# Detecting Subevents using Discourse and Narrative Features

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## Abstract

Recognizing the internal structure of events is a challenging language processing task of great importance for text understanding. We present a supervised model for automatically identifying when one event is a subevent of another. Building on prior work, we introduce several novel features, in particular discourse and narrative features, that significantly improve upon prior state-of-the-art performance. Error analysis further demonstrates the utility of these features. We evaluate our model on the only two annotated corpora with event hierarchies: HiEve and the Intelligence Community corpus. No prior system has been evaluated on both corpora. Our model outperforms previous systems on both corpora, achieving 0.74 BLANC $F_1$ on the Intelligence Community corpus and 0.70 $F_1$ on the HiEve corpus, respectively a 15 and 5 percentage point improvement over previous models.

## 1 Introduction

An event is something that occurs in a certain place at a certain time (Pustejovsky et al., 2003). Understanding events plays a major role in various natural language processing tasks such as information extraction (Humphreys et al., 1997), question answering (Narayanan and Harabagiu, 2004), textual entailment (Haghighi et al., 2005), event coreference (Choubey and Huang, 2018) and contradiction detection (De Marneffe et al., 2008). There has been a significant amount of work on automatic processing of events in text including systems for events extraction, event coreference resolution, and temporal relation detection (Araki, 2018; Ning et al., 2017). However, events are not atomic entities: they often have complex internal structure that can be expressed in a variety of ways (Huttunen et al., 2002; Bejan and Harabagiu, 2008; Hovy et al., 2013).

One of the unsolved problems related to event understanding is the detection of subevents, also referred to as *event hierarchy construction*. As described by Glavaš and Šnajder (2014a), there have been efforts that have focused on detecting temporal and spatial subevent containment individually. However, it is clear that subevent detection requires both simultaneously. The subevent relationship is defined in terms of $(e_1,e_2)$, where $e_1$ and $e_2$ are events: event $e_2$ is a subevent of event $e_1$ if $e_2$ is spatiotemporally contained by $e_1$. More precisely, we say that an event $e_1$ is a parent event of event $e_2$, and $e_2$ is a child event of $e_1$ if (1) $e_1$ is collector event that contains a complex sequence of activities; (2) $e_2$ is one of these activities; and (3) $e_2$ is spatially and temporally contained within $e_1$ (i.e., $e_2$ occur at the same time and same place as $e_1$) (Hovy et al., 2013; Glavaš and Šnajder, 2014b). This subevent relationship is independent of other types of relationships, e.g., causal relationship between the events. Example 1 illustrates a text expression of a complex event hierarchy. Figure 1 shows a corresponding graphical representation of the hierarchy.

> *Egyptian police have said that five protesters were* **killed**$_1$ *when they were* **attacked**$_2$ *by an armed group near the Defense Ministry building in Cairo. The statement said that early this morning, the armed group* **attacked**$_3$ *the demonstrators who have for days been staging their* **protest**$_4$ *against the military government. . . . Police said that the* **attack**$_5$ *on Wednesday* **wounded**$_6$ *at least 50 protesters.*

Example 1: Excerpt from the HiEve corpus (Glavaš et al., 2014a). Events are in bold and given a numerical subscript for reference. In all the examples the identified events are gold annotations, but for clarity not all annotations are included.
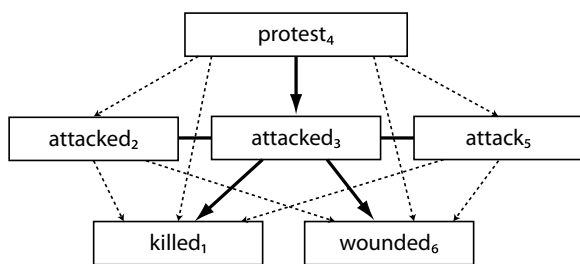
Figure 1: The corresponding event hierarchy of example 1. Bolded arrows indicate subevent relationships and bolded lines indicate event coreference relationships, when they are explicitly indicated in the HiEve annotations. Dashed lines indicate implicit subevent relationship.

In Figure 1, we see that **killed**$_1$ and **wounded**$_6$ are explicitly annotated as subevents of **attacked**$_3$, while that event in turn is a subevent of **protest**$_4$. Events **attacked**$_2$ and **attack**$_5$ are explicitly indicated as coreferent with **attacked**$_3$. These relationships induce the implicit subevent relations shown by dashed lines.

In this work we propose a pairwise model that leverages new discourse and narrative features to significantly improve subevent relation detection. evaluate our model on two corpora, namely, the HiEve corpus (Glavaš et al., 2014a) and the Intelligence Community (IC) corpus[1] (Hovy et al., 2013). We build on feature sets proposed in previous work, but propose several important discourse and narrative level features. We show that our model outperforms current systems on the subevent detection task by a significant margin. An error analysis reveals why these features are important and further details on why the subevent detection task is difficult.

We begin the paper by discussing prior work on subevent detection task (§2). Then we introduce our model and the feature set (§3). Following that, we describe the corpora (§4.1) we used and the experimental setup (§4.2). We then present the evaluation metrics and the performance of our model (§4.3) as well as compare our model performance to previous works (§5). To the end, we show an extensive error analysis (§6) and conclude with a list of contributions (§7).

## 2 Related Work

There are two pieces of prior work that are most related to our work. Araki et al. (2014) pro-

posed a logistic regression model to classify pairs of events into four classes: *coreference*, *subevent*, *sister*, and *no relation*. They then used sister relations and their parents to improve the system performance. Their model was trained and tested on 65 articles from the IC corpus developed by (Hovy et al., 2013). Similarly, Glavaš and Šnajder (2014b) used a logistic regression model to classify pairs of event into three classes: subevent relations (*SuperSub* and *SubSuper*) and *no relation*. They enforced structural coherence which improved the quality of the extracted event hierarchies by 7.6% $F_1$ score. They trained and tested their approach on the HiEve corpus developed by (Glavaš et al., 2014a). Both approaches were evaluated using different evaluations metrics. Araki et al. evaluated their model using BLANC evaluation metric (Recasens and Hovy, 2011) whereas Glavaš and Šnajder evaluated their model using the standard $F_1$ evaluation metric. Both works introduced a variety of features. The main contribution of our work is to note that the subevent detection task requires a better understanding of the discourse. Thus here we introduce several new features, including discourse structure and narrative structure. The error analysis (§6) demonstrates why these features are effective and also reveals more details on why subevent detection is difficult.

## 3 Features

In this section, we explain the features used in our model. As discussed, both the HiEve and IC corpus (Hovy et al., 2013; Glavaš et al., 2014a) are annotated with both subevent and event coreference relationships. We compute features over all pairs of events $(e_1, e_2)$ where $e_1$ precedes $e_2$ in the text. Each pair of events is either related by a forward pointing parent-child relationship (PC), a backward pointing parent-child relationship (CP), or no relation (NoRel). Our features can be divided into five sets as shown in Table 1. In the following sections we first illustrate the features we directly obtained from prior work (§3.1); next we explain the features that were inspired by prior work but that we modified significantly (§3.2); and finally we introduce our new discourse and narrative features (§3.3).

### 3.1 Prior Features

We obtained most of the lexical and syntactic features, and several of the semantic features, directly

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[1]The IC corpus is unfortunately not publically available; we obtained a copy from Hovy et al. (2013).

| Feature Set or Feature | Representation | Description |
|---|---|---|
| **Lexical** | | |
| Event Expression | Bag-of-Events | The surface form of $e_1$ and $e_2$. |
| Same Lemma | Binary | Whether $e_1$ and $e_2$ have the same lemma. |
| Temporal Signals* | Bag-of-Signals | If both events are in the same sentence, the temporal signals appearing in the sentence between the events, based on the temporal signals list from (Derczynski and Gaizauskas, 2010). |
| Event String Similarity | Numeric | The string similarity between surface forms of the events using a Levenshtein distance measure. |
| **Syntactic** | | |
| Major POS | One-hot | The Major POS of $e_1$ and $e_2$ (e.g., Noun, Verb, or Adjective) [2 features]. |
| Same Major POS | Binary | Whether the Major POS of $e_1$ and $e_2$ are the same. |
| POS Tag | One-hot | The POS Tag of $e_1$ and $e_2$. [2 features] |
| Same POS Tag | Binary | Whether the POS Tag of the $e_1$ and $e_2$ are the same. |
| Syntactic Dependency* | One-hot | The ancestor event of the other event in the dependency tree. |
| Determiner | Binary | Whether each event has a determiner. [2 features] |
| **Semantic** | | |
| Semantic Frame | Binary | Whether $e_1$ and $e_2$ have the same semantic frame using SEMAFOR (Das et al., 2010). |
| Event Type* | One-hot | The event type of $e_1$ and $e_2$ extracted from the mapping from frames to event types (Liu et al., 2016). [2 features] |
| Same Event Type | Binary | Whether event types of $e_1$ and $e_2$ are the same. |
| VerbOccan Score | Numeric | The VerbOcean score (Chklovski and Pantel, 2004) between $e_1$ and $e_2$ for each of VerbOcean's five relations. [5 features] |
| Semantic Similarity* | Numeric | The cosine similarity between $e_1$ and $e_2$ embeddings using FastText (Mikolov et al., 2018) pre-trained model (wiki-news-300d-1M). |
| Most Likely Parent Event* | One-hot | Which event is most likely to be a parent of the other event if both exist in the training data (see §3.2). |
| WordNet Similarity | Numeric | The WordNet Similarity scores between $e_1$ and $e_2$ using (Lin, 1998; Wu and Palmer, 1994) similarity measures.[2 features] |
| **Arguments** | | |
| Co-refering Event Arguments* | One-hot | Whether specific arguments of $e_1$ and $e_2$ corefer (Lee et al., 2017). Verb arguments are computed with Allennlp's SRL (Gardner et al., 2018; He et al., 2017), Nouns and Adjectives with SEMAFOR. |
| # of Coreferring Args | Numeric | The number of coreferring arguments between $e_1$ and $e_2$. |
| Event in the Other's Args | One-hot | Whether one event is mentioned in one of the other event's arguments, if both events are in the same sentence. |
| **Discourse & Narrative** | | |
| Sentence Distance | Numeric | The number of sentences between $e_1$ and $e_2$. |
| Event Distance | Numeric | The number of events between $e_1$ and $e_2$. |
| Same Sentence | Binary | Whether $e_1$ and $e_2$ are in the same sentence. |
| Reported Speech | Binary | Whether an event mention is mentioned in a direct speech (see §3.3.1). |
| Non Major Mention | Binary | Whether the sentences, in which the events are mentioned, share co-referential non major mentions (see §3.3.2). |
| RST-DTs Relation | One-hot | The discourse relation between elementary discourse units (EDUs), where $e_1$ or $e_2$ are mentioned in, in Rhetorical Structure Tree Discourse Trees (RST-DTs; see §3.3.1). |

Table 1: Features used in the model. Novel features are underlined. Features modified from prior work are marked with an asterisk.

from prior work on subevent detection (Araki et al., 2014; Glavaš and Šnajder, 2014b). We used spaCy (Honnibal and Montani) to compute lexical and syntactic features.

### 3.2 Modified Features

Five of our features were inspired by those in prior work, but we modified them for our system.

**Temporal Signals** We observed that if a sentence mentions two events from different event hierarchies, then a temporal signal often exists between them (e.g., *after* and *since*). This is illustrated by the first sentence in Example 6. To capture this we used a temporal signals list (Derczynski and Gaizauskas, 2010) to find intervening temporal signal words between the events, and encoded this as a bag of temporal signals.

**Syntactic Dependency** Both prior systems encoded a feature which captured whether one event in a pair was an immediate child (i.e., *governed*) of

the other. We expand that to checking for ancestry more generally. This is encoded as one-hot vector.

**Event Type** We use the mapping from frames to 33 ACE 2005 event types introduced in (Liu et al., 2016) to determine the event type of each event. Prior work relied on the IBM SIRE system to compute event types (Florian et al., 2010). This is encode as a one-hot vector.

**Semantic Similarity** We used the Fast-Text (Mikolov et al., 2018) pre-trained model (`wiki-news-300d-1M`) to measure the semantic similarity between pairs of events. Prior work used the SENNA system for this feature (Collobert et al., 2011). This is encoded as a numeric feature.

**Most Likely Parent Event** Similar to (Araki et al., 2014), we count the number of times in the training data that a particular event lemma and POS pair is observed as a parent of another event lemma/POS pair. For a pair $(e_1, e_2)$, if the lemma and POS of $e_1$ is more often found as a parent of $e_2$, this is encoded as the vector (1,0,0); if the opposite is true, this is encoded as (0,1,0). If there were no observations, this is encoded as (0,0,1). Prior work did not take into account the part of speech, or the direction of the subevent relationship.

**Co-referring Event Arguments** When matching arguments, we allowed ARG0 to match ARG0 or ARG1 and vice versa, and we also examined LOC and TMP modifying arguments. This is encoded as six-place binary vector for ARG0/ARG1, LOC, and TMP.

### 3.3 New Features

The new features are divided into three types: two discourse features (§3.3.1), one narrative feature (§3.3.2) and two semantic features (§3.3.3).

### 3.3.1 Discourse Features

We for the first time investigate the importance of discourse features for detecting subevents. We introduced two new features: rhetorical structure and reported speech.

**Rhetorical Structure** Rhetorical Structure Theory (RST) (Mann and Thompson, 1988) is a hierarchical model aims to identify the discourse structure of a text. The text is first segmented into Elementary Discourse Units (EDUs) which in turn are linked in binary or multi-way discourse relations (see Carlson and Marcu, 2001). Rhetorical analysis has been shown to be beneficial in many NLP tasks including sentiment analysis (So-masundaran, 2010; Lazaridou et al., 2013; Bhatia et al., 2015), text generation (Prasad et al., 2005), information extraction (Maslennikov and Chua, 2007), question answering (Verberne et al., 2007) and coreference resolution (Cristea et al., 1998; Joty et al., 2015). Therefore we hypothesized that discourse structure could be useful to the subevent detection task. We employ the CODRA discourse parser (COmplete probabilistic Discriminative framework for performing Rhetorical Analysis; Joty et al., 2015) to build a discourse tree of each text. We use (Neumann, 2015) for post-processing the CODRA output to build a graph representing the result. We then extract the rhetorical relation between event mentions using the rhetorical relation between the EDUs in which the event are found. The feature is encoded as a one-hot vector covering all 16 main relation classes.

Consider Example 2. When applied to this text, the discourse parser identifies the relation between **raid**$_3$ and **killed**$_4$ as an *Elaboration* relation. Furthermore, the parser also captures a *Topic-Change* relation between **offensive**$_6$ and each of **killed**$_1$, **wounded**$_2$, **raid**$_3$, **killed**$_4$, and **injured**$_5$.

Although the discourse parser is useful primarily for providing information about inter-sentential relationships between events, it can also give useful information about intra-sentential relationships. Consider Example 3. For this text the discourse parser finds the *Background* relation between **abduction**$_1$ and each of **killed**$_2$ and **rescued**$_3$.

**Reported Speech** We also observed that

> *One Palestinian was* **killed**$_1$ *and at least four others were* **wounded**$_2$ *in an Israeli air* **raid**$_3$ *near the southern Gaza town of Rafah on Sunday,* <u>*Palestinian security sources*</u> *said. …* <u>*Palestinian security sources*</u> *said that one Palestinian bystander was* **killed**$_4$ *and at least four others were* **injured**$_5$*. … Israeli troops continued a massive ground and air* **offensive**$_6$ *in the Gaza Strip on Sunday.*

Example 2: Excerpt from IC corpus (Hovy et al., 2013). Events relevant to explaining the discourse features are bolded. Mentions relevant to explaining the narrative feature are underlined. Note that, for clarity, not all events marked in the corpus are bolded here (e.g., Reporting events such as *said*).

> *Mahsud, a former prisoner at Guantanamo Bay, is being hunted for the **abduction**$_1$ of two Chinese engineers, which ended last Thursday when commandos **killed**$_2$ five kidnappers and **rescued**$_3$ one Chinese.*

Example 3: A sentence where intra-sentential discourse relations are useful for discovering subevent relations.

> *The Al-Qaeda linked Army of Ansar al-Sunna claimed responsibility Tuesday for a car bomb **attack**$_1$ which **killed**$_2$ four Iraqi guardsmen . . .*

Example 4: A sentence where one event appears inside the argument for another event. Event **killed**$_2$ is a subevent of **attack**$_1$.

subevents are often reported in direct and indirect speech. Direct speech is speech set off with quotes, while indirect speech is speech reported without quotes. We only considered direct speech in this work, primarily because it is easy to detect; however, subevents are also likely to be reported in indirect speech as can be seen in example 2 where **killed**$_4$ and **injured**$_5$ (which are subevents of **raid**$_3$) are mentioned in indirect speech.

### 3.3.2 Narrative Feature: Non-Major Mentions

We also introduced what we are calling a *narrative* feature that we found informative in detecting subevent relations. This feature recognizes that other entities mentioned in a sentence besides those in the event arguments can be useful in subevent detection. This feature is narrative in the sense that it takes into account whether an entity is central to the story in the text.

In particular, we observed that many sentences which shared an event hierarchy also share some coreferring mentions beside events argument. Despite this, certain entities are so central to the text that they are mentioned nearly everywhere and are thus no especially informative. Therefore we filter out these *major mentions* and encode as a binary feature whether or not the sentences contain the events share a non-major mention.

The trick, of course, is defining what is a *major mention*. A simple and effective way of filtering out major mentions is to measure the distribution of coreference chain lengths (normalized to the number of the corresponding article's chains), and discard all chains with a length above a certain threshold. This threshold can be tuned to the data. In our experiment we estimated the mean and standard deviation of the distribution of coreference chains in each text and filtered out chains that were longer than a single standard deviation above the mean. In Example 2, the threshold of the corresponding article is 2, thus *Palestinian security sources*, which is mentioned only twice, is

not considered a major mention.

### 3.3.3 Semantic Features

**Event in the Other's Arguments** We observed that if an event hierarchy is expressed within a sentence, one of the events is often mentioned as part of the other event's arguments as can be seen in Example 4, where the **attack**$_1$ event appears as ARG0 of **killed**$_2$. Although this feature is related to the *Syntactic Dependency* feature, an event's arguments are not always syntactically dependent on the event head, so it adds useful information.

**Number of Coreferring Arguments** We also include the number of coreferring event arguments as numeric feature.

## 4 Experiment

Here we describe the corpora on which the experiment were performed and the evaluation metrics used to measure the performance of our model. Then we compare the performance of our model with previous models, specifically those of Araki et al. (2014) and Glavaš and Šnajder (2014b).

### 4.1 Corpora

As already mentioned, we used two corpora: the Intelligence Community (IC) (Hovy et al., 2013) corpus and HiEve corpus (Glavaš et al., 2014a) to train and test our model. The IC corpus contains 100 news articles in the Violent Event domain (*attacks, killings, wars, etc*). The HiEve corpus is an open domain corpus that also contains 100 news articles. Both corpora are annotated with both coreference and subevent relations. The inter-annotator agreement for the IC corpus is 0.467 Fleiss's kappa for subevent relations. The approach proposed for temporal relations by (Uz-Zaman and Allen, 2011) was used to measure the inter-annotator agreement in HiEve corpus, resulting in 0.69 $F_1$. There is a small conceptual difference between the annotation of subevent relations in both corpora. The annotation of subevents in the IC corpus follows (Hovy et al., 2013) where they argued that there are three degrees of event iden-

tity: *fully identical*, *quasi-identical* (a.k.a., partial co-reference) and *fully independent* (not identical). Quasi-identity in turn appears in two ways: *membership* or *subevent*. Membership is defined as when an event is a set of multiple instances of the same type of event and the other event is one of the instances. In Example 5, **attack**$_1$ and **operation**$_2$ are members of **blows**$_3$, not subevents. In contrast, the HiEve corpus considers the membership relation as a subevent relation. When training on the IC corpus we considered only the subevent relations, and ignore the membership relations.

> *The Al-Qaeda linked group which said it carried out the deadly **attack**$_1$ against US soldiers in the Iraqi city of Mosul accused the United States … The **operation**$_2$ is one of the heaviest **blows**$_3$ in the city of Mosul …*

Example 5: Illustration of the *membership* quasi-identity relationship of Hovy et al. (2013)

For both corpora we extend the annotations by computing the transitive closure of both co-reference and subevent relations according to the following rules, where $e_1$, $e_2$ and $e_3$ are event mentions, $\equiv$ indicates event coreference, $e_1 > e_2$ indicates $e_1$ is a parent of $e_2$, and $e_1 < e_2$ indicates $e_1$ is a child of $e_2$. All of these rules are taken from the work by Glavaš et al. (2014a). We confirmed that this closure produces a consistent graph, and thus is insensitive to the order of computation of the closure. Table 2 shows the statistics of both corpora.

1. $(e_1 \equiv e_2) \,\&\, (e_2 \equiv e_3) \Rightarrow (e_1 \equiv e_3)$
2. $(e_1 > e_2) \,\&\, (e_2 > e_3) \Rightarrow (e_1 > e_3)$
3. $(e_1 < e_2) \,\&\, (e_2 < e_3) \Rightarrow (e_1 < e_3)$
4. $(e_1 > e_2) \,\&\, (e_2 \equiv e_3) \Rightarrow (e_1 > e_3)$
5. $(e_1 > e_2) \,\&\, (e_1 \equiv e_3) \Rightarrow (e_3 > e_2)$
6. $(e_1 < e_2) \,\&\, (e_2 \equiv e_3) \Rightarrow (e_1 < e_3)$
7. $(e_1 < e_2) \,\&\, (e_1 \equiv e_3) \Rightarrow (e_3 < e_2)$

### 4.2 Experimental Setup

We use Linear SVM classifier from scikit-learn package for classification over the gold annotated event mentions. Linear SVM can handle multi-class classification using a one-vs-rest scheme (Pedregosa et al., 2011). Most of the parameters are default parameters [2], but to address the issue

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[2] `penalty=l2,C=0.01, random_state=0, max_iter=1000, class_weight=balanced, multi_class=ovr.`

|  | IC | HiEve |
|---|---|---|
| # of sentences | 1,973 | 1,377 |
| # of tokens | 48,737 | 34,917 |
| # PC relations, original | 472 | 609 |
| # PC relations, transitive closure | 1632 | 1802 |
| # CP relations, original | 257 | 351 |
| # CP relations, transitive closure | 1665 | 1846 |
| # NoRel relations | 48567 | 42094 |
| Avg # of sents. per article | 19.7 | 13.7 |
| Avg # of sents. in an event boundary | 6.2 | 8.3 |
| Avg # of events per article | 30.5 | 26.0 |
| Avg # of events in each hierarchy | 5.2 | 7.0 |
| Avg # of hierarchies per article | 3.29 | 2.19 |

Table 2: Statistics of IC and HiEve corpora.

of the data imbalance as shown in Table 3, we use the parameter `class_weight=balanced` to assign a higher misclassification penalty on the minority class (PC and CP). We conducted 5-fold cross-validation for the experiment. Average fold statistics are shown in Table 3.

### 4.3 Evaluation and Result

We use the same evaluation metrics used in previous models. (Araki et al., 2014) evaluated their model using BLANC evaluation metric (Recasens and Hovy, 2011) whereas (Glavaš and Šnajder, 2014b) evaluated their model using the standard $F_1$ evaluation metric. The results of the performance averaged across all five folds on the three classes (PC, CP and NoRel) are shown in Table 4 using both evaluation metrics on both corpora. Table 5 shows the comparison between our model and previous models. Although it is not clear to us how Araki et al. handled the direction of the subevent relation, we take the average of our model classes (PC and CP) and compare it with the subevent class in Araki et al.'s work. For Glavaš and Šnajder, we consider only their *coherent* model, which is the best model that does not use the gold coreference relations. Therefore, in Table 5, the reported result of all models are the average of both classes (PC and CP). From Table 5, we can see that our model outperforms both prior models, by 15 and 5 percentage points. We also see that the precision is lower than the recall which indicate that the subevent detection task is still a difficult and complex task that needs more work. In the next two sections we explain why the performance of our model is low on IC corpus compared to the HiEve corpus, as well as an extensive error analysis.

| | IC corpus | | | HiEve corpus | | |
|---|---|---|---|---|---|---|
| | **Training** | **Test** | **Total** | **Training** | **Test** | **Total** |
| # articles | 80 | 20 | 100 | 80 | 20 | 100 |
| # PC (avg.) | 1299.2 | 332.8 | 1632 | 1484 | 318 | 1802 |
| # CP (avg.) | 1317.8 | 347.2 | 1665 | 1456.4 | 389.6 | 1846 |
| # NoRel (avg.) | 39469 | 9098 | 48567 | 35621.2 | 6472.8 | 42094 |

Table 3: Average statistics of the folds. PC stands for parent-child relation. CP stands for child-parent relation. NoRel stands for no relation.

| | | Evaluation Metrics | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | $F_1$ Score | | | BLANC | | | |
| | | | | | Pos Links | | Neg Links | | Avg |
| Corpus | Relation | P | R | $F_1$ | P | R | P | R | $F_1$ |
| HiEve | PC | 0.576 | 0.807 | 0.67 | 0.661 | 0.832 | 0.989 | 0.973 | 0.857 |
| | CP | 0.661 | 0.832 | 0.733 | 0.576 | 0.807 | 0.990 | 0.971 | 0.825 |
| | NoRel | 0.98 | 0.945 | 0.962 | 0.980 | 0.945 | 0.625 | 0.830 | 0.836 |
| IC | PC | 0.469 | 0.564 | 0.506 | 0.455 | 0.549 | 0.982 | 0.973 | 0.735 |
| | CP | 0.454 | 0.550 | 0.492 | 0.468 | 0.564 | 0.983 | 0.975 | 0.743 |
| | NoRel | 0.966 | 0.905 | 0.958 | 0.966 | 0.949 | 0.461 | 0.557 | 0.729 |

Table 4: Our model result on IC corpus (Hovy et al., 2013) and HiEve corpus (Glavaš et al., 2014a) using BLANC and $F_1$ standard evaluation metrics. PC stands for parent-child relation. CP stands for child-parent relation.

## 5 Discussion

As shown in Table 4, our model performs worse on the IC corpus than on HiEve. This is not surprising given the large difference in annotation agreement between IC and HiEve as well as the the removal of *membership* relations on IC corpus (see §4.1). Beside its lower annotation agreement, the IC corpus is also domain specific, with events only related to the intelligence community. This make general resources and tools (e.g., VerbOcean, WordNet) less effective.

We investigated the importance of each of the five feature sets (Table 1) to our model by retraining it while leaving out one set at time. In order of importance they are (1) Syntactic, (2) Semantic, (3) Discourse & Narrative, (4) Lexical, and (5) Arguments. The importance of the syntactic features derived from the fact that children events are most often mentioned in the same sentence as their parent events. The three most important features among the Semantic features are *Most Likely Parent Event*, *Event Type*, and *Semantic Frame*. For the Lexical feature set, the *Event Feature* and *Temporal Signals* are the most important.

## 6 Error Analysis

Inspection of the results revealed several types of errors, aside from the usual noise introduced by the various sub-components, such as the discourse parser or co-reference systems. We cluster the errors into three types: (1) an event pair that should be classified as *PC* but classified as *CP* and vice versa (about 28%); (2) an event pair is wrongly classified as NoRel (missed subevent relation; about 12%); (3) an event pair that is actually NoRel is wrongly classified as subevent (PC or CP; about 60% of the errors).

**Type 1: PC as CP or vice versa** About a third of the model errors were this type. Most of the errors are a result of an incorrect *Event Type* feature. This feature plays a major role in capturing the direction of the subevent relation. For example, if an event $e_1$ with event type *Die* occurs in the text before an event $e_2$ with event type *Attack*, then the direction of the relation is mostly *child-parent* relation. But if $e_2$ occurs before $e_1$, then the direction of the relation is mostly *parent-child*. If the event type is unknown for one of the event mentions, then our model commonly usually fails to capture the direction.

**Type 2: Incorrect NoRel** Most of the type 2 errors occur when an event is far away from its related event, in terms of number of intervening sentences. The larger the distance between events the more likely the model makes this error. For this type of error, we calculated the average number of sentences and the average number of events intervening between a missed pair of event, which the model should capture its subevent relation, and

| Corpus | Model | $F_1$ Score | | | BLANC | | | | |
| | | | | | Pos Links | | Neg Links | | Avg |
| | | P | R | $F_1$ | P | R | P | R | $F_1$ |
|---|---|---|---|---|---|---|---|---|---|
| IC | Araki et al. (2014) | - | - | - | 0.144 | 0.333 | 0.993 | 0.981 | 0.594 |
| | Araki et al. Re-Impl. | 0.242 | 0.285 | 0.262 | - | - | - | - | - |
| | **Our model** | 0.461 | 0.557 | **0.499** | 0.461 | 0.557 | 0.983 | 0.974 | **0.739** |
| HiEve | Glavaš and Šnajder (2014b) | 0.766 | 0.565 | 0.65 | - | - | - | - | - |
| | Glavaš and Šnajder Re-Impl. | - | - | - | 0.562 | 0.750 | 0.983 | 0.971 | 0.813 |
| | **Our model** | 0.618 | 0.82 | **0.701** | 0.618 | 0.82 | 0.99 | 0.972 | **0.841** |

Table 5: Our model performance compared to previous models (Araki et al., 2014; Glavaš and Šnajder, 2014b). Each row represent the average of both classes parent-child (PC) and child-parent (CP). Because the prior systems both did not report both metrics, we approximated the metrics for those systems by reimplementing them.

found that when the distance is greater than 9 sentences and the number of events is greater than 14 events, the more likely the model would conduct this error. Subevents tend to be close to their parents in the text as shown in Table 2. Moreover, we observed that the *Non-Major Mention* (§3.3.2) and *Discourse Relation* features (§3.3.1), were less useful the larger the distance between the events.

**Type 3: False Positive PC or CP** Most of the errors were of this type. There were a variety of causes, but the most common was when a sentence contained multiple event hierarchies. Consider Example 6 where the sentence contains two different event hierarchies, namely, one hierarchy containing **offensive**$_3$ and another containing **abduction**$_4$.

> *Over 90 Palestinians and one Israeli soldier have been **killed**$_1$ since Israel **launched**$_2$ a massive air and ground **offensive**$_3$ into the Gaza Strip on June 28, three days after the **abduction**$_4$ of one Israeli soldier by Palestinian militants in a cross-border **raid**$_5$.*

Example 6: Excerpt from IC corpus (Hovy et al., 2013) showing a passage that results in an error of Type 3.

In this example, **killed**$_1$ and **launched**$_2$ are subevents of **offensive**$_3$, whereas **abduction**$_4$ is a subevent of **raid**$_5$. When processing this example the discourse parser failed to capture the discourse relation between **offensive**$_3$ and **abduction**$_4$ because both events are in the same EDU. Moreover, even though we introduced features such as temporal signals (*after*, *since*, etc.) to capture subevent relation between intra-sentential events, this error can still occur if the intra-sentential events are syntactically related (i.e., **killed**$_1$ syntactically dominates **abduction**$_4$, or there is a causal relation between events).

Based on this observation, we ran an experiment on the IC corpus to examine the impact on subevent detection of having two different events in the same sentence. We construct a subset of the IC corpus (58 articles) which excluded all articles that contain at least one sentence with two different event hierarchy, and re-ran our main experiment. Under these conditions, the model performance increased by 6 and 4.6 points $F_1$ on *PC* and *CP* classes, respectively (because of the smaller set, we used 3 folds instead of 5). Returning to the original corpus, we observed that two different event hierarchies are mostly found in compound and complex sentences, and one of the them is usually background event. This observation indicates that splitting compound or complex sentences into two simple sentences in advance might be useful in detecting subevents. Even though the discourse parser does this splitting automatically, this split is not currently propagated to the other features.

# 7 Contributions

We present a model to detect subevent relation in news articles which outperforms the two prior approaches by 15 and 5 percentage points, respectively. Our model involves several novel discourse and narrative features, as well as a small number of feature modifications. Our error analysis indicates that having two event hierarchies in the same sentence is a major problem, as well as having significant separation between a parent and child event.

# Acknowledgments

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