Abstract

In this paper, a hybrid disambiguation method for the prepositional phrase (PP) attachment and interpretation problem is presented. The data needed, semantic PP interpretation rules and an annotated corpus, is described first. Then the three major steps of the disambiguation method are explained. Cross-validated evaluation results for German (88.6-94.4% correct for binary attachment ambiguities, 83.3-92.5% correct for interpretation ambiguities) show that disambiguation methods combining interpretation rules and statistical methods might yield significantly better results than non-hybrid disambiguation methods.

1 Introduction

The problem of prepositional phrase (PP) attachment ambiguity is one of the most famous problems in natural language processing (NLP). In recent years, many statistical solutions have been proposed: lexical associations (see (Hindle and Rooth, 1993)); error-driven transformation learning (see (Brill and Resnik, 1994), extensions by (Yeh and Vilain, 1998)); back-off estimation (see (Collins and Brooks, 1995), extended to the multiple PP attachment problem by (Merlo et al., 1997)); loglinear model (see (Franz, 1996b), (Franz, 1996a, pp. 97-108)); maximum entropy model (see (Ratnaparkhi, 1998; Ratnaparkhi et al., 1994)).

The disambiguation method in this paper has two key features. First, it tries to solve the PP attachment problem and the PP interpretation problem. Second, it is hybrid as it combines more traditional PP interpretation rules and statistical methods.

2 Data

2.1 PP interpretation rules

One central component for the disambiguation method presented in this paper are semantic interpretation rules for PPs. A PP interpretation rule consists of a premise and a conclusion. The premise of an interpretation rule describes under which conditions the PP interpretation specified by the rule's conclusion can be valid. Two example rules for the local and contents interpretation of 'fiber' ('about'/'above'/'on'/'over'/'via'/...) are shown in Figure 1. As (at least) five more interpretations of 'fiber' are possible, the ambiguity degree for the interpretation of such a PP is (at least) seven.

The premise of a rule is a set of feature structure constraints (including negated and disjunctive constraints and defining an underspecified feature structure) that refer to the following features of the preposition’s sister NP (nominal phrase) and the preposition’s mother NP or V (verb). (The features that are only refered to for the sister NP are marked by an S.)

**case** (S) syntactic case: genitive, dative, and accusative for German PPs

**num** (S) syntactic number: singular and plural in German

**sort** a semantic sort value (atomic or disjunctive value) from a predefined ontology (see (Helbig and Schulz, 1997)) comprising 45 sorts. The most important
The semantic network node cl corresponds to the mother, the node c2 to the sister, and c3 etc. are additional nodes. A disjunction of feature values is introduced by dis.

Figure 1: PP interpretation rules for two interpretations of ‘über’

sorts for nouns are object and its sub-
sorts con-object (concrete object, with sub-
sorts dis-object (discrete object) and sub-
stance) and abs-object (abstract object, with subsorts tem-abstractum (temporal abstractum), abs-situation (abstract sit-
uation), attribute, etc.). Verbs can belong
to sort stat-situation (static situation) or sort dyn-situation (dynamic situation, with subsorts action and event). A disjunctive value represents a concept family (as intro-
duced by (Bierwisch, 1983); closely related are dotted types, see for example (Buitelaar, 1998)), e.g., the noun ‘book’ comprises a physical object variant and an abstract in-
formation variant.

etype extension type for distinguishing indi-
viduals (‘child’, ‘table’), sets of individuals
(‘men’, ‘group’, ‘people’), etc.

The rest of the features are semantic Boolean features as shown in Table 1.2

The conclusion of a rule is a semantic inter-
pretation of the PP, which can be valid if the
premise is satisfied by the sister and the mother. The rules’ semantic representation uses a mul-
tilayered extended semantic network formalism
(MESNET, see for example (Helbig and Schulz, 1997)), which has been successfully applied in various areas (e.g., in the Virtual Knowledge Factory, see (Knoll et al., 1998)).

Besides the premise and the conclusion,
each rule contains a mnemonic identifier like
in.loc (which consists of the preposition’s ortho-
graphic form followed by an abbreviation de-
derived from the semantic interpretation in the conclusion), a short explanation, and a set of example sentences that can be interpreted using this rule.

From a set of rules for 160 German prepo-
ositions collected by (Tjaden, 1996), all rules for six important (i.e., frequent) prepositions were taken as a starting point for development and evaluation of a hybrid disambiguation method. Sentences were retrieved from a development test corpus to refine these rules.

2.2 Corpus

While PP interpretation rules form the rule component of the hybrid disambiguation method, an annotated corpus serves as the source of the statistical component. For each preposition under investigation, a number of candidate sentences that possibly show at-
tachment ambiguity for this preposition were automatically extracted from a corpus. This corpus is based on the online version of the Süddeutsche Zeitung, starting from August 1997. The corpus is marked up according to the Corpus Encoding Standard (see (Ide et al., 1996)) and word, sentence, and paragraph identi-
fiers are assigned.

The preposition in a candidate sentence is semiautomatically annotated with five at-
tributes:

sister The position of the right-most word of
the preposition’s sister NP. Postnominal genitive NPs modifying the main sister NP
are included in this annotation.

2Of course, other sets of such features are possible; the choice was made by selecting relevant features from the set of semantic features in an existent German inheritance lexicon (see (Harttrumpf and Schulz, 1997)), which contains 7000 lexemes and is used by the disambiguation method.
Table 1: Semantic Boolean features in PP interpretation rules

| feature name | description of entities with positive (+) value | examples |
|--------------|-----------------------------------------------|----------|
| animate (S)  | an animate entity                              | ‘animal’, ‘person’, ‘tree’ |
| geogr        | a geographical concept                         | ‘city’, ‘country’ |
| human        | a human entity                                 | ‘child’, ‘president’ |
| info         | an entity that carries information              | ‘book’, ‘concert’ |
| instit       | an institution                                 | ‘company’, ‘parliament’ |
| instru (S)   | an entity that can be used as an instrument    | ‘hammer’, ‘ladder’ |
| legper       | a legal person                                 | ‘company’, ‘woman’ |
| mental       | a mental state or process                      | ‘fear’, ‘happiness’ |
| method       | a method                                       | ‘compression’, ‘filtering’ |
| potag        | a (potential) agent                            | ‘horse’, ‘man’ |

mother The position of the syntactic head word of the mother NP or V.
amother The list of alternative mothers represented by the position of the syntactic head word of an NP or V. An alternative mother is a syntactically possible mother distinct from the (correct) mother. All alternative mothers plus the (correct) mother form the set of candidate mothers for PP attachment.
c-id A character string that identifies the semantic reading of the preposition and corresponds to the identifier in a PP interpretation rule (see Figure 1).
c A character string for comments and documentation purposes.

The preposition in corpus sentence (1) is annotated as shown by the SGML element in (2). The meaning of this annotation can be illustrated as in (3): the PP’s sister ends at ‘Seite’; the PP attaches to ‘gebaut’, and could syntactically also be attached to the NP with head ‘Depot’ or the NP with head ‘Museums’; the interpretation of the PP is a local one (auf.loc).3

(1) Und wieso wird das neue Depot gebaut, nachdem die Planungen für die Thüringer Talseite schon fertig waren?
And why is the new depot of the German-German Museum built on the Bavarian side, after the planning for the Thuringian side of the valley has already been completed?

(2) 19971002bay_c.p3.s2.w10 (article bay_c, 1997-10-02, paragraph 3, sentence 2, word 10): (w c-id="auf.loc" sister="12" mother="13" amother="6/9")auf(/w)

(3) Und wieso wird das neue Depot des Deutsch-Deutschen Museums auf bayerischer Seite gebaut, nachdem die Planungen für die Thüringer Talseite schon fertig waren?

The annotation process is semiautomatic: the machine guesses the attribute values following some heuristics; these guesses have to be checked and possibly extended or corrected by a human annotator. This kind of annotation, of course, is labor-intensive. But due to the development of an Tcl/Tk annotation tool optimized for manual annotation speed, the average annotation time per candidate sentence dropped under 30 seconds. Furthermore, the following sections show that a small set of annotated sentences achieves promising results for PP attachment and interpretation. The lexicon (see footnote 2) had to be extended for the nouns and

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3 Please note that the translations of sentences (1) and (4) are not ambiguous.
verbs annotated as head words of sisters or candidate mothers that were not in the lexicon and could not be analyzed by a compound analysis module.

Some candidate sentences were excluded from the investigation because the PP involves a problem that is supposed to be solved by other NLP modules and could disturb the evaluation of the PP disambiguation module (e.g., by producing noise for the statistical part). All exclusion criteria are listed in Table 2 with percentages of instances of such exclusions relative to the number of candidate sentences. In short, sentences are excluded when their PP ambiguity problem

- can be solved by separate components (for support verb constructions and idioms) or
- can only be solved if the PP attachment and interpretation is supported by another component (for complex named entities, ellipsis resolution, and foreign language expressions).

The first 120 non-excluded candidate sentences for each preposition were chosen and randomly split into eight parts for cross validation. Eight evaluations were carried out with one part being the evaluation test corpus and the remaining seven parts being the evaluation training corpus.

Sometimes, it makes no semantic difference whether a PP in a sentence attaches to an NP or a V. This is known as systematic ambiguity (or systematic indeterminacy, see [Hindle and Rooth, 1993, p. 112]). Two subtypes of this phenomenon are systematic locative ambiguity (see corpus sentence (4)) and systematic contents ambiguity.

(4) Bis ein *Bescheid* aus Karlsruhe* eintritt*, kann es Monate dauern.

It might take months until a notification from Karlsruhe comes in.

The frequency of such ambiguities depends heavily on the preposition; on the average, there were 4.3% cases of systematic ambiguity. For English, ([Hindle and Rooth, 1993, p. 116]) report that 77 out of 880 sentences (8.75%) were systematically ambiguous. In such sentences, an attachment can be considered correct if it is one of the two attachments connected by systematic ambiguity; both parsing results will lead to identical results in an NLP application if it contains sufficiently developed inference components. Table 3 shows for the evaluation corpus (720 sentences) where the PP attaches to (columns V, NP1, NP2 (the second closest NP), NP3, NP4), how many attachments are syntactically possible (number of candidate mothers; columns labeled 1 to 5), and how frequent systematic ambiguity is (last column).

## 3 Hybrid disambiguation method

### 3.1 Basic ideas

PP attachment is one of the most famous problems in NLP. But where a PP attaches to, is only half of the story of the PP's contribution to an utterance; the other half is how it is to be interpreted. And clearly, these two questions are not independent. So, why not tackle both problems at once, trying to achieve for both problems results that are better than the results obtained by an isolated PP attachment component and an isolated PP interpretation component? As both problems depend on each other, there is the strong hope that this is the case. To investigate this hypothesis, such a disambiguation method was developed and evaluated.

The input to the disambiguation method is the feature structure p for the preposition, the feature structure s for the parse of the preposition's sister NP, and the feature structures cmi for the (trivial) parses of the syntactic head words of all candidate mothers. The output is the mother the PP is to be attached to and the interpretation the preposition plus the sister NP contribute to the meaning of the enclosing sentence.

The overall structure of this disambiguation method comprises three steps. First, all sets

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5All annotated sentences showing systematic ambiguity contain only the two candidate mothers that are related by the underlying systematic ambiguity.

6These annotated sentences are available for research.
of possible interpretations $P_{I_i}$ of the PP plus a given candidate mother $cm_i$ are determined by applying the PP interpretation rules. Second, for each set of possible interpretations $P_{I_i}$, one interpretation $s_{I_i}$ is selected using interpretation statistics (on semantics). Third, among all selected $s_{I_i}$, one interpretation is chosen based on attachment statistics (on semantics and syntax) and additional factors. These steps will be presented in more detail in the following three subsections.

### Table 2: Exclusion criteria for candidate sentences

| short name    | description                                                                 | % of tokens |
|---------------|-----------------------------------------------------------------------------|-------------|
| cne-amother   | amother is a complex named entity (titles of books, etc.)                   | 0.1         |
| cne-mother    | mother is a complex named entity (titles of books, etc.)                    | 0.4         |
| cne-sister    | sister is a complex named entity (titles of books, etc.)                    | 0.6         |
| ell-amother   | amother is elliptic                                                          | 0.1         |
| ell-mother    | mother is elliptic                                                          | 0.1         |
| ell-sister    | sister is elliptic                                                          | 0.5         |
| fle-amother   | amother is a foreign language expression                                     | 0.1         |
| fle-mother    | mother is a foreign language expression                                      | 0.1         |
| idi-amother   | amother is an idiom (or part of an idiom)                                   | 0.1         |
| idi-mother    | mother is an idiom                                                           | 0.4         |
| idi-pp        | PP is an idiom                                                              | 3.6         |
| idi-pp-mother | PP plus mother is an idiom                                                  | 0.9         |
| idi-pp-v      | PP plus verb is an idiom                                                    | 0.5         |
| problem       | unclassified problem                                                        | 0.7         |
| svc           | PP is part of a support verb construction                                   | 0.5         |
| svc-amother   | amother of the PP is a support verb construction                             | 0.3         |
| svc-mother    | mother of the PP is a support verb construction                              | 1.0         |
| sum           |                                                                             | 10.1        |

### Table 3: Attachment data from the evaluation corpus

| preposition | V | NP1 | NP2 | NP3 | NP4 | 1  | 2  | 3  | 4  | 5  | sys. amb. % |
|-------------|---|-----|-----|-----|-----|----|----|----|----|----|-------------|
| auf         | 56.7 | 38.3 | 5.0 | 0.0 | 0.0 | 13.3 | 58.3 | 24.2 | 2.5 | 1.7 | 5.0         |
| aus         | 22.5 | 75.0 | 2.5 | 0.0 | 0.0 | 35.8 | 51.7 | 8.3  | 4.2 | 0.0 | 10.0        |
| bei         | 52.5 | 42.5 | 5.0 | 0.0 | 0.0 | 30.8 | 51.7 | 14.2 | 1.7 | 1.7 | 6.7         |
| über        | 37.1 | 57.1 | 5.0 | 0.8 | 0.0 | 17.5 | 66.7 | 13.3 | 0.8 | 1.7 | 2.5         |
| vor         | 41.3 | 52.1 | 5.0 | 1.7 | 0.0 | 23.3 | 61.7 | 13.3 | 1.6 | 0.0 | 0.8         |
| wegen       | 62.1 | 26.3 | 10.0 | 1.7 | 0.0 | 9.2  | 74.2 | 14.2 | 1.7 | 0.8 | 0.8         |
| average     | 45.4 | 48.5 | 5.4 | 0.7 | 0.0 | 21.7 | 60.7 | 14.6 | 2.1 | 1.0 | 4.3         |

#### 3.2 Application of interpretation rules

Step 1 of the disambiguation method (determining possible interpretations $P_{I_i}$) is driven by testing the premises of PP interpretation rules. From the set of interpretations $P_{I_i}$ whose rule premises are satisfied, interpretations are removed that violate adjunct constraints from the lexicon or constraints from the underlying semantic formalism\(^7\) (see step 1 in Figure 2).

\(^7\)Of course, constraints from the semantic formalism could be added to the rules. But this would introduce redundancy which would make the rules difficult to develop and maintain.
\( n \) is the number of possible attachments \((cm_1, \ldots, cm_n)\).

\( m \) is the number of rules for preposition \(p\) \((r_1, \ldots, r_m)\).

1. for each candidate mother \(cm_i\)
   
   (a) \( PI_i' = \{(p, s, cm_i, r_j) | 1 \leq j \leq m, \text{premise of rule } r_j \text{ is satisfied by sister } s \text{ and } cm_i\} \)
   
   (b) \( PI_i = \text{set of all } (p, s, cm_i, r) \in PI_i' \text{ which fulfill the following conditions:} \)
   
   \begin{itemize}
   \item Semantic relations in the conclusion of \(r\) are licensed by compatible relations listed in the feature structure \(cm_i\), which come from lexical entries (or lexical defaults).
   \item Semantic relations in the conclusion of \(r\) do not violate the signature constraints that are defined for these relations in the underlying semantic network formalism.
   \end{itemize}

2. for each candidate mother \(cm_i\) with nonempty \(PI_i\)
   
   (a) \( si_i = \arg\max_{pi} rf(r, \{(r_j | \exists(p, s, cm_i, r_j) \in PI_i)\}, \text{where } pi = (p, s, cm_i, r) \in PI_i \)

3. for each candidate mother \(cm_i\) with nonempty \(PI_i\)
   
   (a) \( d = \text{distance in words between candidate mother } cm_i \text{ and the PP } (p \text{ plus } s) \)
   
   (b) \( \text{score}_{si_i} = rf((r, \text{cat}(cm_i)), \{(r_j, \text{cat}(cm_k)) | 1 \leq k \leq n, PI_k \neq \emptyset, si_k = (p, s, cm_k, r_j)\}) + \text{score}_{\text{dist}}(d), \text{where } si_i = (p, s, cm_i, r) \)

\( si = \arg\max_{si_i} \text{score}_{si_i}, \text{where } 1 \leq i \leq n, PI_i \neq \emptyset \)

Figure 2: Disambiguation algorithm

To simplify Figure 2, the treatment of complements is excluded. Interpretations that are licensed by lexical complement information for candidate mothers are also determined in step 1. Experiments showed that it is a good strategy to prefer complement interpretations over adjunct interpretations, which are described in the following steps.\(^8\) Attachment cases where prepositional objects as complements are involved are the easy ones for statistical disambiguation techniques (see for example (Hindle and Rooth, 1993)); in a hybrid system, one can expect such complement information to be in the lexicon, at least in part. The problem is alleviated as the interpretation rules (which are developed for adjuncts) produce correct results for many complements; but this topic needs further research.

### 3.3 Interpretation disambiguation

The result of step 1 can be viewed as an attachment-interpretation matrix \((ai_{i,j})\) with size \(n \times m\). A matrix element \(ai_{i,j}\) corresponds to attaching the PP to candidate mother \(cm_i\) under interpretation \(r_j\) and represents some kind of preference score.

To solve the attachment and interpretation problem (i.e., to select the right matrix element), statistics can be used. There are numerous statistical approaches (see section 1), but in the presented approach a statistical component is combined with a rule component (see step 1). This rule component reduces the degree of ambiguity (i.e., marks elements in matrix \((ai_{i,j})\) as possible or impossible) and delivers high-level semantic information (the possible semantic interpretations of the PP for a given candidate mother) for statistical disambiguation.

The strategy adopted in this disambiguation method is to do the remaining disambiguation in two steps: first disambiguate the interpretations for each attachment possibility, then disambiguate the attachments based on the first step's result. So, in step 2 of the disambiguation method, one interpretation for each candidate mother is chosen. As Table 4 shows, most of the time the correct rule fires (given the correct mother; see recall column), but false rules fire too (see precision column) because interpretation rules refer only to a limited depth.
Table 4: Results of PP interpretation rules for (correct) mothers

| preposition | readings | recall % | precision % |
|-------------|----------|----------|-------------|
| auf         | 9        | 100.0    | 100.0       |
| aus         | 6        | 97.4     | 39.8        |
| bei         | 4        | 93.7     | 69.8        |
| über        | 7        | 100.0    | 65.4        |
| vor         | 6        | 98.3     | 54.7        |
| wegen       | 1        | 100.0    | 100.0       |

\[ r_f(aus.pars, \{aus.origl, aus.pars, aus.sourc\}) = 1.0 \]
\[ r_f((aus.temp, np), \{aus.cstr, v\}, (aus.temp, np)) = 1.0 \]

Figure 3: Statistical example data for interpretation and attachment

of semantics, which can be delivered by realistic parsers for nontrivial domains. Therefore, there is the need to disambiguate for interpretation. Here statistics derived from the annotated corpus come into play: relative frequencies are calculated, which serve as estimated probabilities.

As usual in statistical methods for disambiguation, there is a trade-off between depth of learned information (e.g., number and type of features) and non-sparseness of the resulting matrix-like structure representing the learning results: the deeper the information, the sparser the matrix. A good compromise for the problem at hand is to regard only the interpretation (identified by the rule id) and to establish a limit \( n_{int} \) for the number of interpretations. Empirical results showed that three is a reasonable choice for \( n_{int} \). An example of an entry in the interpretation statistics is given in the first line of Figure 3 and can be paraphrased as follows: The interpretation \( aus.pars \) wins in 100% of the learned cases if the interpretations \( aus.origl \) and \( aus.sourc \) are possible too.

If there are more than three possible interpretations, standard techniques for reducing to several triples can be used (backed-off estimation, see for example (Katz, 1987), (Collins and Brooks, 1995)). The relative frequency of rule \( r_i \) being the correct interpretation among \( I = \{r_1, r_2, \ldots, r_n\} \) is estimated for \( n > n_{int} \) as in equation (5):

\[
rf(r_i, I) := \frac{\sum_{c \in C_i} rf(r_i, c)}{|C_i|}
\]

where \( C_i \) is the set of all subsets of \( I \) with \( n_{int} \) elements that contain \( r_i \).

In step 2 of the disambiguation algorithm (see middle of Figure 2), the rule that maximizes the (estimated) relative frequency must be found for each candidate mother.

### 3.4 Attachment disambiguation

After step 2, the attachment-interpretation matrix \( (a_{i,j}) \) contains in each row (attachment) one element marked as selected. What remains to be done is to choose among all attachments with selected interpretation \( s_i \); one interpretation \( s_i \).

For this disambiguation task, attachment statistics are employed. This time the compromise between depth of learned information and non-sparseness can contain more information than just the interpretation id as experiments showed. A three-valued syntactic-semantic feature \( cat \) is added. It describes the candidate mother with three possible values:

- \( v \) a verb
- \( nps \) an NP that describes a situation (at least partially), e.g., ‘continuation’
- \( np \) an NP that does not describe a situation, e.g., ‘house’

The second line of Figure 3 contains an example that expresses the fact that if the interpretation \( aus.temp \) for a nominal candidate mother and the interpretation \( aus.cstr \) for a verbal candidate mother compete then the first is correct (in the training corpus) with relative frequency 1. If one adds even more information to attachment statistics (e.g., the position of NP candidate mothers like \( np_2 \) for the second closest NP) the attachment data for the annotations in this paper becomes too sparse.

9There might be rows where no element is marked because none of the rules fired and passed filtering (see section 3.2).
As for the interpretation statistics in step 2, standard techniques can reduce tuples that are longer than \(2^{\text{hart}}\) to several shorter ones. The relative frequency of \((r_i, \text{cat}(cm_i))\) belonging to the correct attachment among \(A = \{(r_1, \text{cat}(cm_1)), \ldots, (r_n, \text{cat}(cm_n))\}\) is estimated for \(n > n_{\text{att}}\) as in equation (6):

\[
rf((r_i, \text{cat}(cm_i)), A) := \sum_{c \in C_i} \frac{rf((r_i, \text{cat}(cm_i)), c)}{|C_i|}
\]

where \(C_i\) is the set of all subsets of \(A\) with \(n_{\text{att}}\) elements that contain \((r_i, \text{cat}(cm_i))\).

These relative frequencies for the selected interpretations \(s_i\) serve as initial values for an attachment score. Other factors can add to this score, so that the attachment decision should improve; of course, the value is only a score, not a relative frequency any more. Different factors (e.g., distance between candidate mother and the PP; in this way, one can simulate the right-association principle, see (Kimball, 1973)) were evaluated. The following distance scoring function \(score_{dist}\) turned out to be useful:

\[
score_{dist}(d) := \begin{cases} 
\text{dist}_w(m_d - \min(d, m_d)) \\
\text{dist}_v(m_d - \min(d, dist_v, m_d)) 
\end{cases}
\]

for NP mothers

for V mothers

Good values for the parameters \(\text{dist}_w\) (weight of the distance factor) and \(\text{dist}_v\) (modification for verbal mothers) depend on the preposition at hand and are learned by testing pairs of values from the range 0.0 to 2.0 (see Table 5).

Comparison of the attachment results is possible, but difficult. One reason is that the best reported disambiguation results for binary PP attachment ambiguities (84.5%, (Collins and Brooks, 1995); 88.0% using a semantic dictionary, (Stetina and Nagao, 1997)) are for English. Because word order is freer in German than in English, the frequency and degree of attachment ambiguity is probably higher in German. There are only few evaluation results for German: (Mehl et al., 1998) achieve 73.9% correctness for the preposition ‘mit’ (‘with’/‘to’/...) using a statistical lexical association method.

Of course, the evaluation corpus is not large (720 sentences); so, the results reported in this paper must be treated with some caution. But as the selected prepositions show diverse numbers of readings (1–9, see Table 4) and the results are cross-validated, it is likely that the reported results will not deteriorate for larger corpora.

### Table 5: Good parameters for the attachment scoring function \(score_{dist}\)

| Preposition | \(\text{dist}_w\) | \(\text{dist}_v\) |
|-------------|-----------------|-----------------|
| auf, vor, wegen | 0.8 | 0.6 |
| aus | 1.2 | 1.0 |
| bei | 1.2 | 0.8 |
| über | 0.8 | 0.2 |

5 Conclusions

In this paper, a new hybrid disambiguation method which uses PP interpretation rules and
Table 6: Results of hybrid disambiguation

| preposition | attachment for ambiguity degree | interpretation att. and int. |
|-------------|---------------------------------|-------------------------------|
|             | 1 2 3 4 5 ≥2 ≥3                 |                               |
| auf         | 100.0 88.6 75.9 100.0 100.0      | 85.6 79.4 92.5 86.7           |
| aus         | 100.0 90.3 80.0 80.0 88.3         | 80.0 90.8 85.8 85.8           |
| bei         | 100.0 90.3 82.4 50.0 50.0 86.7    | 76.2 91.7 85.0                |
| über        | 100.0 88.8 81.3 100.0 100.0 87.9  | 84.2 83.3 83.3                |
| vor         | 100.0 89.2 75.0 100.0 87.0        | 77.8 89.2 81.7                |
| wegen       | 100.0 94.4 70.6 100.0 100.0 90.8  | 75.0 100.0 91.7               |

statistics about attachment and interpretation in an annotated corpus was described. It yields results with competitive correctness for both the PP attachment problem and the PP interpretation problem.

Some questions had to be left open, e.g., a nontrivial reading disambiguation\(^\text{11}\) for candidate mothers and sister NPs. Questions concerning the requisite manual work (maintaining rules and some parts of annotating corpora) arise: How much does this work pay off and how could more of this work be automated? The disambiguation method should be evaluated for larger corpora (more sentences, more prepositions) in future research. The ongoing use of the disambiguation method in natural language interfaces will provide valuable feedback.

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