Bachelorthesis

Improving Anaphora Resolution Through Corpus Mined Gender Information

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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.

Duisburg, im November 1492

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Jan Henry van der Vegte

Contents

1 Introduction **1**
- 1.1 Background . . . 1
- 1.2 Motivation . . . 2

2 Related Work **4**
- 2.1 Rule-based techniques . . . 4
  - 2.1.1 Limited knowledge anaphora resolution . . . 4
  - 2.1.2 CogNIAC . . . 5
  - 2.1.3 Hobbs algorithm . . . 6
- 2.2 Machine learning-based techniques . . . 6
  - 2.2.1 Anaphors in coreference resolution . . . 6
  - 2.2.2 Bergsma . . . 7

3 Concept **8**

4 Implementation **9**

5 Evaluation **10**

6 Conclusion **11**
- 6.1 Summary . . . 11
- 6.2 Outlook . . . 11

List of Figures **iii**

List of Tables **iv**

Listings **v**

References **vi**

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 need 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.

The procedure of determining whether two expressions refer to each other, meaning that they are instances of the same entity, is called anaphora resolution. The word to be resolved is termed anaphora, while its predecessor is the antecedent. It differs from coreference resolution by only resolving words, which can only be interpreted through its antecedent (Recasens et al. 2007) (1), while all corefering expressions are considered in coreference resolution (2).

(1) [Aberfoyle] describes [itself] as [The Gateway to [the Trossachs]].
(resolve ”itself” to ”Aberfoyle”)

(2) As late as 1790, all the residents in the parish of [Aberfoyle] spoke [Scottish Gaelic]. From 1882 [the village] was served by [Aberfoyle railway station].
(resolve ”the village” to ”Aberfoyle”)

Resolving noun phrases is a growing task in Natural Language Processing (NLP) and increased its relevance in the last decades, that it has even developed into a standalone subtask in the DARPA Message Understanding Conference in 1995 (MUC-6 1995). The International Workshop on Semantic Evaluation (SemEval) ran a coreference resolution task on multiple languages (Recasens et al. 2010), emphasizing the importance of coreference resolution systems. There are several important applications of coreference and anaphora resolution, such as Information Extraction (IE) (McCarthy & Lehnert 1995), Question Answering (QA) (Morton 2000), and Summarization (Steinberger et al. 2007). Information Extraction has set itself the objective of summarizing relevant information

from documents. Anaphora resolution is needed, because the sought entity is often referenced through different words (for instance personal pronouns). McCarthy and Lehnert described it as a classification problem: ”given two references, do they refer to the same object or different objects.”
The Question Answering task described by Morton has the goal to find a 250 byte string excerpt out of a number of documents as the answer to a query. Annotated coreference chains were used to link all instances of the same entity in a document. Occurrences in an other sentence are given a lower weight for prediction. The use of annotated coreference chains improved the prediction slightly.
Steinberger et al. figured out that the additional use of anaphoric information improved their performance score over solely Latent Semantic Analysis (LSA) summarization.

A lot of different information sources including syntactic, semantic, and pragmatic knowledge is needed since selecting a possible antecedent is a decision under high ambiguity. The decisive factor for determination might be for instance gender agreement or the distance between antecedent and anaphora. Sometimes there is no decisive factor at all. Examples for the importance of gender agreement are shown in (3) and (4), the influence of word distance could simplified be described as it is more likely to find the antecedent in proximity to its anaphora.

(3) John and Jill had a date, but he didn’t come. (resolve ”he” to ”John”).

(4) John and Jill had a date, but she didn’t come. (resolve ”she” to ”Jill”).

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. 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 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 - the distribution will be smoothed to avoid 0-probabilities). In 2005, Bergsma obtained encouraging results with the use of gender probabilities. More precisely, adding corpus mined gender frequencies improved their accuracy by approximately 10 %.

In this work i will present a machine learning approach to anaphora resolution, focusing on third-person pronominal anaphors. The two main purposes are to determine the impact of gender probability and to compare it to gender information treated as hard constraint. First of all, it should be evaluated whether the improvement through gender frequencies can be replicated on different data sets. 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.

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establish your territory (say what the topic is about) and/or niche (show why there needs to be further research on your topic) shortly introduce your research/what you will do in your thesis (make hypotheses; state the research questions)

Chapter 2

Related Work

Anaphora resolution systems emerged into two different strategies. The first one are rule-based techniques, which focus more on theoretical considerations. The second strategy uses machine learning and is based on annotated data. In the following chapter i will briefly present both and discuss their advantages and disadvantages, followed by exemplary realisations.

2.1 Rule-based techniques

Rule-based techniques rely on human understandment of syntactic and semantic principles of natural language. Clues that could be helpful for identifying the antecedent 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.

2.1.1 Limited knowledge anaphora resolution

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. The algorithm was informally desribed by Mitkov in three steps:

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

2. Select from the noun phrases identified only those which agree in gender and number with the pronominal anaphor 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

Antecedent indicators are for instance Definiteness (whether the noun phrase contains a definite article) or ”Non-prepositional” noun phrases (whether the noun phrase is part of a prepositional phrase). A positive indicator score increases the likelihood that the selected noun phrase is the antecedent and vice versa.

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. 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.

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 anaphor 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 anaphor 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 anaphor is the subject of the current sentence, then pick i as the antecedent

2.1.3 Hobbs algorithm

The Hobbs algorithm described by (Hobbs 1978) relies on parsed syntax trees containing the grammatical structure. Simply put, 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. As long as no matching antecedent is found, the preceding sentence will be searched.

2.2 Machine learning-based techniques

In most machine learning-based techniques, principles are learned 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. In machine learning, tend to have little information on linguistic principles, as the algorithm should learn autonomously. This causes the algorithm to be less domain specific, but increases the risk to miss relevant clues. However, top-performing machine learning approaches achieve accuracy scores comparable to state-of-the-art non-learning techniques (Soon et al. 2001).
Additionally, machine learning algorithms are usually more time-consuming due to the learning process.

2.2.1 Anaphors in coreference resolution

In coreference resolution all noun phrases referring to the same entity in the real world are linked. 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. Pronominal anaphors are included and can be extracted by choosing the previous entity of the same coreference chain. A coreference resolution system proposed by (Soon et al. 2001) used a feature set of 12 different features. 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). To specify most of the features, several pre-processing steps, such as noun phrase identification and part-of-speech tagging, need to be executed. For instance, sentence segmentation is required to determine the sentence distance. To derive gender information of a noun, information of their semantic classes is needed. Soon et al. assumed, 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 can be 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. 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.

(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 coreference likelihood. The majority of the new features are based on syntactical principles. For instance, binding constraints must be fulfilled and one phrase is not allowed 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 F1-measure compared to the initial approach by (Soon et al. 2001).

2.2.2 Bergsma

provide background information needed to understand your thesis assures your readers that you are familiar with the important research that has been carried out in your area establishes your research w.r.t. research in your field

e.g.

- conceptual framework
- structured overview on comparable approaches
- different perspectives on your topic

a

Chapter 3

Concept

Chapter 4

Implementation

Chapter 5

Evaluation

Chapter 6

Conclusion

6.1 Summary

What was done? What was learnt?

6.2 Outlook

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

Appendix

References

List of Figures

List of Tables

2.1 CogNIAC core rules 5

Listings

References

Baldwin, B. (1997). Cogniac: high precision coreference with limited knowledge and linguistic resources. In *Proceedings of a workshop on operational factors in practical, robust anaphora resolution for unrestricted texts* (pp. 38–45).

Bergsma, S. (2005). Automatic acquisition of gender information for anaphora resolution. In *Conference of the canadian society for computational studies of intelligence* (pp. 342–353).

Evans, R., & Orasan, C. (2000). Improving anaphora resolution by identifying animate entities in texts. In *Proceedings of the discourse anaphora and reference resolution conference (daarc2000)* (pp. 154–162).

Hobbs, J. R. (1978). Resolving pronoun references. *Lingua*, *44*(4), 311–338.

McCarthy, J. F., & Lehnert, W. G. (1995). Using decision trees for coreference resolution. *arXiv preprint cmp-lg/9505043*.

Mitkov, R. (1998). Robust pronoun resolution with limited knowledge. In *Proceedings of the 36th annual meeting of the association for computational linguistics and 17th international conference on computational linguistics-volume 2* (pp. 869–875).

Morton, T. S. (2000). Coreference for nlp applications. In *Proceedings of the 38th annual meeting on association for computational linguistics* (pp. 173–180).

Ng, V., & Cardie, C. (2002). Improving machine learning approaches to coreference resolution. In *Proceedings of the 40th annual meeting on association for computational linguistics* (pp. 104–111).

Recasens, M., Màrquez, L., Sapena, E., Martí, M. A., Taulé, M., Hoste, V., ... Versley, Y. (2010). Semeval-2010 task 1: Coreference resolution in multiple languages. In *Proceedings of the 5th international workshop on semantic evaluation* (pp. 1–8).

Recasens, M., Marti, M. A., & Taulé, M. (2007). Where anaphora and coreference meet. annotation in the spanish cess-ece corpus. In *Proceedings of ranlp.*

Soon, W. M., Ng, H. T., & Lim, D. C. Y. (2001). A machine learning approach to coreference resolution of noun phrases. *Computational linguistics*, *27*(4), 521–544.

Steinberger, J., Poesio, M., Kabadjov, M. A., & Ježek, K. (2007). Two uses of anaphora resolution in summarization. *Information Processing & Management*, *43*(6), 1663–1680.