Abstract

This paper describes a domain-independent, machine-learning based approach to temporally anchoring and ordering events in news. The approach achieves 84.6% accuracy in temporally anchoring events and 75.4% accuracy in partially ordering them.

1 Introduction

Practical NLP applications such as text summarization and question-answering place increasing demands on the processing of temporal information. In multidocument summarization of news, it is important to know the relative order of events so as to correctly merge and present information. In question-answering, one would like to be able to ask when an event occurs, or what events occurred prior to a particular event. Such capabilities presuppose an ability to infer the temporal order of events in discourse.

A number of different knowledge sources appear to be involved in inferring event ordering (Lascarides and Asher 1993), including tense and aspect (1), temporal adverbials (2), and world knowledge (3).

(1) Max entered the room. He had drunk/was drinking the wine.
(2) A drunken man died in the central Phillipines when he put a firecracker under his armpit.
(3) U. N. Secretary- General Boutros Boutros-Ghali Sunday opened a meeting of ...Boutros-Ghali arrived in Nairobi from South Africa, ...

As (Bell 1999) has pointed out, the temporal structure of news is dictated by perceived news value rather than chronology. Thus, the latest news is often presented first, instead of events being described in order of occurrence (the latter ordering is called the narrative convention).

2 Linguistic Processing

This paper describes a domain-independent approach to temporally anchoring and ordering events in news. The approach is motivated by a pilot experiment with 8 subjects providing news event-ordering judgments which revealed that the narrative convention applied only 47% of the time in ordering the events in successive past-tense clauses. Our approach involves mixed-initiative corpus annotation, with automatic tagging to identify clause structure, tense, aspect, and temporal adverbials, as well as tagging of reference times and anchoring of events with respect to reference times. We report on machine learning results from event-time anchoring judgments.
To generate this `tval` feature, the simple algorithm in Figure 1 was used. The system also anchors the event’s time with respect to the `tval` (at, before, or after) when the `tval` is an explicit reference time. This feature is called `anchor-explicit`. All in all, the features shown in Table 1 were computed for each clause.

```plaintext
history_list := {doc_date}
for each finite clause c do
  rtime = timex2(c)
  if rtime then
    tval(c) = rtime
    unless type(c, rel_clause)
      push(rtime, history_list)
  elsif reporting_verb(c) then
    tval(c) = doc_date
  elsif ∃j s.t. inside_quote(c, j) then
    tval(c) = tval(j)
  else tval(c) = last (history_list)
Figure 1: Algorithm for Computing Reference Time (tval)
```

### Table 1: Linguistic Features for each Clause

- **CTYPE**: clause is a regular clause, complement clause, or relative clause
- **CINDEX**: subclause index
- **PARA**: paragraph number
- **SENT**: sentence number
- **SCONJ**: subordinating conjunction (e.g., while, since, before)
- **TPREP**: preposition in a TIMEX2 PP
- **TIMEX2**: string in the TIMEX2 tag
- **TMOD**: temporal modifier not attached to a TIMEX2, (e.g., after [an alteration])
- **QUOTE**: number of words in quotes
- **REPPROP**: reporting verb in clause
- **STATIVE**: stative verb in clause
- **ACCOMP**: accomplishment verb
- **ASPECTSHIFT**: shift in aspect from previous clause
- **G-ASPECT**: grammatical aspect (progressive, perfect, nil)
- **TENSE**: tense of clause {past, present, future, nil}
- **TENSESHIFT**: shift in tense from previous clause
- **ANCHOR_EXPLICIT**: {<, >, =, undefined}
- **TVAL**: reference time for clause, i.e., a time value

### Table 2: Accuracy of Anchoring Rules

|          | ANCHORS | TVAL-MOVES |
|----------|---------|------------|
|          | (AT) 76.9 | (KEEP) 65.75 |
| C5.0 Rules | 80.2 (±1.8) | 71.8 (±0.5) |

## 3 Learning Anchoring Rules

A human unconnected with our project corrected the `tval`, based on a set of annotation guidelines, on a sample of 2069 clauses extracted at random from the North American News Corpus. She also anchored the event’s time with respect to the `tval` (AT, BEF, AFT, or undefined). This feature (not a machine feature) is called `anchors`.

The corrections showed that the algorithm in Figure 1 was right on `tval` for 1231 out of 2069, giving an accuracy of 59%. Tracking the sequence of corrected `tval` revealed that the `tval` of the previous clause was kept 65.75% of the time, that it reverted to some other previous `tval` 22.99% of the time, and that it shifted to a new `tval` 11.26% of the times. Most of the errors in computed `tval` had to do with the `tval` being assigned erroneously the document date rather than reverting to a non-immediately previous `tval`. Finally, the `anchor-explicit` relation is correct 83.8% of the time; however, just guessing “at” for the explicit anchor will get an accuracy of 90.2%.

We then used this training data to train a statistical classifier, C5.0 Rules (Quinlan 1997), to learn (1) anchors relation rules and (2) rules for tracking the `tval` moves (keep, revert, shift) across successive clauses. The accuracy of anchors rules as well as `tval` change rules are shown in Table 2. It can be seen that accuracy of machine learning here is significantly better than the majority class. The `tval`, tense, and tense shift play a useful role in anchoring, revealing that the `tval` is a useful abstraction. Here are some of the rules learnt (here is the clause index, assumed to stand for the event time of the clause):

- If no sconj and no tmod and no tprep and tval-class = day then anchors(‘AT’, , , tval) 80.4% accurate (156 examples).
- If tense is present and no sconj and tval-class = month then anchors(‘AT’, , , tval) 77.8 (7).
- If tense is present and no sconj and tval-class = month then anchors(‘AT’, , , tval) 77.8 (7).

See www.umiacs.umd.edu/~bonnie/ LCS_Data-base_Documentation.html.

1 The statives and accomplishments were computed from UMaryland’s LCS lexicon, based on (Dorr and Olsen 1997).

2 Since the TIMEX2 and `tval` values form an open class, they were automatically grouped into classes based on the granularity of the time expression, namely, {time-of-day, day, week, month, year, or non-specific}.
 anchors(BEF, \( t_e \), tval) 83 (4).
If tense shift is present2past and no explicit time and no sconj, then anchors(AT, \( t_e \), tval) 90 (30)

4  Partially Ordering Links

Based on the best machine-learned rules for the anchors relation, anchors tuples are generated for each document. The tvals in the document’s anchor tuples are also partially ordered, yielding tuples consisting of ordered pairs of tvals. Two sets of tuples are then used to provide a partial ordering of events in the document, in the form of links tuples: \( \text{links}(R, e_i, e_j) \), where \( e_i \) and \( e_j \) are the events corresponding to clauses \( i \) and \( j \), and \( R \) is in \{at, bef, aft, or undefined\}. One of the authors evaluated the partial ordering for accuracy, on seven documents. The results of this evaluation are shown in Table 3. #Correct-anchor is the number of the anchors tuples correctly classified and #total is the total number of anchors tuples classified. Link Recall is the percentage of human generated links tuples (723 in all) that are correctly identified by machine learned rules. Link Precision is the percentage of the machine generated links tuples that are correct.

| #Clauses | #Words | #correct-anchor / #total-anchor | Link Recall | Link Precision |
|----------|--------|---------------------------------|-------------|---------------|
| 40       | 525    | 15/18 (83.3%)                   | 44/65 (67.7%) | 53/63 (84.1%) |
| 18       | 335    | 12/13 (92.3%)                   | 59/59 (100%)  | 59/62 (95.2%)  |
| 27       | 509    | 17/22 (77.2%)                   | 23/40 (57.5%)  | 23/38 (39.7%)  |
| 38       | 617    | 21/27 (77.8%)                   | 94/172 (54.7%) | 94/190 (49.5%) |
| 22       | 296    | 11/12 (91.7%)                   | 39/42 (92.9%)  | 39/49 (79.6%)  |
| 14       | 242    | 6/7 (85.7%)                     | 6/6 (100%)    | 6/7 (85.7%)    |
| 35       | 447    | 28/31 (90.3%)                   | 297/339 (87.6%) | 289/335 (86.3%) |
| 194      | 2971   | 110/130 (84.6%)                 | 562/723 (77.7%) | 563/764 (73.7%) |

Table 3: Document-Level Accuracy of Learnt Rules

5  Conclusion

Note that the naïve algorithm for tval is only 59% correct. While improvements to the naïve algorithm are clearly possible based on the corrected tval, to adequately test the machine learnt rules we use the corrected tval.

Overall, our approach achieves 84.6% accuracy in anchoring events and 75.4% F-measure in partially ordering them. These numbers compare favorably with the previous literature: (Filatova and Hovy 2001) obtained 82% accuracy on anchoring for a single type of event/topic on 172 clauses, while (Mani and Wilson 2000) obtained accuracy of 59.4% on anchoring over 663 verb contexts. Our approach is also distinct in its use of human experimentation, machine learning and the variety of linguistically motivated features (including temporal adverbials) that are brought to bear.

Future work will examine the role of aspectual features, learning from skewed distributions dominated by AT (an overwhelming majority of news events occur at the reference times), and the incorporation of unsupervised learning methods.

References

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