Bachelorthesis

Improving Anaphora Resolution Through Corpus Mined Gender Information

Jan Henry van der Vegte

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Reviewer:

Professor Dr.-Ing. Torsten Zesch
Prof. Dr. rer. soc. Heinz Ulrich Hoppe

University of Duisburg-Essen
Faculty of Engineering
Department of Computer and Cognitive Sciences
Language Technology Lab 47057 Duisburg

Erklärung

Hiermit erkläre ich, dass ich die vorliegende Arbeit ohne fremde Hilfe selbstständig verfasst und nur die angegebenen Quellen und Hilfsmittel benutzt habe. Ich versichere weiterhin, dass ich diese Arbeit noch keinem anderen Prüfungsgremium vorgelegt habe.

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Jan Henry van der Vegte, Datum

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Chapter 1

Introduction

1.1 Background

In the last decades, the amount of textual information in media has increased severely, making automatic text comprehension indispensable. Since textual data found online is mostly unstructured, which means that there is no formal structure in pre-defined manner, various information needs to be added in order to make automatic understanding possible. For several natural language processing (NLP) tasks, referential relationships between words in a document need to be set. For instance, in the following sentence the pronouns *he* and *him* refer to previously mentioned entities in the text:

Peter took John's car. He is now angry with him.

A noun that does not have a specified meaning and can only be interpreted through its referential relation (such as *he* or *him*) is called **anaphora** (Recasens et al. 2007). The most recent noun or noun phrase[1] regarding to the same real-world entity can be seen as the point of reference and is therefore termed **antecedent**. Thus, the process of determining the antecedent for a considered anaphora is named **anaphora resolution**. The previous example with resolved anaphoras is shown in Figure 1.1.

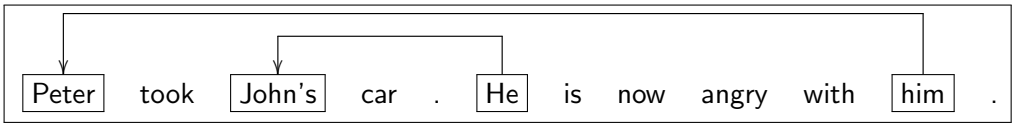


Figure 1.1: Visualization of anaphora resolution

Anaphora resolution can be considered as a subtask of **coreference resolution** as coreference resolution aims for linking all occurrences of a real-world entity in a text (Figure 1.2). Therefore, anaphoras are a part of it.

[1] A noun phrase is a group of words "revolving around a head noun" (Jurafsky & Martin 2014)

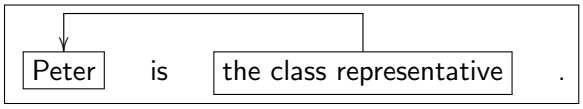


Figure 1.2: Visualization of coreference resolution

Resolving noun phrases is a growing task in Natural Language Processing (NLP) and increased its relevance in the last decades to the extent that it even became a standalone subtask in the DARPA Message Understanding Conference in 1995 (Chinchor & Sundheim 1995). The International Workshop on Semantic Evaluation (SemEval) conducted a coreference resolution task on multiple languages (Recasens et al. 2010) emphasizing its importance. There are several fundamental applications of coreference and anaphora resolution, such as Information Extraction (IE) (McCarthy & Lehnert 1995) and Question Answering (QA) (Morton 2000).
Information Extraction targets to summarize relevant information from documents. Anaphora resolution is required as the quested entity is often referenced through various words, amongst others personal pronouns. McCarthy & Lehnert (1995) described the latter as a classification problem: "Given two references, do they refer to the same object or different objects."
The question answering task described by Morton seeks to find a 250 byte string excerpt out of a number of documents as the answer for a query. Annotated coreference chains were used to link all instances of the same entity in a document. Occurrences in another sentence are given a lower weight for prediction. The use of annotated coreference chains improved the prediction slightly.
Various information sources including syntactic, semantic, and pragmatic knowledge are needed since selecting a possible antecedent is a decision under high ambiguity. The decisive factor for determination might be e.g. gender agreement or the distance between antecedent and anaphora. For instance, in Figure 1.3 the contextual information is used that *John* is commonly a masculine first name and will therefore refer to *he*.

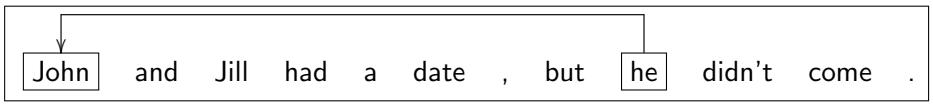


Figure 1.3: Masculine gender match

In contrast to that, the female pronoun *she* in Figure 1.4 will most likely refer to *Jill*.

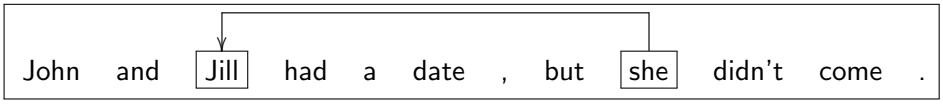


Figure 1.4: Feminine gender match

1.2 Motivation

Significant factors of uncertainty are gender and number, because they are hard to determine. At first, information is needed whether a noun is male, female, neutral, or plural.[2] Honorifics like "Mr." and "Mrs." are gender indicators, but not sufficient due to their sparsity. Stereotypical occupations and gender indicating suffixes like policeman and policewoman turned out to be no longer reliable (Evans & Orasan 2000). For that reason, gender and number information needs to be learned from an external source.

There are two different strategies for implementing reliable gender information:
Firstly, gender can be treated as a hard constraint. This means that either the most likely gender is assigned or, in case of uncertainty, no assignment is made at all. The leading coreference resolution systems mostly use hard constraint gender information (Soon et al. 2001). The gender of to the most frequent sense of a noun is assumed.
Secondly, gender can be expressed through probabilities. If a noun is male in 70 of 100 cases, the probability for it to be male is 70 % (note that this is simplified - those distribution will mostly be smoothed to avoid 0-probabilities). Bergsma (2005) reported an increase of accuracy due to this implementation method.

This work will present a machine learning approach to anaphora resolution, focusing on third-person pronominal anaphoras. The two main purposes are to determine the impact of gender probability and to compare it to gender information treated as a hard constraint. First of all, it should be evaluated whether the improvement through gender frequencies Bergsma (2005) reported can be replicated on different data. In a second step, the gender frequencies will be replaced by the assignment of the most frequent gender to examine the influence of nothing but the gender implementation strategy. This is necessary as usage of different data sets and algorithms makes the comparison of papers inconclusive. Finally, it needs to be examined whether the hypothesis that corpus based gender frequencies have a higher impact than gender constraints can be confirmed.

[2] In the following work plural will be also considered as gender since it occurs as a seperate category, especially if pronouns are observed.

Chapter 2

Related Work

Anaphora resolution systems emerged into two different strategies. First of all, there are rule-based techniques, which focus more on theoretical considerations. The second strategy uses machine learning and is based on annotated data. The following chapter will briefly present both and discuss their advantages and disadvantages, followed by exemplary realisations. Since anaphora resolution is a subtask of coreference resolution, coreference resolution systems will be considered as well.

2.1 Rule-Based Techniques

Rule-based techniques rely on manual understanding and implementation of syntactic and semantic principles in natural language (Kennedy & Boguraev 1996; Mitkov 1994; Ingria & Stallard 1989). Clues that could be helpful for antecedent identification are manually implemented as rules. To identify relevant clues, prior knowledge about linguistic principles (such as binding principles) is necessary. Since rules might be domain-specific, the implementation would most likely be worse on other domains. Refinements for different domains would make the development even more complex and time-consuming. Nevertheless, rule-based techniques are much more transparent in contrast to machine learning. In the last section, a comparing evaluation of both techniques will be presented.

2.1.1 The Naive Hobbs algorithm

The Naive Hobbs algorithm described by (Hobbs 1978) relies on parsed syntax trees containing the grammatical structure. Put simply, the tree containing the anaphora is searched left-to-right with breadth-first search and the algorithm stops when a matching noun phrase is found. Noun phrases mismatching in gender or number are neglected. The algorithm also limits the list of possible antecedents, as for instance the antecedent can not occur in the same non-dividable noun phrase. As long as no matching antecedent is found, the preceding sentence will be searched successively.

Hobbs reported an accuracy score of 88.3 % on the pronouns “he”,“she”,“it”, and “them” with only using the algorithmic approach. The usage of additional constraints improved the accuracy to 91.7 %.

2.1.2 CogNIAC

Another rule-based approach was presented by (Baldwin 1997) with CogNIAC, a high precision pronoun resolution system. It only resolves pronouns when high confidence rules (shown in Table 2.1) are satisfied in order to avoid decisions under ambiguity and to ensure that only very likely antecedents are attached (high precision). This might lead to a neglect of less probable but still correct antecedents and lower the recall score. For each pronoun, the rules are applied one by one. If the given rule has found a matching candidate, it will be accepted. Otherwise, the next rule will be applied. If none matches the candidates, it will be left unresolved as this implicates a higher ambiguity. In order to apply Baldwins high confidence rules, information on sentences, part-of-speech, and noun phrases is required and therefore annotated. Semantic category information such as gender and number is determined through various databases. Confirming their prediction, (Baldwin 1997) reported a high precision score (97 %), but inferior recall (60 %) on their training data consisting of 198 pronouns.
As can be seen the order of rules leads from higher to lower precision: if only one possible antecedent can be found (rule 1) it is most likely the correct antecedent while rule 6 indicates more ambiguity as it relies on more content-related information. Human understanding of syntax and semantics is needed to determine a specific order of rules. Therefore, adding new rules might not improve the performance even though those rules are reasonable in itself. Most rule-based systems struggle with that problem.
In a second evaluation, CogNIAC was compared to the Hobbs Algorithm (Baldwin 1997; Hobbs 1978) on singular third-person pronoun resolution. In order to maximize the ambiguity, the training data texts were narrations about same gender characters. To make accuracy scores comparable, Baldwin (1997) added lower precision rules, such as the most recent antecedent should be picked if no other rule found a matching noun phrase. The Accuracy scores reported were nearly equal (78.8% on the Hobbs Algorithm, 77.9% on CogNIAC), underlining the reason of existence of various approaches.

2.1.3 Anaphora Resolution with Limited Knowledge

A domain independent approach by Mitkov (1998) tried to eliminate the disadvantages of previous rule-based systems. Mitkov renounced complex syntax and semantic analysis in order to keep the algorithm as less domain specific as possible. Only a part-of-speech tagger and a simple noun phrase identifitcation module were applied. The algorithm was informally described by Mitkov in three steps:

Table 2.1: CogNIAC core rules

Rule	Description
1) Unique in Discourse	If there is a single possible antecedent PAi in the read-in portion of the entire discourse, then pick PAi as the antecedent.
2) Reflexive	Pick nearest possible antecedent in read-in portion of current sentence if the anaphora is a reflexive pronoun
3) Unique in Current + Prior	If there is a single possible antecedent i in the prior sentence and the read-in portion of the current sentence, then pick i as the antecedent:
4) Possessive Pro	If the anaphora is a possessive pronoun and there is a single exact string match i of the possessive in the prior sentence, then pick i as the antecedent:
5) Unique Current Sentence	If there is a single possible antecedent in the read-in portion of the current sentence, then pick i as the antecedent
6) Unique Subject/ Subject Pronoun	If the subject of the prior sentence contains a single possible antecedent i, and the anaphora is the subject of the current sentence, then pick i as the antecedent

1. Examine the current sentence and the two preceding sentences (if available). Look for noun phrases only to the left of the anaphora

2. Select from the noun phrases identified only those which agree in gender and number with the pronominal anaphora and group them as a set of potential candidates

3. Apply the antecedent indicators to each potential candidate and assign scores; the candidate with the highest aggregate score is proposed as antecedent

Overall, a set of 10 antecedent indicators were used which indicate either a high or a low likelihood for the noun phrase to be the antecedent. Negative indicators such as definiteness (whether the noun phrase contains a definite article, whereby indefinite phrases decrease the likelihood) and positive indicators like term preference (if the noun phrase is a term in the field, the likelihood is increased). The score values are integers from -1 to 2.
Mitkov reported a success rate of 89.7 % on random sample texts of technical manuals. A modified approach could also be applied for polish (Mitkov & Stys 2000) and arabic (Mitkov et al. 1998) with similar success rates. A comparing evaluation to Baldwins CogNIAC (Baldwin 1997) indicated a superiority of Mitkovs approach (Mitkov 1998) as

CogNIAC had a lower success rate of approximately 15 % on the previously described data set. The stated reason for the comparison was that the approaches showed several similarities as both require few preprocessing and gain their information mostly from part-of-speech tags and noun phrases.
The superiority of (Mitkov 1998) could be explained by its handling of uncertainty as the antecedent indicators are not implemented as hard constraints. Basically, Mitkovs anaphora resolution system can be described as a combination between rule-based and statistical techniques in order to use the best of both worlds.

In 2002, a revised version of the original approach by Mitkov was presented (Mitkov et al. 2002). An improved version called MARS had some smaller and greater changes:
First of all, three new antecedent indicators and a module for identification of pleonastic pronouns[1] and non-nominal pronominal anaphoras were added. Additionally, the implementation of some previous features was changed as other preprocessing tools were used.

A modular anaphora resolution tool called GuiTAR relying on Mitkovs MARS-algorithm (Mitkov et al. 2002) was developed by Poesio & Kabadjov (2004). It was designed to be domain-unspecific and usable off-the-shelf which means that preprocessing steps such as part-of-speech tagging and named entity recognition will be added on itself. Either raw text data or XML files can be used as the input. In case of raw text data, XML files with annotated part-of-speech tags, noun phrase boundaries, pronoun categories etc. will be created. (Poesio 2004) reported an F-measure of 64.2 % for personal pronouns on raw text data of the GNOME corpus (Poesio & Kabadjov 2004). In comparison, the baseline approach (choosing the most recent antecedent) achieved an F-measure of 50.5 % on the same data.

2.2 Machine Learning-Based Techniques

Most machine learning-based techniques learn principles from annotated text corpora (Soon et al. 2001; Bergsma 2005), which include the correct label for each instance. In this context, a label will contain the information whether a noun phrase is the antecedent. A decisive factor of machine learning is that irrelevant information (presented through features) has a lower impact on success factors (the accuracy for instance) compared to rule-based techniques, as the algorithm automatically learns to rate those as irrelevant and vice versa. Therefore, machine learning approaches tend to have little information on linguistic principles as the algorithm should learn those autonomously. This causes the algorithm to be fewer domain specific, but increases the risk to miss relevant clues. However, top-performing machine learning approaches achieve accuracy scores comparable to best non-learning techniques (Soon et al. 2001).

[1] A pleonastic pronoun is non-referential. For example, the *it* in “it is raining”

Additionally, machine learning algorithms are usually more time-consuming due to the learning process.

2.2.1 Anaphoras in Coreference Resolution

As already stated, coreference resolution aims for linking all noun phrases referring to the same entity in the real world in a document. The most common kind of storing coreferential information is through coreference chains, in which the current element always points towards the following same entity-element. Another way of storing coreferences is to define a unique ID for each real-life entity. All occurrences in the text will be assigned to their belonging IDs.

An often quoted coreference resolution system using machine learning was proposed by Soon et al. (2001). In this case, a decision tree classifier was chosen. A natural language processing pipeline was used for the identification of markables. The pipeline identified among other annotations part-of-speech tags, noun phrases, named entities, and semantic classes. A high value was placed on designing generic features to make them domain-independent. In total, a set of 12 different features was used. It covers inter alia a distance feature (standing for the distance in sentences between two elements), a gender agreement feature (whether the gender matches), and a number agreement feature (whether the number matches). Deriving gender information of a noun requires information of their semantic classes. Soon et al. (2001) worked with the simplified assumption that the semantic class of a noun phrase is the semantic class of the most frequent sense of the considered noun in WordNet. Gender agreement was assumed if both phrases got the same semantic class (for example "male") or if one is the parent of the other (such as phrase one is considered as "person" and phrase two as "male"). In order to make machine learning possible, training instances need to be generated.
To generate positive training instances, Soon et al. (2001) used every noun phrase in a coreference chain and its predecessor in the same chain. Each intervening noun phrase forms a negative instance with the considered noun phrase.

The researchers reported an F-measure of 62.6 % on the MUC-6 data and comparable results on the MUC-7 data. A comparison with official MUC-scores indicated, that their system performed at the upper bound of the considered systems. Those values and the used feature set are often referred as a baseline for further systems (Versley et al. 2008).

(Ng & Cardie 2002) extended their work and improved it through additional features, a different training set creation, and a clustering algorithm to find the noun phrase with the highest likelihood of coreference. The majority of the new features is based on syntactical principles. For instance, binding constraints must be fulfilled and one phrase is not allowed to span another. Positive training instances are not created through their preceding antecedent, but through their most confident one. In addition, they started to search for a related antecedent from right-to-left for a highly likely antecedent (in

contrast to starting the right-to-left search for the first previous noun phrase). Ng and Cardie reported a significant increase in precision and F-measure compared to the initial approach by (Soon et al. 2001).

2.2.2 BART

In 2008, Versley et al. introduced a coreference resolution system for raw text data which extended the previously described approach by Soon et al. (2001). The ambition for BART was to keep it as modular as possible so that it could be applied to many different subtasks of coreference resolution. BART consists of a preprocessing pipeline for parsing, part-of-speech tagging, and further basic information and a mention factory for mainly gender and number identification. Additionaly, a feature extraction module and therefore a matching decoder and encoder is included. The decoder generates the training data while the encoder prepares the testing data. Similar to (Soon et al. 2001) the feature labels are binarized which means that an anaphora either contains the correct or wrong antecedent. Accordingly, the feature labels are either true or false.
A subsequent approach on multiple languages with BART (Broscheit, Poesio, et al. 2010) used a feature set of seven features for all classification types, including a gender agreement, number agreement, string match, and distance feature. The procedure of gaining gender and number information was adopted by Soon et al. (2001).

An F-measure of approximately 55.6 % on Bnews articles of the ACE-2 corpora was reported with the usage of the basic feature set (Versley et al. 2008). With additional language-dependent features, BART was successfully transferred to german (Broscheit, Ponzetto, et al. 2010), polish (Kopec & Ogrodniczuk 2012), and italian (Poesio et al. 2010).

(Reiter et al. 2011) indicated that a great weakness of BART is the implementation of gender information as in their evaluation even noun phrases with explicit gender information were linked incorrectly.

2.2.3 Pronoun Resolution in Spoken Dialogue

As already mentioned, machine learning approaches are less domain-specific than rule-based systems. For that reason (Strube & Müller 2003) presented a corpus-based approach for pronoun resolution in spoken language. Still, several extensions and adaptions had to be done as spoken dialogue differs from written texts gravely. Firstly, the number of pleonastic pronouns in spoken dialogue is substantially increased. Secondly, a not ignorable amount of anaphoras in spoken dialogue don not have a clearly defined antecedent so that even humans can not determine them. Eckert & Strube (2000) called them vague anaphoras and figured out that 13.2 % of all anaphoras in their examined corpus fall into that category.

A corpus of twenty switchboard dialogues was used. In order to generate training data, a list of all potential anaphoras was created. Potential anaphoras are all non-definite noun phrases except for first and second person pronouns. Each element in the remaining list forms a pair with every preceding noun phrase that does not disagree in gender, number, or person. If the instances corefer they were labeled P, else N. For all anaphoras without explicit noun phrase antecedents, other phrases (for instance verb phrases) in the last two sentences were used to form pairs.
The feature set with a total of 25 features included noun-phrase features, coreference-level features and spoken dialogue features. Noun-phrase features rely on further preprocessing such as gender, number, or the grammatical function of the anaphora or the antecedent. Coreference-level features could be described as low-level preprocessing features. Those features mainly describe the distance between the antecedent and the anaphora, for instance, in words or sentences. The features especially for spoken dialogue contain, for instance, information on how many noun phrases are located between anaphora and antecedent. A decision tree classifier with 20-fold cross-validation was applied. (Strube & Müller 2003) reported an F-measure of 47.42 % for the full classifier, including all pronouns and all features.

2.2.4 Corpus- and Web-Mined Gender Information

Bergsma (2005) presented a machine learning approach to anaphora resolution, which treats gender information not as a hard constraint, but as a probability distribution of possible outcomes. A majority of previous approaches assigned either a specific gender and number (e.g. masculine, feminine, neutral, or plural) or, in case of uncertainty, no gender at all (Soon et al. 2001; Broscheit, Poesio, et al. 2010). Another motivation was that Kennedy & Boguraev (1996) reported to attribute 35 % of their resolution errors to gender mismatch. Only third-person pronouns were considered.

The gender information was derived of two sources: a text corpus and the web. For the former, all occurrences of nouns and pronouns in lexico-syntactic patterns are counted. Five different patterns for reflexives, possessives, nominatives, predicates, and designators were used (Table 2.2). A reflexive masculine occurrence would be for instance "John likes himself". In this case, a counter for "John" with masculine gender and reflexive pronoun will be increased. This procedure was repeated for all other patterns and remaining genders and numbers (masculine, feminine, neutral, and plural). Bergsma (2005) applied lots of textual data in order to offset parser errors and other noise sources. The whole data set included the AQUAINT corpus (Graff 2002) as well as the Reuters corpus (Rose et al. 2002). In total, a data set of approximately six gigabytes of text was used.

Since a text corpus, no matter how big it is, can not contain all possible words and word combinations, the web was used as a second information source. The Google API was used to count the web pages that appear if a noun, the Google wildcard operator

Table 2.2: Gender Corpus Patterns

Gender Corpus Indicators	Contained Elements	Pattern
1) Reflexive	himself, herself, itself, and themselves	*noun + verb + reflexive*
2) Possessive	his, her, its, and their	*noun + verb + possessive + noun*
3) Nominative	he, she, it, and they	*noun + verb + nominative + verb*
4) Predicate	he, she, it, and they	*pronoun* + is/are [a] + *noun*
5) Designator	Mr. and Mrs.	*designator + noun*

("*"), and the gender indicator were searched. For instance, if the gender of "John" should be determined, a Google request will be sent with all gender indicating elements of Table 2.2 (John * himself, John * herself, John * itself, etc.). In the following step, the probabilities for each gender will be determined through the five corpus sources and the five web sources. The naive approach would be that the probability of the indicator to be masculine is the percentage of all cases in that the word occurs with its masculine indicator. For instance, in Table 2.3 the cumulated frequency of "Alex" occurring with "himself" is 60. In total, "Alex" was found 100 times with a reflexive pronoun. As a consequence, the probability for "Alex" to be masculine would be estimated at 60 % from reflexive indicators. This approach leads to three major problems. First of all, zero-probabilities would indicate that there is no possibility for noun to belong to that gender. This might be true - some words might never be part of a certain gender. On the other hand, however, it might just be a rare event and an occurrence would be found with a larger or different text corpus. Secondly, adding a further count could change the likelihood enormous for small frequencies. This leads to the third problem: a measure is needed to determine the certainty of a likelihood. A 70 % probability of a word to be masculine is more meaningful if 1000 cases are considered rather than 10.

In order to solve those problems, Bergsma (2005) treated the counts as a Beta distribution in a Bayesian approach. More precisely, two parameters named α and β are considered. For each gender, α determines the count of the considered event plus one (in order to avoid zero-probabilities) while β represents the count of all not considered events plus one. The α and β values of the previous "Alex" example with reflexive indicators for masculine gender would be $\alpha = 61$ and $\beta = 41$. The mean value of it is computed as:

$$\mu = \frac{\alpha}{\alpha + \beta}$$

A complete distribution is presented in Table 2.3. Note that, unlike the naive approach, these values can only be partially compared to one another, as each of them represents

a single distribution. Furthermore, the percentages do not sum up to 100 %.

Table 2.3: Gender Frequencies Example

Gender/Number	Occurrences	Naive Approach	Bayesian Approach
1) Masculine	60	$\frac{60}{100} = 60\ \%$	$\frac{61}{102} \approx 59.8\ \%$
2) Feminine	30	$\frac{30}{100} = 30\ \%$	$\frac{31}{102} \approx 30.4\ \%$
3) Neutral	10	$\frac{10}{100} = 10\ \%$	$\frac{11}{102} \approx 10.8\ \%$
4) Plural	0	$\frac{0}{100} = 0\ \%$	$\frac{1}{102} \approx 0.1\ \%$

Bergsma (2005) expressed the certainty through the variance of Beta distributions:

$$\sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

In case of little or no counts at all, the variance will be approximately 1/12. The classifier should automatically learn that distributions with that variance will not be meaningful.

In order to prove the accuracy of their gender classification, Bergsma (2005) built several SVM-Classifiers. Overall, a set of 20 features was used: Each of the five gender indicators (reflexive, possessive, etc.) has its mean and its variance as features (in this case, the standard deviation was used which is the square root of the variance). Each of the gender indicators was implemented corpus-based as well as web-based. All gender features led to an F-measure of 92 %. Separate classifiers for either web-based or corpus-based information yielded to an F-measure of 85.4 % for the corpus-based and 90.4 % for the web-based approach.

Various pronoun resolution classifiers were build in order to determine the influence of several aspects. In general, each classifier searches, beginning by the certain anaphora, the text backwards until a matching antecedent is found. The matching criteria vary depending upon the complexity of the classifier. The search backwards of the more complex classifiers was limited so that only the current and the previous sentence was considered, because a corpus observation showed that more than 97 % of all antecedents could be found in that range. If no accepted antecedent was found a threshold was reduced so that antecedents with lower likelihood might be accepted. This procedure was repeated until the first candidate exceed the threshold.

The baseline approach was to always select the most recent noun phrase as antecedent.

An accuracy of 26.0 % was reported.

A first improvement consisted of the use of only explicit gender indicators such as "Mr." and "Mrs." to determine the gender. The first previous antecedent that does not mismatch will be chosen. The accuracy was improved up to 30.8%. In a third baseline approach, the previously mentioned gender SVM-classifiers were used to detect a gender match or mismatch. Underlining the importance of gender and number agreement, the accuracy rose up to 59.4 %.

The first machine learning approach included a feature set of 39 features, whereby most of the features were binarized. The features can be separated into three categories. First of all, there are pronoun-related features that determine the gender and number of the pronoun. Secondly, antecedent-related features which provide for instance information on the grammatical relation of the noun phrase or whether it is a person or an organization. The third group of features describes the relation of pronoun and antecedent and contains features that rely on linguistic principles (such as if binding principles are satisfied) as well as features that only require basic preprocessing steps (sentence and word distance, for instance). In order to apply those, the texts were tokenized, parsed, and noun phrases were linked. The training instance creation procedure was adopted by Soon et al. (2001) and was previously described in Section 2.2.1. In total, 1251 positive and 2909 negative training instances were created.

The classifier reached a performance score of 62.3 % which is above all previous approaches. The additional use of corpus and web frequency features and three other gender affecting features led to a performance score of 73.3 %.

2.3 A Comparison of Both Strategies

Aone & Bennett (1995) did a comparison of a previously build manually designed resolver (MDR) (Aone & McKee 1993) and their in 1995 introduced machine learning-based resolver (MLR).
This section will briefly explain both implementations in order draw an appropriate conclusion of the comparison.

2.3.1 A Manually Designed Resolver (MDR)

The manually designed resolver was build to be language-independent, extensible, robust, and tunable for specific domains. The used information was derived through three different knowledge bases: the *Discourse Knowledge Source*, the *Discourse Phenomenon*, and the *Discourse Domain*.
The former contains antecedent generators to determine all possible antecedents, a sys-

tem to filter out unwanted antecedent candidates, and an orderer to rank the candidates from highest to lowest likelihood. All of these components rely on specific rules and functions. For instance, the filter removes candidates of mismatching gender. Even though some the rules are only applied on specific languages, (Aone & McKee 1993) reported that most of them are language-independent.
The *Discourse Phenomenon* contains all possible part-of-speech categories in which the anaphora could occur in a hierarchical order. For instance, "third-person" pronoun is a subclass of "pronoun". Each class includes its definition, two resolution strategies (a second one is needed if the main strategy fails), and specific language information if a category only exists in a certain language.
The third knowledge base is responsible for domain-specific information.

A module called *Discourse Administrator* was used to determine the application domain and in a further step to select and filter the knowledge bases in order to generate the best possible resolution system. Therefore, the information stored in each knowledge base is heavily dependent on the considered language and domain. The general resolution process is as follows: The discourse phenomena are used to determine all anaphoras. In a second step, the discourse knowledge sources are applied in order to generate and filter all possible candidates. If only one remains, it will be chosen as antecedent. Otherwise, one or more orderers are applied and the best candidate will be chosen by order. If no candidate was found at all, the second strategy specified in the discourse phenomenon will be applied.

2.3.2 A Machine Learning-Based Resolver (MLR)

The machine learning-based resolver presented by Aone & Bennett (1995) used pairwise training examples containing information on the anaphora and its possible antecedent. A whole set of 66 features was used. Aone & Bennett (1995) divided most of them into one of four subcategories, namely lexical, syntactic, semantic, and positional. The feature selection inspired by the manually designed resolver (Aone & McKee 1993), but were generalized and changed in order to be domain- and language independent.

In total, six different classifiers depending on three parameters were trained. The first parameter was called anaphoric chain. If its value is true, a correct antecedent is detected if the candidate is part of the same anaphoric chains which means that both refer to the same real-world entity. Otherwise, just the preceding same-world entity will be accepted as correct antecedent. This parameter also affects the training instance generation. In case of anaphoric chains, all co-refering phrases will form positive training instances with its anaphora. In the other case, just the preceding co-refering phrase will be used for positive instances. In both cases, the remaining phrases will form negative training instances with the anaphora. The second parameter determines whether the decision tree will use further information of the anaphoric type (for instance whether the real-world entity of the anaphora is a proper name). A third parameter deter-

mines the pruning-factor of its decision tree. A high pruning-factor indicates a higher generalization while decision trees with a lower factor tend to overfit.

2.3.3 Evaluation

The comparison was evaluated on Japanese newspaper articles. In total, 1271 anaphoras were used. As it can be seen in Table 2.4, all machine learning approaches using anaphoric chains outperformed the manual approach independent of their pruning-factor, while the approach without the usage of anaphoric chains performed slightly worse. The different pruning factors seemed to have a rather low impact on the performance.

As the manually designed resolver also detects only the preceding same-world entity, it would be most reasonable to compare it to the MLR-6. Even though the manual approach performed better, no language specific information or relevance of features need to be determined as the algorithm learned it autonomously (Aone & Bennett 1995). Aone & Bennett (1995) interpreted the results as optimistic for machine learning techniques.

Table 2.4: Aone & Bennett Evaluation

Algorithm	Anaphoric Chains	Anaphoric Type	Confidence	F-measure
MLR-1	yes	no	100 %	76.27
MLR-2	yes	no	75 %	77.30
MLR-3	yes	no	50 %	76.43
MLR-4	yes	no	25 %	77.28
MLR-5	yes	yes	75 %	74.54
MLR-6	no	no	75 %	67.03

MDR	69.57

Chapter 3

Data

Most machine learning approaches require annotated corpora in order to make the learning process possible. In this case, the training corpora must contain information on the correct antecedent for each anaphora. Since this work is designed to learn gender information through frequencies, a second information source is needed. This chapter will briefly describe both information sources.

3.1 WikiCoref

Ghaddar & Langlais (2016) presented with WikiCoref a coreference-annotated corpus of english Wikipedia articles. Wikipedia differs from most web corpora as it is highly structured. The Wikipedia guidelines[1] contain various restrictions on grammar and vocabulary and also define the structure of articles in terms of sections and paragraphs. In contrast, most other web-mined sources are heavily unstructured and could contain colloquial language as well as ungrammatical text.
An excerpt of 30 articles was used to build the corpus. (Ghaddar & Langlais 2016) figured out that more than 35 % of all Wikipedia articles contain less than 100 words and only 11 % more than 1000 words. Articles with few word counts (less than 200 words) were not considered as they do not contain enough information for meaningful coreference resolution. Hence articles can not be chosen completely random, a uniform distribution of categorized article sizes leading from less than 1000 to more than 5000 words was strived. Additionally, articles with too many out links were not considered. In order to keep the corpus domain-independent, articles of different topics were selected.

To detect entities, a combination of a coreference resolution system, an entity detection module, and anchored links in the article was used. The coreference chains detected by the module were manually corrected and missing ones were added. All coreferring entities were linked through a joint identification number representing the real-world entity.

[1] https://en.wikipedia.org/wiki/Wikipedia:Manual_of_Style

[Aberfoyle]$_1$ is [a village in the region of Stirling, Scotland, northwest of [Glasgow]$_2$]$_1$.

[The town]$_1$ is situated on [the River Forth]$_3$ at the base of [Craigmore]$_4$ (420 metres high).

In total, the corpus contains 59652 tokens[2] in 2229 sentences with an average of 2000 tokens per document. For the inter-annotator agreement an MUC F1 score (Vilain et al. 1995) of 83,3 % was reported.

3.2 Gender Corpus

An automatic approach to learning gender information through corpus- and web-based frequencies was introduced by Bergsma (2005) and explained in Section 2.2.4 of this work. Bergsma & Lin (2006) pointed out two disadvantages of the previous approach. First of all, sending Google requests for each possible antecedent on large corpora is time-consuming and therefore not cost-efficient. Secondly, the corpus- and web-based implementations are not symmetric as some occurrences can only be found with the web-based approach. For instance, the corpus-based approach merely accepts a verb between a noun and a reflexive pronoun while the Google wildcard operator ("*") is not limited to any grammatical category. Therefore, a new corpus mined frequency distribution of gender and number information was mined using a corpus of approximately 85 GB. Overall, an accuracy of 90,3 % on gender determination was reported. Bergsma & Lin (2006) made the mined gender and number frequencies openly accessible for the NLP community.[3]

[2] "A token is an instance of a sequence of characters in some particular document that are grouped together as a useful semantic unit for processing." (http://nlp.stanford.edu/IR-book/html/htmledition/tokenization-1.html)

[3] Available for download at http://www.clsp.jhu.edu/~sbergsma/Gender/Data/

Chapter 4

Methodology

This chapter will present the whole procedure of the implemented anaphora resolution system with all of its stages. The complete system can also be examined online.[1]

4.1 Preprocessing

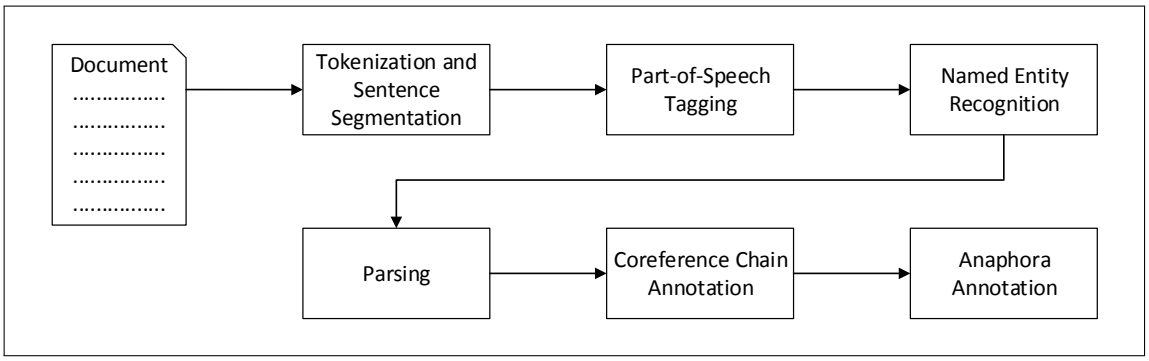


Figure 4.1: Natural language preprocessing pipeline

First of all, the required information of the training corpus needs to be extracted. The natural language preprocessing pipeline shown in Table 4.1 was used. The WikiCoref annotation scheme already includes information on tokens, sentences, and coreferential chains and could easily be extracted.

Still, several other information is missing in order to apply feature values (for instance, information on nominal phrases and part of speech). The *Stanford CoreNLP* toolset (Manning et al. 2014) was used to gain those informations. More precisely, its part-of-speech tagger, named entity recognizer, and parser were applied. A Part-of-Speech tagger annotates for each token a word class. Word classes are, for instance, nouns or verbs. Additionally, the tagger differentiates also on more specific details like number

[1]The download is available at https://github.com/HenryvanderVegte/henryvdv.BA

or tense. In total, the tagset contains 52 different tags (the whole tagset is shown in Appendix A.1). Note that the assigned labels for the part-of-speech tagger and the parser are simplified in the following examples in order to reduce its complexity. For instance, the implemented part-of-speech tagger will differentiate between singular and plural nouns while only the tag *noun* is used in the examples.
The named entity recognizer identifies amongst other entities persons, organizations, and dates.
An illustrative example of these elements is shown in Figure 4.2.

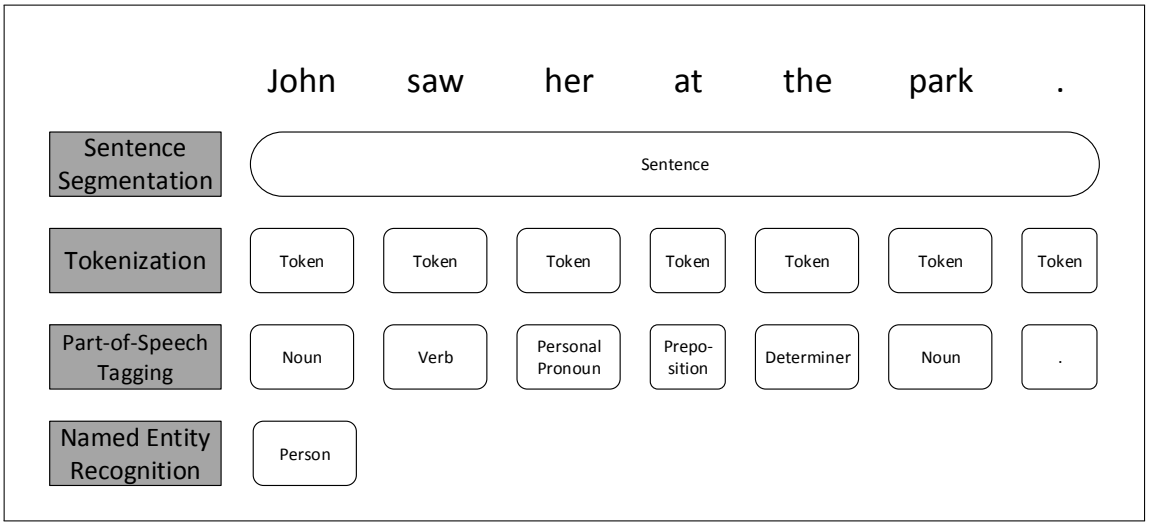


Figure 4.2: Annotation example

The Parser can be subdivided into two different modules named constituent parser and dependency parser.

The constituent parser divides the sentence into sub-phrases in a hierarchical order. The type of the phrase is defined by the central word in it (also called head word) (Jurafsky & Martin 2014). For instance, if the head word is a noun, the considered phrase is called noun-phrase. The most common kind of illustration is through a dependency parsed tree as shown in Figure 4.3.

The dependency parser describes the relationship of words among each other. A word that dependends on another is linked directed to it. Additionally, the relationship between both words is annotated. Most graphic representations visualize the relationship through pointed arrows based on the dependent word. An exemplary dependency parsed model is shown in Figure 4.4. The arrow description will thereby represent the type of the relationship. The abbreviations subj., mod., obj., and det. represent subjects, modifiers, object, and determiners. The starting point of the arrow is called the dependent while arrowhead points to its governor.

Note that the level of granularity of the used tags is reduced in the examples in order to

keep them as comprehensible as possible. For instance, the dependency tag "subject" is subdivided into clausal subject, clausal passive subject, nominal subject, and nominal passive subject. A whole list of all used constituency tags is given in Appendix A.2 and of all used dependency tags in Appendix A.3.

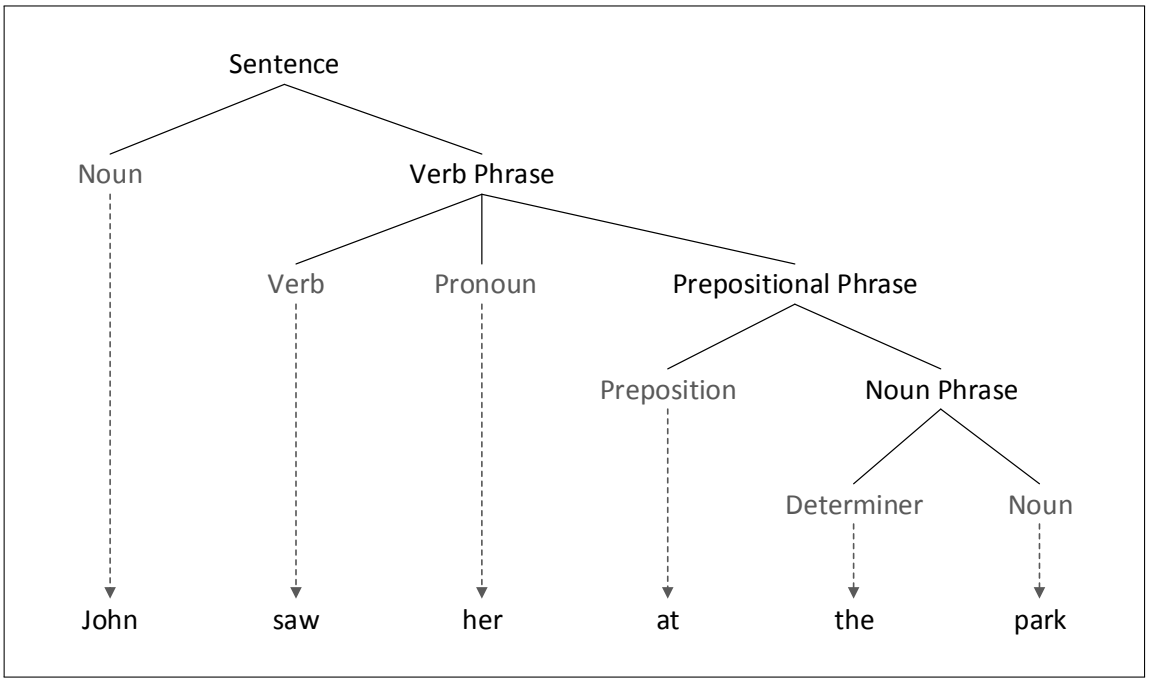


Figure 4.3: Simplified Constituency-parsed Tree

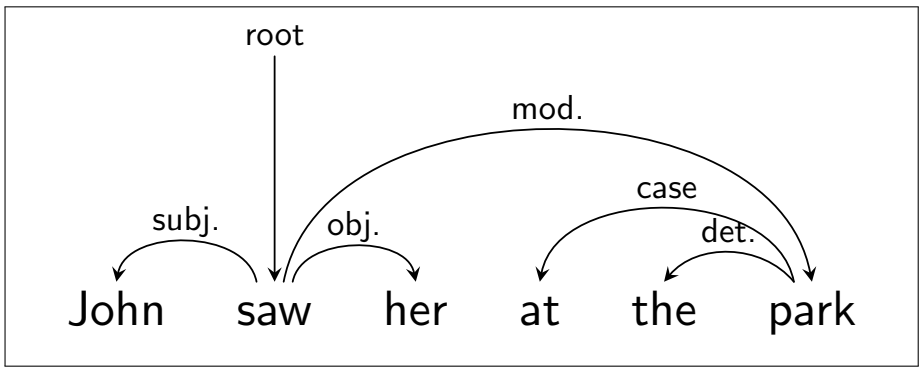


Figure 4.4: Dependency-parsed example

Coreferential information in WikiCoref is stored through a joint identification number for each coreferring annotation and can therefore be easily extracted. The third-person pronominal anaphoras were extracted of the coreference chain as follows: For each pronoun in the current document, search for the preceding phrase of its coreference chain. The pronoun will be tagged as the anaphora and the preceding phrase as the

antecedent.

As soon as all relevant information is annotated, a training set needs to be created. In order to do so, the procedure used by Soon et al. (2001) was adopted. As already stated in Section 2.2.1, all anaphoras and their respective antecedents form thereby positive feature vectors while all intermediate noun phrases form negative feature vectors with their corresponding anaphoras. For instance, a sequence of noun phrases A-B-C-D with A coreferring D and D as a pronoun is considered. In this case the pair (A,D) forms a positive instance while (C,D) and (B,D) form negative instances.
The idea of selecting that approach is as follows: A human would reject all intermediate noun phrases due to several indicators that exclude the candidate for some reason. In contrast, noun phrases earlier in the text than the antecedent could be legitimate candidates if the antecedent did not exist. In conclusion, a valid rejection of candidates preceding the antecedent is only possible if the antecedent is already detected. However, if the antecedent is already detected no further examination needs to be done. With the algorithm of Soon et al. (2001), 904 positive and 2846 negative feature vectors were created in total.

The anaphora set consists of 17 reflexives (herself, himself, themselves, itself), 379 nominatives (he, she, they), and 508 possessives (their, its, her, his). There are several ways of dealing with the pronoun *it* as it could either be referential or pleonastic (like the *it* in "it is raining"). Pronoun resolution systems either decide to manually exclude pleonastic pronouns (Kennedy & Boguraev 1996; Bergsma 2005), or to identify and filter them.The identification of pleonastic pronoun can be considered as a natural language processing task on its own with several different approaches, leading from machine learning (Boyd et al. 2005) to rule-based systems (Lappin & Leass 1994).
As the number of occurences of *it* is not decisive, it will be neglected in this work.

4.2 Feature Set

The whole feature set can be divided in four different categories. There are features that only affect the anaphora, features that only affect the antecedent, features that describe the relationship between both, and features that are related to gender information. A whole list of features is shown in Table 4.1. The features are mostly adopted by Bergsma (2005), however there are several different implementations especially in the gender features.

4.2.1 Pronoun Features

As the list of resolved pronouns is limited, a simple rule for each feature determines the gender values (for instance, if the pronoun is whether "he", "his", or "himself", it is

Table 4.1: Pronoun Resolution Feature Set

Feature Type	Feature	Description
Pronoun referred	Masculine	If pronoun is masculine: 1, else: 0
	Feminine	If pronoun is feminine: 1, else: 0
	Neutral	If pronoun is neutral: 1, else: 0
	Plural	If pronoun is plural: 1, else: 0
Antecedent referred	Antecedent Frequency	Number of occurrences / 10.0
	Subject	If antecedent contains subject: 1, else: 0
	Object	If antecedent contains object: 1, else: 0
	Predicate	If antecedent contains predicate: 1, else: 0
	Head-Word Emphasis	If antecedent parent is no noun: 1, else: 0
	Definite	If antecedent has definite article: 1, else: 0
	Pronominal	If antecedent contains pronoun: 1, else: 0
	Conjunction	If antecedent is not part of conjunction: 1, else: 0
	Prenominal Modifier	If antecedent contains prenominal modifier: 1, else: 0
	Organization	If antecedent contains organization: 1, else: 0
	Person	If antecedent contains person: 1, else: 0
	Time	If antecedent contains time units: 1, else: 0
	Date	If antecedent contains date: 1, else: 0
	Money	If antecedent contains monetary name: 1, else: 0
	Number	If the antecedent contains a number: 1, else: 0
	His/Her	If antecedents first word is his or her: 1, else: 0
	He/His	If antecedents first word is he or his: 1, else: 0
Pronoun and antecedent referred	Binding Theory	If binding principles B is satisfied: 1, else: 0
	Same Sentence	If both are in the same sentence: 1, else: 0
	Intra-Sentence Diff.	Difference in sentences / 50.0
	In Previous Sentence	If antecedent is in previous sentence: 1, else: 0
	Inter-Sentence Diff.	Difference in tokens / 50.0
	Prepositional Parallel	If both depend on the same preposition: 1, else: 0
	Quotation Situation	If both are in or out quotes: 1, else: 0
	Singular Match	If both are singular: 1, else: 0
	Plural Match	If both are plural: 1, else: 0
Gender referred	Standard Gender Match	If gender is known and matches: 1, else: 0
	Standard Gender Mismatch	If gender is known and mismatches: 1, else: 0
	Pronoun Mismatch	If both are pronouns and mismatch: 1, else: 0
	Masculine Mean	Mean μ of masculine distribution
	Masculine Std. Deviation	Std. deviation σ of masculine distribution
	Feminine Mean	Mean μ of feminine distribution
	Feminine Std. Deviation	Std. deviation σ of feminine distribution
	Neutral Mean	Mean μ of neutral distribution
	Neutral Std. Deviation	Std. deviation σ of neutral distribution
	Plural Mean	Mean μ of plural distribution
	Plural Std. Deviation	Std. deviation σ of plural distribution

considered as masculine).

4.2.2 Antecedent Features

The antecedent frequency is one of the few not binarized features. It is especially useful on Wikipedia articles, as they mostly address only a small amount of entities which are described in particular.
The information on grammatical relations for subject, object, and predicate features is gained through the dependency relationship of the covered words in the antecedent (Figure 4.4).
In order to get the Head-Word Emphasis feature value, the head noun needs to be identified (for instance, in the head noun of the phrase "the park" is "park" in Figure 4.3). In a second step, the part-of-speech tags were used to check if the parent word is a noun. Information on definite articles, pronouns, and conjunctions can be observed through the part-of-speech tags, too. The prenominal modifier value is observed through dependencies (an example for a modifier is also in Figure 4.4) and the part-of-speech tag of its governing word. The features from organization to number are derived through the named entity values of the named entity recognizer module (Figure 4.1). The last two features in this category are implemented through simple comparisons.

4.2.3 Pronoun-Antecedent Features

The most complex feature might be the binding theory implementation and needs therefore further explanation. The used principles of binding theory were formulated by Chomsky (1993). Principle A of binding theory is that an anaphora must be bound by an antecedent. Since the implemented pronoun resolution is based on that assumption, it does not need to be verified. In order to explain Principle B, three sentences will be considered:

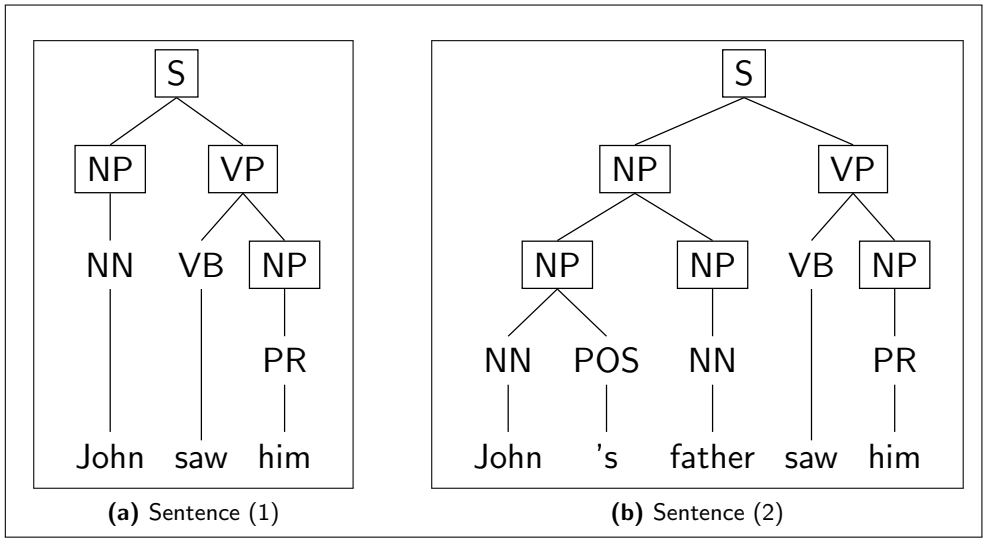
(1) John saw him.

(2) John's father saw him.

(3) John thinks that Peter saw him.

In (1) it is obvious, that the pronoun "him" cannot refer to John. Unlike that, (2) and (3) do not have that restriction. However, in (2) the pronoun cannot refer to "John's father". A simplified explanatory apporach would be, that "John" in (1) and "John's father" in (2) are not deep enough in the sentence structure to appear as antecedent. Therefore, the constituency trees of the sentences will be considered. Note that in the following visualizations (Figure 4.5) the framed words represent the phrase or sentence

level, while the not framed represent the part-of-speech tags. S stands for Sentence, NP for noun phrase, and VP for Verb Phrase. On part-of-speech level, NN means noun, VB verb, PR pronoun, and POS for a possessive ending.



(a) Sentence (1) **(b)** Sentence (2)

Figure 4.5: Constituency-parsed examples 1 and 2

As it can be seen in Figure 4.5, "John" is deeper buried in the sentence structure in (2) than in (1). This relationship can be expressed through c-commands. Its definition is: "α c-commands β if every node dominating α dominates β."[2] In (1) the node "John" c-commands the node "him, but not in (2). A first idea would be that a phrase that c-commands the anaphora cannot be the antecedent. That works for the first two sentences, but fails in the third one (Figure 4.6). The new Tags are SB for subordinating clauses with an introduction, S' for subordinating clauses, and IN for prepositions.

In this case "John" c-commands "him", but appears as a possible candidate. As the subordinating clause seems to have an impact on the c-command rules, another limitation called binding domain needs to be considered. The binding domain determines the parts of the sentence in which a candidate can be excluded if it c-commands the anaphora. The binding domain is either defined as the smallest clause containing the anaphora, or the smallest clause containing the anaphora and a noun phrase that c-commands the anaphora. The former definition is chosen if the anaphora is the subject of a clause.

Finally, Principle B can be defined as: An antecedent candidate can be excluded if it c-commands the anaphora and if it is located in its binding domain.

Principle C defines the handling of R-expressions. Those are noun phrases that are neither anaphoras nor pronouns (Crystal 2011). For instance, names fall into that category. An example of an r-expression would be the "John" in "He saw John". "He"

[2] http://web.mit.edu/norvin/www/24.902/binding.html

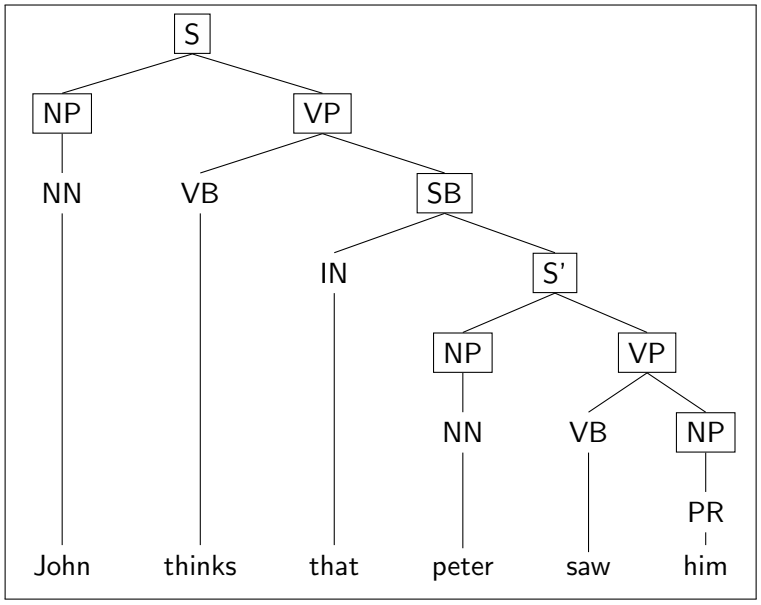


Figure 4.6: Constituency-parsed example 3

and "John" cannot corefer, even though principle B is satisfied. Therefore, Principle C is defined as: "R-expressions must be free" (Chomsky 1993), or formulated differently: A corefering phrase is not allowed to c-command the r-expression. Principle C was implemented in this work, even though it might make a great difference as no cataphoras are detected by the implemented system.[3]

The next features that need further explanation are the singular and plural match implementations. The information on whether the pronoun is singular or plural is gained easily as the pronoun is considered as plural if it is "their","they", or "themselves". The information on the antecedent is gained through its part-of-speech tag, as the used tags (Appendix A.1) contain information on singular or plural.

4.2.4 Gender Features

The standard gender match or mismatch is detected through explicit surface clues. A noun phrase is considered as male or female if it contains a gender indicating designator like "Mr." or "Mrs.". A list of english honorifics was used to find those.[4] A second surface hint on gender agreement is if both are or contain pronouns of the same category (masculine, feminine, neutral, or plural). Finally, corpus mined gender frequencies were assigned. The procedure is similar to the in Section 3.2 described approach of Bergsma

[3]Cataphoras are cases in which the referring noun stands is further in the text than its pronoun. For instance, in "When he saw him, John smiled" (Cutting et al. 2005, p. 10)

[4]The used list is available at: http://self.gutenberg.org/articles/English_honorifics

(2005) but with the corpus frequencies presented by Bergsma & Lin (2006). For instance, the α value for a masculine distribution would be the count of all masculine occurences of the noun plus one and its β would be the count of all times the noun occured with any other gender plus one. The mean and standard deviation values are calculated as it is decribed in Section 3.2.

4.3 Baseline Approach

The implemented baseline system detects always the previous noun phrase as the correct antecedent. Similar anaphora resolution systems also used this technique (Poesio & Kabadjov 2004; Bergsma 2005).

4.4 Machine learning-based Classifiers

Several Support Vector Machine (SVM) classifiers were build in order to determine the influence of specific features or groups. The used implementation is SVM$^{\text{light}}$ with a linear kernel (Joachims 1999). The anaphora resolution algorithm is as follows: for each anaphora, the preceding noun phrases will be searched successively, beginning with the nearest. If no accepted noun phrase is found in the current and the previous sentence, the algorithm will terminate and assign a False Negative (FN) value for this anaphora. This means, that the algorithm assumes that the correct antecedent was falsely identified as wrong and therefore missed. This approach is different to Bergsma (2005), as it does not lower the threshold for acceptance until a matching antecedent is found. Even though the implementation of Bergsma (2005) will increase the accuracy of the system (because the correct antecedent can be found in the initially neglected candidates while the implementation in this work cannot find those), it might distort the results. The pronoun resolution should rather aim for finding the correct antecedent in the regarded candidates.
The chosen sentence distance is motivated by a look in the data. Approximately 97.4 % of all considered antecedents could be found in the same or previous sentence of the anaphora.

Chapter 5

Evaluation

This chapter will present different performance measures and comparing evaluations in order to draw an appropriate conclusion. Additionally, a closer look at the errors made by the implemented system will give a hint on possible improvements.

5.1 Results

A precision measure indicates in how many percent of all cases the classifier identified the correct antecedent relative to the sum of all correct identified and falsely neglected antecedents. A recall measure indicates the amount of all correct identified cases relative to all identified cases. The F-measure is a balanced mean of both values.

The baseline achieved an accuracy of 26 %, just like what Bergsma (2005) reported as baseline on the American National Corpus (Ide & Macleod 2001). Calculating the precision is not useful in this case as the baseline does not neglect any cases. Therefore, the precision would always be 100 %. The recall measure is identical to the accuracy in that case.

Table 5.1: Pronoun Resolution Performance Scores

Method	Accuracy	Precision	Recall	F-measure
SVM Classifier (without corpus gender)	61.9 %	95.8 %	63.6 %	76.5 %
SVM Classifier (with corpus gender frequencies)	63.4 %	92.6 %	66.8 %	77.6 %
SVM Classifier (with corpus gender constraints)	64 %	92.6 %	67.4 %	78 %

Table 5.1 shows the results of the SVM classifiers. All results were calculated with a 10-fold-crossvalidation on all 30 documents. The whole resolution system with all features received an F-measure of 76.5 % and an accuracy of 61.9 % which is more than twice as much as the baseline accuracy, indicating the clear benefit of the implemented system. A comparison with other anaphora resolution systems is only partially reasonable since different data sets and implementations were used. Still, the high precision

rule-based approach presentend by Baldwin (1997) in Section 2.1.2 received similar precision and recall measures on the MUC-6 data set (Grishman & Sundheim 1996). The in Section 2.3.3 described approach by Aone & Bennett (1995) achieved an F-measure of approximately 77 % for their best machine-learned classifiers on Japanese newspaper articles.

Bergsma (2005) received with a similar approach an accuracy of 73.3 %. The inferiority of the implemented system could be explained through various reasons.
First of all, a slightly greater feature set was used by Bergsma. Secondly, the implemented approach uses only corpus mined gender information, while Bergsma (2005) also counts web occurrences through Google requests. Since a corpus can't cover extremely sparse events, Google might give information on those. Thirdly, Bergsma's implementation lowered the threshold if no accepted antecedent was found in the current and last sentence, while the implemented system in this work accepts none in that case. Therefore, the approach of Bergsma (2005) was also implemented in this work. A slight increase in accuracy of 1.4 % (to a total of 63.3 %) was recorded.

The corpus mined gender frequencies had only a slight impact on the classifiers performance, but caused an increased accuracy and F-measure. In order to associate the increase to the gender frequencies, a third classifier was build. It used the whole feature set except for the gender means and standard deviations. Four new variables were added instead. Each variable represents a gender. The corpus frequencies were used to determine the most frequent gender of an antecedent candidate. The variable representing the most frequent outcome was set to one while the others were set to zero. For instance, *Peter* was found 4479 times masculine, 76 times feminine, 81 times neutral, and 120 times plural. Since 4479 is the highest, the new variable representing the masculine gender will be set to one while all other new variables will be set to zero. This hard constraint implementation performed slightly better than the classifier using gender frequencies.

In order to explain that results, an error analysis on six random chosen documents was done.

5.2 Error Analysis

The errors made by the anaphora resolution system can be divided into six different categories (Table 5.2).

The most frequent error was that the an instance of the requested anaphora was found, but not the nearest. For instance, in Figure 5.1 *Kirk* was detected while *minister of Aberfoyle parish* was the correct antecedent. However, both refer to the same real-world entity. Since a classifier detecting another noun phrase representing the same real-world entity is only partially wrong, the impact on the performance score of this error might

Table 5.2: Types and frequencies of errors

Type	Frequency	Percentage
Another previous instance detected	15	30.6 %
Wrong antecedent	10	20.4 %
Gender mismatch	8	16.3 %
No accepted antecedent	7	14.3 %
Wrong bound	6	12.2 %
Other	3	8.1 %

also be relevant. Therefore, a seperate SVM classifier with corpus gender frequencies was build which also accepts previous real-world entities as the correct antecedent. This information was derived through coreference chains (pictured in Figure 4.1). A 10-fold crossvalidation yielded an accuracy increase of 5.1 %.

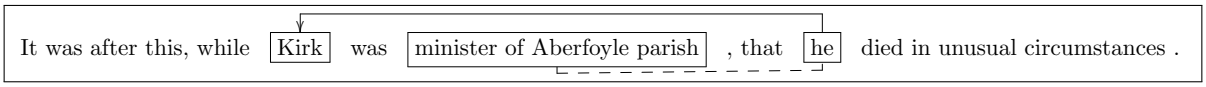


Figure 5.1: Previous instance error example

In 10 of 49 cases, a wrong antecedent that does not explicitly disagree in gender was detected. Figure 5.2 shows an example of this case: *they* referred to *the French* but *The Swedes* was detected instead.

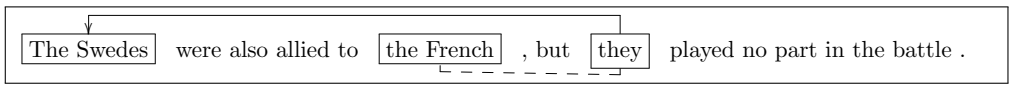


Figure 5.2: Wrong antecedent error example

Figure 5.3 shows a case in which the system clearly identified an noun phrase of the wrong gender. The corpus mined gender frequencies indicating a μ of approximately 90.5 % for *Sarah* to be female while its masculine μ was only 2.4 %.

No accepted antecedent means that the classifier has searched backwards through the current and previous sentence and none of the examined noun phrases has been detected as the antecedent. In four of those cases the antecedent was more than one sentence distant and therefore no correct antecedent could be found by the algorithm.

A wrong bound means that the correct antecedent might be detected, but not exactly as the annotation scheme expected:

> Sarah Eldridge's son-in-law John Tizard inherited her share of the business, and when he died in 1871 the Popes assumed full control.

In the example above, *Sarah Eldridge's son-in-law John Tizard* was labelled as the

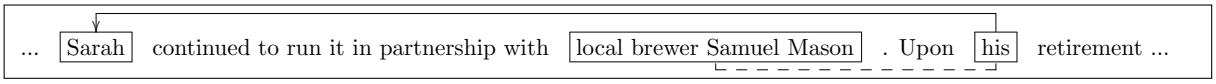


Figure 5.3: Gender mismatch example

correct antecedent for the pronoun *he* while the system detected *Sarah Eldridge's son-in-law*. One could argue that the system nonetheless detected the correct phrase. However, in some cases another span might change the complete meaning of the phrase. For instance, if the detected noun phrase is *Gonzales 's musical style* and the correct antecedent is *Gonzales's*.

The least frequent category of errors includes all remaining error types caused by parsing errors, other noise, or unclear bindings. For instance, *their* in Figure 5.4 could either refer to *Their commanders* or *the Swedish troops*

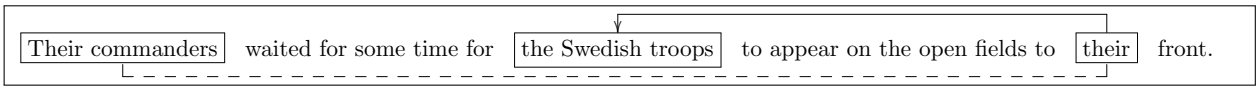


Figure 5.4: Ambiguity example

Chapter 6

Conclusion

In this thesis, three different implementations of machine-learning based classifiers using Support Vector Machines (SVM) for pronominal anaphora resolution were presented in order to determine the influence of corpus mined gender frequencies. This section will first of all summarize the implemented systems, followed by a discussion of the results and explanatory approaches. Finally, the last section will describe what could be done in future work and how the system could exert influence on other domains and scopes.

6.1 Summary

This work presented a pronominal anaphora resolution system using various information sources including syntactic, semantic, and corpus mined gender knowledge. A preprocessing pipeline including part-of-speech tagging, named entity recognition, constituency parsing, and dependency parsing was implemented in order to gain relevant information for feature assignment. In total, a feature set of 33 features was used (excluding gender probability features). Various implementations were done. First of all, a baseline system that assigns always the most recent noun phrase as antecedent was implemented. The first SVM classifier without usage of corpus mined gender information outperformed the baseline approach by far, indicating a clear benefit of machine learning in anaphora resolution.

A first improvement consisted in using corpus mined gender probabilities for the antecedent candidates. Therefore, eight new features were added. The gender information was expressed through the mean and standard deviation of the *Beta* distribution for each gender. The performance increased slightly.

Another classifier was build using the same gender corpus frequencies, but assigning only the most frequent gender outcome as the correct gender for each considered noun. Four new features were added, one for each gender. This approach outperformed both previous implementations marginal.

Conspicious thereby is that both implementations using corpus mined gender informa-

tion impaired its precision but increased its recall in comparison to the initial classifier.

Corpus mined gender information seems to improve anaphora resolution on Wikipedia articles, yet the gain of 10 % in performance Bergsma (2005) reported through corpus mined frequencies could not be replicated. Additionally, the hard constraint gender implementation seems to have a higher impact on the classifier than the frequencies. Therefore, the hypothesis presented in the introduction (Section 1.2) can only be partially confirmed.

6.2 Discussion

The reported results depend on many factors. First of all, Wikipedia articles are a very specific domain. The article guidelines described in Section 3.1 aim for a high structure, implying as less ambiguity as possible. Wikipedia articles often focus on a single entity, which is mostly referred through pronouns. Therefore, cases with gender ambiguity in which the corpus mined frequencies give useful hints might be sparse. The error analysis indicated that a gender mismatch is accountable for approximately 16 % of all errors. Kennedy & Boguraev (1996) associated 35 % of their pronoun resolution errors on various texts (including inter alia news stories and magazine articles) to a mismatching gender. Since this work used different approaches and measures, a comparison is limited in its validity. Still, it might give a hint that gender mismatch is a lesser source of error in Wikipedia (for instance, it might be more likely to find those occurrences in dialogue). Secondly, the implementation strategy differs from Bergsma (2005) since no web mining frequencies were used. Although Bergsma & Lin (2006) indicated that the frequency distribution used in this approach performed only slightly worse than their previous corpus- and web mined frequencies (Bergsma 2005), it might influence the performance of the implemented classifier.
Additionally, Bergsma (2005) split the corpus and web mined gender frequencies respectively in five categories. Therefore, the classifier had also the possibility to learn whether a word occurs with a reflexive, possessive, nominative, predicate, or designator (a further description is located in Section 2.2.4). Not only the gender, but also in which case a noun occurs with a specific gender might have an impact on pronoun resolution.

The quality of preprocessing also affects the results, as parsing errors or falsely linked antecedents are unavoidable on huge corpora. In pronoun resolution some ambiguity might result of cases in which no clearly identifiable antecedent exists or multiple candidates are equally likely.

Another impact on performance measures are cases in which world knowledge is required. For finding all antecedents, the algorithm needs to draw conclusions and recognize contextual relationships. Baldwin (1997) considered anaphora resolution as an "A.I. complete" task, meaning that the creation of a flawless anaphora resolution sys-

tem requires a generally intelligent computer (Shapiro 1992). The Winograd Schema Challenge[1] is a test of artificial intelligence which adresses those hard cases. The participating systems need to identify the correct antecedent for a pronominal anaphora. The antecedent candidates share the same semantic class which makes the identification challenging. For instance, a question in the challenge might be:

> The cat tried to climb in the box but got stuck because it was too big.
> What was too big?[2]

The pronoun *it* could either refer to *The cat* or *the box*. The identification of the correct antecedent requires background information on sizes ("if A is in B, then B is bigger") and additionally needs to identify that "but got stuck" indicates that the cat was too big. The implemented algorithm will most likely fail to identify the correct antecedent in those cases since it does not provide any kind of world knowledge.

6.3 Outlook

What can/has to be/may be done in future research? Impact on other branches of science? society?

[1] A detailed description is available at http://www.nuance.com/company/news-room/press-releases/Winograd-Schema-Challenge.docx

[2] The example was taken from https://artistdetective.wordpress.com/

Appendix

A Appendix

Table A.1: Part-of-Speech Tagset

Number	Tag	Description
1.	CC	Coordinating conjunction
2.	CD	Cardinal number
3.	DT	Determiner
4.	EX	Existential there
5.	FW	Foreign word
6.	IN	Preposition or subordinating conjunction
7.	JJ	Adjective
8.	JJR	Adjective, comparative
9.	JJS	Adjective, superlative
10.	LS	List item marker
11.	MD	Modal
12.	NN	Noun, singular or mass
13.	NNS	Noun, plural
14.	NNP	Proper noun, singular
15.	NNPS	Proper noun, plural
16.	PDT	Predeterminer
17.	POS	Possessive ending
18.	PRP	Personal pronoun
19.	PRP	Possessive pronoun
20.	RB	Adverb
21.	RBR	Adverb, comparative
22.	RBS	Adverb, superlative
23.	RP	Particle
24.	SYM	Symbol
25.	TO	to
26.	UH	Interjection
27.	VB	Verb, base form
28.	VBD	Verb, past tense
29.	VBG	Verb, gerund or present participle
30.	VBN	Verb, past participle
31.	VBP	Verb, non-3rd person singular present
32.	VBZ	Verb, 3rd person singular present
33.	WDT	Wh-determiner
34.	WP	Wh-pronoun

Table A.2: Constituency Tagset

Number	Tag	Description
1.	ADJP	Adjective Phrase
2.	ADVP	Adverb Phrase
3.	CONJP	Conjunction Phrase
4.	FRAG	Fragment
5.	INTJ	Interjection
6.	LST	List marker
7.	NAC	Not a Constituent
8.	NP	Noun Phrase
9.	NX	Used within certain complex NPs to mark the head of the NP
10.	PP	Prepositional Phrase
11.	PRN	Parenthetical
12.	PRT	Particle
13.	QP	Quantifier Phrase
14.	RRC	Reduced Relative Clause
15.	UCP	Unlike Coordinated Phrase
16.	VP	Verb Phrase
17.	WHADJP	Wh-adjective Phrase
18.	WHAVP	Wh-adverb Phrase
19.	WHNP	Wh-noun Phrase
20.	WHPP	Wh-prepositional Phrase
20.	X	Unknown, uncertain, or unbracketable
21.	S	Simple Declarative Clause
22.	SBAR	Clause introduced by a subordinating conjunction
23.	SBARQ	Direct question introduced by a wh-word or a wh-phrase
24.	SINV	Inverted declarative sentence
25.	SQ	Inverted Yes/No Question, or Main Clause of a Wh-question

Table A.3: Dependency Tagset

Number	Tag	Description
1.	acl	clausal modifier of noun (adjectival clause)
2.	advcl	adverbial clause modifier
3.	advmod	adverbial modifier
4.	amod	adjectival modifier
5.	appos	appositional modifier
6.	aux	auxiliary
7.	auxpass	passive auxiliary
8.	case	case marking
9.	cc	coordinating conjunction
10.	ccomp	clausal complement
11.	compound	compound
12.	conj	conjunct
13.	cop	copula
14.	csubj	clausal subject
15.	csubjpass	clausal passive subject
16.	dep	unspecified dependency
17.	det	determiner
18.	discourse	discourse element
19.	dislocated	dislocated elements
20.	dobj	direct object
21.	expl	expletive
22.	foreign	foreign words
23.	goeswith	goes with
24.	iobj	indirect object
25.	list	list
26.	mark	marker
27.	mwe	multi-word expression
28.	name	name
29.	neg	negation modifier
30.	nmod	nominal modifier
31.	nsubj	nominal subject
32.	nsubjpass	passive nominal subject
33.	nummod	numeric modifier
34.	parataxis	parataxis
35.	punct	punctuation
36.	remnant	remnant in ellipsis
37.	root	root
38.	vocative	vocative
39.	xcomp	open clausal complement

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