STARTS Z. To infer the temporal relation between X and Z one must query the endpoints in the timegraph. In this case, one would get the following sequence of endpoints: sX < ex = sY < eZ. After retrieving the sequence of endpoints one just needs to validate if that sequence is a valid interval relation. In this example, one can conclude that the temporal relation between X and Z is MEETS.

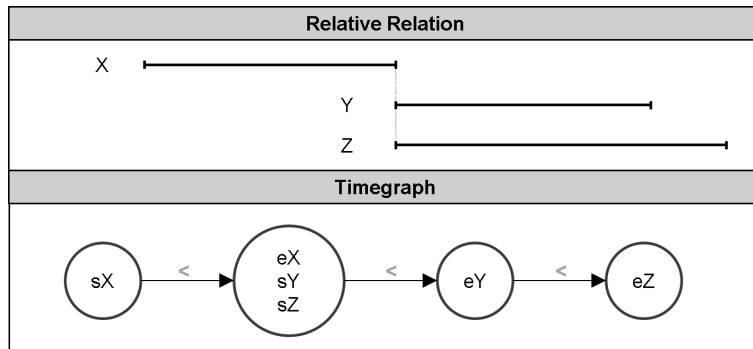


Figure 5: On the top part of the image is the relative relations between entities X, Y, and Z. On the bottom is the graphical representation of the timegraph that would be generated.

To get a practical understanding of the runtime of the temporal closure algorithm, we executed it on all documents currently available in tieval. On a computer with an Intel Core i5-8500 CPU, the algorithm took less than half a second for 95% of the documents, while the worst-case scenario took roughly 1.6 seconds.

This finalizes the presentation of the main functionalities, and some inner workings, of the first version of tieval. The current version already provides functionalities that (we believe) will be beneficial for the TIE community. However, we already have some ideas to further improve this library. These ideas are discussed in section 5.

4 Observations

While building tieval, and in particular the datasets module, we found some inconsistencies in the corpus we were working with. For instances, we found that the articles APW20000115.0209 and APW20000107.0088 of the AQUAINT corpus contained the same news article, differing only in the annotations and in the value of the document creation time. This type of inconsistencies were mitigated by implementing data cleaning processes that changed the original annotations. Consequently, the results on the tieval framework will (most frequently) not resemble the exact result that was reported in previous works, even if the same model is employed.

5 Conclusion and Future Work

This work presented the first public release of the `tieval` package, an open-source Python library for the development and evaluation of TIE systems. `tieval` provides several functionalities to facilitate research in this field. These include the import of multiple benchmark corpora in different formats, domain-specific operations such as temporal closure or transformation from interval to point relations, out-of-the-box baseline systems, and evaluation measures for TIE tasks. Therefore, it provides the community with a standard way to benchmark TIE systems in a fair and comparable way, while enabling the development of reproducible systems.

For future versions of the package, we aim to extend its functionalities. One idea we are keen to implement is visualization techniques to display the relative timeline of events from the annotations. In addition, we will add methods to include other levels of information when available such as coreference resolution in the MeanTime corpus Minard et al. [2016] and causality relations in the TCR corpus Ning et al. [2018b]. We also intend to extend the list of supported corpora and baseline models, in particular, to support corpora that cast the TIE task as a question-answer problem, such as MCTaco Zhou et al. [2019] and TORQUE Ning et al. [2020]. This will allow us to produce a reproducibility study to investigate several state-of-the-art systems and benchmark them in the different corpora.

References

- Ricardo Campos, Gaël Dias, Alípio M Jorge, and Adam Jatowt. Survey of temporal information retrieval and related applications. *ACM Computing Surveys (CSUR)*, 47(2):1–41, 2014.
- Artuur Leeuwenberg and Marie-Francine Moens. A survey on temporal reasoning for temporal information extraction from text. *Journal of Artificial Intelligence Research*, 66:341–380, 2019.
- Aakanksha Naik, Luke Breitfeller, and Carolyn Rose. Tddiscourse: A dataset for discourse-level temporal ordering of events. In *Proceedings of the 20th Annual SIGdial Meeting on Discourse and Dialogue*, pages 239–249, 2019.
- Qiang Ning, Hao Wu, and Dan Roth. A multi-axis annotation scheme for event temporal relations. *arXiv preprint arXiv:1804.07828*, 2018a.
- Naushad UzZaman, Hector Llorens, Leon Derczynski, James Allen, Marc Verhagen, and James Pustejovsky. Semeval-2013 task 1: Tempeval-3: Evaluating time expressions, events, and temporal relations. In *Second Joint Conference on Lexical and Computational Semantics (*SEM), Volume 2: Proceedings of the Seventh International Workshop on Semantic Evaluation (SemEval 2013)*, pages 1–9, 2013.
- Marc Verhagen, Robert Gaizauskas, Frank Schilder, Mark Hepple, Graham Katz, and James Pustejovsky. Semeval-2007 task 15: Tempeval temporal relation identification. In *Proceedings of the Fourth International Workshop on Semantic Evaluations (SemEval-2007)*, pages 75–80, 2007.
- Marc Verhagen, Roser Sauri, Tommaso Caselli, and James Pustejovsky. Semeval-2010 task 13: Tempeval-2. In *Proceedings of the 5th International Workshop on Semantic Evaluation*, pages 57–62, 2010.
- Naushad UzZaman and James Allen. Temporal evaluation. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 351–356, 2011.
- Anne-Lyse Minard, Manuela Speranza, Ruben Urizar, Begona Altuna, Marieke Van Erp, Anneleen Schoen, and Chantal Van Son. Meantime, the newsreader multilingual event and time corpus. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16)*, pages 4417–4422, 2016.
- Xiao Ling and Daniel S Weld. Temporal information extraction. In *Twenty-Fourth AAAI Conference on Artificial Intelligence*, 2010.
- Leon Derczynski, Jannik Strotgen, Ricardo Campos, and Omar Alonso. Time and information retrieval: Introduction to the special issue. *Inf. Process. Manag.*, 51:786–790, 2015.
- James Pustejovsky, José M Castano, Robert Ingria, Roser Sauri, Robert J Gaizauskas, Andrea Setzer, Graham Katz, and Dragomir R Radev. Timeml: Robust specification of event and temporal expressions in text. *New Directions in Question Answering*, 3:28–34, 2003a.
- Ricardo Campos, Gaël Dias, Alípio Mário Jorge, and Célia Nunes. Identifying top relevant dates for implicit time sensitive queries. *Information Retrieval Journal*, 20(4):363–398, 2017.
- James F Allen. Maintaining knowledge about temporal intervals. *Communications of the ACM*, 26(11):832–843, 1983.
- James Pustejovsky, Patrick Hanks, Roser Sauri, Andrew See, Robert Gaizauskas, Andrea Setzer, Dragomir Radev, Beth Sundheim, David Day, Lisa Ferro, et al. The timebank corpus. In *Corpus Linguistics*, volume 2003, page 40. Lancaster, UK., 2003b.

- David Graff. *The AQUAINT Corpus of English News Text LDC2002T31*. Linguistic Data Consortium, 2002.
- Hui Li, Jannik Strötgen, Julian Zell, and Michael Gertz. Chinese temporal tagging with heidelttime. In *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, Volume 2: Short Papers*, pages 133–137, 2014.
- André Bittar, Pascal Amsili, Pascal Denis, and Laurence Danlos. French timebank: an iso-timeml annotated reference corpus. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 130–134, 2011.
- Tommaso Caselli, Valentina Bartalesi Lenzi, Rachele Sprugnoli, Emanuele Pianta, and Irina Prodanof. Annotating events, temporal expressions and relations in italian: the it-timeml experience for the ita-timebank. In *Proceedings of the 5th Linguistic Annotation Workshop*, pages 143–151, 2011.
- Marta Guerrero Nieto and Roser Saurí. Modes timebank 1.0. *Linguistic Data Consortium (LDC), Philadelphia, PA, USA*, 2012.
- Francisco Costa and António Branco. TimeBankPT: A TimeML annotated corpus of Portuguese. In *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC'12)*, pages 3727–3734, Istanbul, Turkey, May 2012. European Language Resources Association (ELRA). URL http://www.lrec-conf.org/proceedings/lrec2012/pdf/246_Paper.pdf.
- Weiyi Sun, Anna Rumshisky, and Ozlem Uzuner. Evaluating temporal relations in clinical text: 2012 i2b2 challenge. *Journal of the American Medical Informatics Association*, 20(5):806–813, 2013.
- William F Styler IV, Steven Bethard, Sean Finan, Martha Palmer, Sameer Pradhan, Piet C De Groen, Brad Erickson, Timothy Miller, Chen Lin, Guergana Savova, et al. Temporal annotation in the clinical domain. *Transactions of the Association for Computational Linguistics*, 2:143–154, 2014.
- Taylor Cassidy, Bill McDowell, Nathanel Chambers, and Steven Bethard. An annotation framework for dense event ordering. Technical report, CARNEGIE-MELLON UNIV PITTSBURGH PA, 2014.
- Qiang Ning, Zhili Feng, Hao Wu, and Dan Roth. Joint reasoning for temporal and causal relations. *arXiv preprint arXiv:1906.04941*, 2018b.
- Tim O’Gorman, Kristin Wright-Bettner, and Martha Palmer. Richer event description: Integrating event coreference with temporal, causal and bridging annotation. In *Proceedings of the 2nd Workshop on Computing News Storylines (CNS 2016)*, pages 47–56, 2016.
- Nils Reimers, Nazanin Dehghani, and Iryna Gurevych. Temporal anchoring of events for the timebank corpus. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2195–2204, 2016.
- Artuur Leeuwenberg and Marie-Francine Moens. Towards extracting absolute event timelines from english clinical reports. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 28:2710–2719, 2020.
- Wei-Te Chen and Will Styler. Anafora: A web-based general purpose annotation tool. In *Proceedings of the 2013 NAACL HLT Demonstration Session*, pages 14–19. Association for Computational Linguistics, 2013. URL <http://www.aclweb.org/anthology/N13-3004>.
- Jannik Strötgen, Julian Zell, and Michael Gertz. Heidelttime: Tuning english and developing spanish resources for tempeval-3. In *Second Joint Conference on Lexical and Computational Semantics (*SEM), Volume 2: Proceedings of the Seventh International Workshop on Semantic Evaluation (SemEval 2013)*, pages 15–19, 2013.
- Qiang Ning, Sanjay Subramanian, and Dan Roth. An improved neural baseline for temporal relation extraction. *arXiv preprint arXiv:1909.00429*, 2019.
- Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. In *NAACL*, 2018.
- Qiang Ning, Hao Wu, Haoruo Peng, and Dan Roth. Improving temporal relation extraction with a globally acquired statistical resource. *arXiv preprint arXiv:1804.06020*, 2018c.
- Alfonso Gerevini, Lenhart Schubert, and Stephanie Schaeffer. Temporal reasoning in timegraph i–ii. *ACM SIGART Bulletin*, 4(3):21–25, 1993.
- Ben Zhou, Daniel Khashabi, Qiang Ning, and Dan Roth. "going on a vacation" takes longer than "going for a walk": A study of temporal commonsense understanding. *arXiv preprint arXiv:1909.03065*, 2019.
- Qiang Ning, Hao Wu, Rujun Han, Nanyun Peng, Matt Gardner, and Dan Roth. Torque: A reading comprehension dataset of temporal ordering questions. *arXiv preprint arXiv:2005.00242*, 2020.