Knowledge-Lean Coreference Resolution and its Relation to Textual Cohesion and Coherence

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Abstract

In this paper we present a new empirical method for coreference resolution, implemented in the COCKTAIL system. The results of COCKTAIL are used for lightweight abduction of cohesion and coherence structures. We show that referential cohesion can be integrated with lexical cohesion to produce pragmatic knowledge. Upon this knowledge coherence abduction takes place.

1 Motivation

Coreference evaluation was introduced as a new domain-independent task at the 6th Message Understanding Conference (MUC-6) in 1995. The task focused on a subset of coreference, namely the identity coreference, established between nouns, pronouns and noun phrases (including proper names) that refer to the same entity. In defining the coreference task (cf. (Hirschman and Chinchor, 1997)) special care was taken to use the coreference output not only for supporting Information Extraction (IE), the central task of the MUCs, but also to create means for research on coreference and discourse phenomena independent of IE.

Annotated corpora were made available, using SGML tagging within the text stream. The annotated texts served as training examples for a variety of coreference resolution methods, that had to focus not only on precision and recall, but also on robustness. Two general classes of approaches were distinguished. The first class is characterized by adaptations of previously known reference algorithms (e.g. (Lappin and Leass, 1994), (Brennan et al., 1987)) to the scarce syntactic and semantic knowledge available in an IE system (e.g. (Kameyama, 1997)). The second class is based on statistical and machine learning techniques that rely on the tagged corpora to extract features of the coreferential relations (e.g. (Aone and Bennett, 1994) (Kehler, 1997)).

In the past two MUC competitions, the high scoring systems achieved a recall in the high 50's to low 60's and a precision in the low 70's (cf. (Hirschman et al., 1998)). A study1 of the contribution of each form of coreference to the overall performance shows that generally, proper name anaphora resolution have the highest precision (69%), followed by pronominal reference (62%). The worse precision is obtained by the resolution of definite nominals anaphors (46%). However, these results need to be contrasted with the distribution of coreferential links on the tagged corpora. The majority of coreference links (38.42%) connect names of people, organizations or locations. In addition, 19.68% of the tagged coreference links are accounted by appositives. Only 16.35% of the tagged coreferences are pronominal. Nominal anaphors account for 25.55% of the coreference links, and their resolution is generally poorly represented in IE systems.

Due to the distribution of coreference links in newswire texts, a coreference module that is merely capable of handling recognition of appositives with high precision and incorporates rules of name alias identification can achieve a baseline coreference precision up to 58.1%, without sophisticated syntactic or discourse information. Precision increase is obtained by extending high-performance pronominal resolution methods (e.g. (Lappin and Leass, 1994)) to nominal coreference as well. Such enhancements rely on semantic and discourse knowledge.

In this paper we describe COCKTAIL, a high-performance coreference resolution system that operates on a mixture of heuristics that combine semantic and discourse information. The resulting

1The study, reported in (Kameyama, 1997), was performed on the coreference module of SRI's FASTUS (Appelet et al., 1993), an IE system representative of today's IE technology.
coreference chains are shown to contribute in the derivation of cohesive chains and coherence graphs. Both cohesive and coherence structures are considered, partly because of their incremental complexity and partly because the tradition (started with (Hobbs, 1979)) of studying the interaction of coreference and coherence. Section 2 presents COCKTAIL and the coreference methods it built upon. Sections 3 and 4 describe the derivation the cohesion and coherence structures.

2 Coreference Resolution

Coreference resolution relies on a combination of linguistic and cognitive aspects of language. Linguistic constraints are provided mostly by the syntactic modeling of language, whereas computational models of discourse bring forward the cognitive assumptions of anaphora resolution. Three different methods of combining anaphoric constraints are known to date. The first one integrates anaphora resolution in computational models of discourse interpretation. Dynamic properties of discourse, especially focusing and centering are invoked as the primary basis for identifying antecedents. Such computational methods were presented in (Grosz et al., 1995) and (Weber, 1988).

A second category of approaches combines a variety of syntactic, semantic and discourse factors as a multi-dimensional metric for ranking antecedent candidates. Anaphora resolution is determined by a composite of several distinct scoring procedures, each of which scores the prominence of the candidate with respect to a specific type of information. The systems described in (Asher and Wada, 1988) (Carbonell and Brown, 1988) and (Rich and Luperfoy, 1988) are examples of the mixed evaluation strategy.

Alternatively, other discourse-based methods consider coreference resolution a by-product of the recognition of coherence relations between sentences. Such methods were presented in (Hobbs et al., 1993) and (Wilensky, 1978). Although AI-complete, this approach has the appeal that it resolves the most complicated cases of coreference, uncovered by syntactic or semantic cues. We have revisited these methods by setting the relation between coreference and coherence on empirical grounds.

2.1 Pronominal Coreference

Two tendencies characterize current pronominal coreference algorithms. The first one makes use of the advances in the parsing technology or on the availability of large parsed corpora (e.g. Treebank (Marcus et al.1993)) to produce algorithms inspired by Hobbs' baseline method (Hobbs, 1978). For example, the Resolution of Anaphora Procedure (RAP) introduced in (Lappin and Leass, 1994) combines syntactic information with agreement and salience constraints. Recently, a probabilistic approach to pronominal coreference resolution was also devised (Ge et al., 1998), using the parsed data available from Treebank. The knowledge-based method of Lappin and Lease produces better results. Nevertheless, RAPSTAT, a version of RAP obtained by using statistically measured preference patterns for the antecedents, produced a slight enhancement of performance over RAP.

Other pronominal resolution approaches promote knowledge-poor methods (Mitkov, 1998), either by using an ordered set of general heuristics or by combining scores assigned to candidate antecedents. The Cogniac algorithm (Baldwin, 1997) uses six heuristic rules to resolve coreference, whereas the algorithm presented in (Mitkov, 1998) is based on a limited set of preferences (e.g. definitiveness, lexical reiteration or immediate reference). Both these algorithms rely only on part-of-speech tagging of texts and on patterns for NP identification. Their performance (close to 90% for certain types of pronouns) indicates that full syntactic knowledge is not required by certain forms of pronominal coreference.

The same claim is made in (Kennedy and Boguraev, 1996) and (Kameyama, 1997), where algorithms approximating RAP for poorer syntactic input obtain precision of 75% and 71%, respectively, a surprising small precision decay from RAP's 86%. These results prompted us to devise COCKTAIL, a coreference resolution system, as a mixture of heuristics performing on the various syntactic, semantic and discourse cues. COCKTAIL is a composite of heuristics learned from the tagged corpora, which has the following novel characteristics:

1. COCKTAIL covers both nominal and pronoun coreference, but distinct sets of heuristics operate for different forms of anaphors. We have devised separate heuristics for reflexive, possessive, relative, 3rd person and 1st person pronouns. Similarly, definite nominals are treated differently than bare or indefinite nominals.

2. COCKTAIL performs semantic checks between antecedents and anaphors. These checks combine sor
tal constraints from WordNet with co-occurrence information from (a) Treebank and (b) conceptual glosses of WordNet.

3. In COCKTAIL antecedents are sought not only in the accessible text region, but we also throughout the current coreference chains. In this way cohesive information, represented as reference chains, is employed in the resolution process.

4. The heuristics of COCKTAIL allow for lexicalizations (e.g. when the anaphor is an adjunct of a communication verb) and of simplified coherence cues (e.g.
when the anaphor is the subject of verb add, the antecedent may be a preceding subject of a communication verb.

To exemplify some COCKTAIL heuristics that resolve pronominal coreference, we first present heuristics applicable for reflexive pronoun and then we list heuristics for possessive pronouns and 3rd person pronoun resolution. Brevity imposes the omission of heuristics for other forms of pronoun resolution. COCKTAIL operates by successively applying the following heuristics to the pronoun Pro:

- **Heuristic 1-Reflexive (H1R)**
  - Search for PN, the closest proper name from Pron in the same sentence, in right to left order.
  - if (PN agrees in number and gender with Pron) if (PN belongs to coreference chain CC) then Pick the element from CC which is closest to Pron in Text.
  - else Pick PN.

- **Heuristic 2-Reflexive (H2R)**
  - Search for a sequence Noun-Relative Pronoun, in the same sentence, in right to left order.
  - if (Noun agrees in number and gender with Pron) if (Noun belongs to coreference chain CC) then Pick the element from CC which is closest to Pron in Text.
  - else Pick Noun.

- **Heuristic 3-Reflexive (H3R)**
  - Search for Pron', the closest pronoun from Pron in the same sentence, in right to left order.
  - if (Pron' agrees in number and gender with Pron) if (Pron' belongs to coreference chain CC) then Pick the element from CC which is closest to Pron in Text.
  - else Pick Pron'.

- **Heuristic 4-Reflexive (H4R)**
  - Search for Noun, the closest common noun from Pron in the same sentence, in right to left order.
  - if (Noun agrees in number and gender with Pron) then Pick Noun.

Resolution examples for reflexive pronouns are illustrated in Table 1. The antecedents produced by COCKTAIL are boldfaced, whereas the referring expressions are emphasized. Both referring expressions and resolved antecedents and underlined. Precision results are listed in Table 2.

Antecedents of reflexive pronouns are always sought in the same sentence. Antecedents of other types of pronouns are sought in preceding sentences too, starting from the immediately preceding sentence. Inside the sentence, the search for a specific word is performed from the current position towards the beginning of the sentence, whereas in the preceding sentences, the search starts at the beginning of the sentence and proceeds in a left to right fashion. The same search order was used in (Kameyama, 1997). From now on, we indicate this search by Search1. This search is employed by heuristics for possessive pronoun resolution:

- **Heuristic 1-Possessive (H1Pos)**
  - Search1 for a possessive construct of the form [noun1's noun2], if ([Pron noun0] and [noun1's noun2] agree in gender, number and are semantically consistent) then if (noun2 belongs to coreference chain CC) and there is an element from CC which is closest to Pron in Text, Pick that element. Pick noun2.

- **Heuristic 2-Possessive (H2Pos)**
  - Search1 for PN, the closest proper name from Pron if (PN agrees in number and gender with Pron) if (PN belongs to coreference chain CC) then Pick the element from CC which is closest to Pron in Text.

- **Heuristic 3-Possessive (H3Pos)**
  - Search1 for Pro', the closest pronoun from Pron if (Pron' agrees in number and gender with Pron) if (Pron' belongs to coreference chain CC) and there is an element from CC which is closest to Pron in Text, Pick that element. else Pick Pron'.

- **Heuristic 4-Possessive (H4Pos)**
  - Search1 for Noun, the closest common noun from Pron if (Noun agrees in number and gender with Pron)
if (Noun belongs to coreference chain CC)
and there is an element from CC which is
closest to Pron in Text, Pick that element.
else Pick Noun

Examples and precision results are listed in Ta-
ble 3 and Table 4, respectively.

| Heuristic | H1Pos | H2Pos | H3Pos | H4Pos |
|-----------|-------|-------|-------|-------|
| Precision on 100 random pronouns | 96% | 93% | 76% | 86% |

Table 3: Examples of possessive pronouns

Table 4: Coreference precision (possessive pronouns)

Given a possessive pronoun in a sequence [Pron Noun], the antecedent Ante of Pron is semanti-
cally consistent if the same possessive relationship
can be established between Ante and Noun. the
problem is that the possessive relation semantically
and there is an element from CC which is
closest to Pron in Text, Pick that element.
else Pick Pron'.

Other pronominal coreference heuristics employ
Search2, a search procedure that enhances Search1,
since it prefers antecedents that are immediately
beneath the nominalization Noun.

Cocktail's test of semantic consistency blends to-
gether information available from WordNet and on
statistics gathered from Treebank. Different consist-
ency checks are modeled for each of the heuristics.
We detail here the check that applies to heuristic
H1Pos, that resolves the possessive from the first ex-
ample listed in Table 3. For this heuristic, we have
to test whether from the possessive [Ante Noun1] we
can grant the possessive [Ante Noun] as well. There
are three cases that allow us to do so:

- **Case 1**: Noun1 and Noun0 corefer.
- **Case 2**: There is a sense s1 of Noun1 and a sense s0 of
  Noun0 such that a synonym of Noun1 is or of its
  immediate hypernym is in the gloss of Noun0 or vice versa.
- **Case 3**: There is a sense s1 of Noun1 and a sense
  s0 of Noun0 such that a common concept is found in
  their glosses.

Cases 2 and 3 extend to synsets obtained through
derivational morphology as well (e.g. nomina-
lations). For cases 2 and 3 COCKTAIL reinforces
the coreference hypothesis by using a possessive-
similarity metric based on Resnik's similarity mea-
sures for noun groups (Resnik, 1995). From a subset
of Treebank, we collect all possessives, and measure
whether the similarity class of Noun0, Noun1 and
their eventual common concept is above a threshold
produced off-line.
olution. From our initial experiments, we do not see the need for special semantic consistency checks, since all heuristics performed with precision in excess of 90%. Part of this is explained by our usage of pleonastic filters and of recognizers of idiomatic usage. Table 5 illustrates some of the successful coreference resolutions.

Table 5: Examples of 3rd person pronouns

| He says that in many years as a banker he has grown accustomed to dealing with honest people 99% of the time. |
| Sen. Byrd takes pains to reassure the voter that he will see to it that the trade picture improves. |
| A nurse who deals with the new patient admits she isn't afraid of her temper. |

2.2 Nominal Coreference

Noun phrases can represent referring expressions in a variety of cases. For example, it is known that not all definite NPs are anaphoric. Conditions that define anaphoric NPs are still under research (cf. (Poesio and Vieira, 1998)). In the tagged corpora, we have found only 20.93% of the nominal coreference cases to be definites, the majority (78.85%) being bare nominals, and only 1.32% were indefinites. However, more than 50% of the nominal referring expressions were names of people, organizations or locations. Adding to this, 15.22% of nominal coreference links are accounted by appositives. Based on this evidence, COCKTAIL implements special rules for name alias identification and for robust recognition of appositions. Moreover, the heuristics for nominal coreference resolution apply Search3, and enhancement of Search7 that searches starting with the coreference chains, and then with the accessible text. To resolve nominal coreference, COCKTAIL successively applies the following heuristics:

- **Heuristic 1-Nominal(H1Nom)**
  if (Noun is the head of an appositive) then Pick the preceding NP.

- **Heuristic 2-Nominal(H2Nom)**
  if (Noun belongs to an NP, Search3 for NP
  such that Noun=same_name(head(NP),head(NP')) or Noun=same_name(adj(NP),adj(NP'))) then if (Noun' belongs to coreference chain CC) then Pick the element from CC which is closest to Noun in Text.
  else Pick Noun'.

- **Heuristic 3-Nominal(H3Nom)**
  if Noun is the head of an NP then Search7 for proper name PN

- **Heuristic 4-Nominal(H4Nom)**
  Search3 for a proper name PN with the same category as Noun
  if (PN belongs to coreference chain CC) and there is an element from CC which is close to Noun in Text, Pick that element.
  else Pick PN.

- **Heuristic 5-Nominal(H5Nom)**
  Search3 Noun' a synonym or hyponym of Noun
  if (Noun' belongs to coreference chain CC) and there is an element from CC which is closest to Noun in Text, Pick that element.
  else Pick Noun'.

- **Heuristic 6-Nominal(H6Nom)**
  Search3 for Noun either in definites or in NPs having adjuncts in coreference chain CC
  if Ante semantically consistent with Noun
  if (Ante belongs to coreference chain CC) and there is an element from CC which is closest to Noun in Text, Pick that element.
  else Pick Ante.

- **Heuristic 7-Nominal(H7Nom)**
  if (Noun or one of his hypernyms or holonyms is a nominalization N) then Search for the verb V deriving N or one of its synonyms)
  then Pick NP, the closest adjunct of V
  if (NP belongs to coreference chain CC) and there is an element from CC which is closest to Noun in Text, Pick that element.
  else Pick NP

- **Heuristic 8-Nominal(H8Nom)**
  if (Noun is the head of a prepositional phrase preceded by a nominalization N)
  then Search for the verb V deriving N or one of its synonyms)
  then Pick NP, the closest adjunct of V
  if (NP belongs to coreference chain CC) and there is an element from CC which is closest to Noun in Text, Pick that element.
  else Pick Noun

- **Heuristic 9-Nominal(H9Nom)**
  Search3 for Noun', a metonymy whose coercion is Noun
  Pick Noun'

Some non-trivial examples are listed in Table 6. Heuristic H1Nom uses coreference cases indicated by appositions, whereas heuristic H2Nom promotes
Mr. Iacocca led Chrysler through one of the largest stock sales ever for a U.S. industrial company, raising $1.78 billion. Chrysler is using most of the proceeds to reduce its $4.4 billion unfunded pension liability.

We read where the Clinton White House is seeking a deputy to chief of staff Mack McLarty to impose some disciplined coherence on the place's rambunctious young staff.

Table 6: Examples of nominal coreference

| Heuristic | H1Nom | H2Nom | H3Nom | H4Nom |
|-----------|-------|-------|-------|-------|
| Precision on 100 random nominals |
| H5Nom | H6Nom | H7Nom | H8Nom |
| 77%   | 82%   | 89%   | 63%   |
structure, useful for the abduction of coherence relations from the knowledge encoded in WordNet.

Here we describe a new cohesion structure that (a) incorporates both lexical and referential cohesion and (b) produces a unique chain that contains not only single words, but also textual entities encompassing head-adjunct lists. We use the finite-state parses of FASTUS (Appelt et al., 1993) for recognizing these entities, but the method extends to any basic phrasal parser.

We produce this novel cohesive structure to exploit the close relation between text cohesion and coherence. It is known (cf. [Harabagiu, 1999]) that cohesion, as a surface indicator of the text coherence, can indicate the lexico-semantic knowledge upon which coherence is inferred. Our aim is to use this cohesive chain for producing axiomatic knowledge for CICERO, a TACITUS-like system that abducts coherence relations. TACITUS (Hobbs et al., 1993) is a successful abductive system when provided with extensive pragmatic and linguistic knowledge. CICERO is designed as a lightweight version of TACITUS, that performs reliable abductions with minimal knowledge and effective searches. Translating all the lexical, morphological, syntactic and semantic ambiguities from texts would make the search intractable. Our solution for CICERO is to use a cohesive chain to create manageable knowledge upon which the abduction can be performed. Section 4 describes this knowledge and the operation of CICERO.

Our cohesive chain is a linked structure consisting of three parts: (1) the connected text entity; (2) its incoming and outgoing pointers and (3) a lexico-semantic graph, containing paths of WordNet concepts and relations. The lexico-semantic structure is later translated in the axiomatic knowledge that supports coherence inference. To exemplify the cohesion chain, we use the following text, spanned by the coreference chains produced with COCKTAIL:

[Toys R Us] named Michael Goldstein [chief executive officer], ending years of speculations about who will succeed [Charles Lazarus], [the toy retailer]’s founder and chief architect. 4

[Robert Nakasone, former vice chairman] and widely regarded as the other serious contender for [the top executive]’s job, was named president and chief operating officer, both new positions.

1. if (current NG belongs to a coreference chain)
2. if (the antecedent is already in the chain)
3. if (the coreference is not an appositive)
4. Add relation r to LSS
5. Add entity to the lexico-semantic structure(TE)

The derivation of the lexico-semantic structure (LSS) follows the steps:

1. for every relation of a TE
2. for every word w in a TE
if (there is a concept C in LSS such that there is a collocation [w C] in a gloss from the hierarchy(w))

Add w to LSS
3. if (word w is already in LSS)

Add new connection to w in LSS

For example, in the first TE illustrated in Figure 1, we have the relation Object(name, CEO). We find an Object relation also in the gloss of appoint, the hypernym of sense 3 of verb name. The new Object relation connect verb assume with the synset {duty, responsibility, obligation}. A hypernym of CEO is manager, collocating with position in the gloss of managership. Noun position belongs to the hierarchy of duty, thus the new Object relation can be added to the LSS.

Figure 1: Cohesion chain

4 Text Coherence

We base our consideration of textual coherence on the definitions introduced in (Hobbs, 1985). The formal definition of relations that capture the coherence between textual assertions is based on the relations between the states they infer, their changes and their logical connections. States, changes and logical connections can be retrieved from pragmatic knowledge, accessible in lexical knowledge bases like WordNet. The complex structure of our cohesion chains help guiding these inferences.

For each textual unit, defined from the parse of the text, axiomatic knowledge produced. The acquisition of axiomatic knowledge is cued by the concepts and relations from the LSS portion of the cohesion chain, and is mined from WordNet. CICERO, our system, adds to this knowledge axioms that feature the characteristics of every coherence relation. CICERO's job is to abduct the coherence structure of a text. To do so, it follows the steps:

1. for every textual unit TU_i
2. Derive pragmatic knowledge for TU_i
3. for every pair (TU_i, TU_j), i ≠ j
4. for every coherence relation R_k
5. hypothesize R_k(TU_i, TU_j)
6. Perform abduction R_k(TU_i, TU_j)
7. Choose cheapest abduction

For the text illustrated in Section 3, this procedure generates the coherence graph illustrated in Figure 2.

Figure 2: Coherence graph

We exemplify the operation of CICERO on this text by presenting the way it derives the Elaboration relation between the textual unit from the first sentence that announces the nomination of Michael Goldstein (TU_i) and the textual unit from the same sentence that deals with the succession of Charles Lazarus (TU_j). First, CICERO generates the knowledge upon which the abductions can be performed. This knowledge is represented in axiomatic form, using the notation proposed in (Hobbs et al., 1993) and previously implemented in TACITUS. In this formalism each text unit represents an event or a state, thus has a special variable e associated with it. Events are lexicalized by verbs, which are mapped into predicates verb(e, x, y), where x represents the subject of the event, and y represents its object (in the case of intransitive verbs, y is not attached to a predicate,
whereas in the case of bitransitive verbs, $y$ is mapped into $y_1$ and $y_2$). Moreover, predicates from the text are related to other predicates, derived from a knowledge base. These relations are captured in first order predicate calculus. For example, the pragmatic knowledge used for the derivation of the Elaboration relation between $TU_a$ and $TU_is$:

$$
\begin{align*}
TU_a: & \quad \text{assign}(e_1, z_1) & \rightarrow & \text{position}_1 \wedge \text{person}(z_2) \\
& \quad \text{vacant-position}(e_1) & \rightarrow & \text{assign}(e_2, z_1) \wedge \text{position}_1
\end{align*}
$$

In the next step, all coherence relations are hypothesized, and the cost of their abduction is obtained. The appendix lists the LISP function created on the fly by CICERO that produces the abduction of the Elaboration function. Because of the computational expense, an intermediary step simplifies the axiomatic knowledge. The appendix lists also the full abduction and its cost. CICERO is a system still under development, and at present we did not evaluate the precision of its results.

5 Conclusion

We have introduced a new empirical method for coreference resolution, implemented in the COCKTAIL system. The results of this algorithm are used to guide the abduction of coherence relations, as performed in our CICERO system. In an intermediary step, a rich cohesion structure is produced. This novel relation between coreference and coherence contrasts with the traditional view that coreference is a by-product of coherence resolution. Moreover, we reiterate the belief that coherence builds up from cohesion.

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**Appendix**

```plaintext
(defn name-success)
(compile-axioms
'((not (name-success))
 (assumption-position e1 e1)
 (elaboration e1 e1) (AND))))

(named-success)
(compile-logic
'((not (name-success))
 (assumption-position e1 e1)
 (elaboration e1 e1) (AND))))
```

> (named-success)
0 Cost: 20 initial logical form:
(AND)
1 Cost: 22.0 from expanding CORREL E1 E2 E3,10.0,0) (USE-SPECULATIONS E3 A),10.0,0) (CORREL E1 E2 E3)
2 Cost: 22.0 from expanding HD-SPECULATIONS in 0 with axiom 3.0:
(CORREL E1 E2 E3,10.0,0) (USE-SPECULATIONS E3 A),10.0,0) (CORREL E2 E3)
3 Cost: 24.0 from expanding ELABORATION in 1 using axiom 1.1:
(ASSUMPTION-E P I E2 E3) (ELABORATION E2 E4) (USE-SPECULATIONS E3 A) (CORREL E1 E2 E3)
8 Cost: 10 from expanding NAME in 3 using axiom 4.0:
(CORREL E1 E2 E3) (NAME-E P I E4) (USE-SPECULATIONS E3 A),10.0,0) (NAME-E P I E3)
9 Cost: 8.0 from expanding HD-SPECULATIONS in 3 with axiom 2.0:
(CORREL E1 E2 E3) (NAME-E P I E4) (USE-SPECULATIONS E3 A),10.0,0) (NAME-E P I E3)
10 Cost: 8.0 from expanding HD-SPECULATIONS in 3 with axiom 2.0:
(CORREL E1 E2 E3) (NAME-E P I E4) (USE-SPECULATIONS E3 A),10.0,0) (NAME-E P I E3)
```

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