Corry: A System for Coreference Resolution

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Abstract

Corry is a system for coreference resolution in English. It supports both local (Soon et al. (2001)-style) and global (Integer Linear Programming, Denis and Baldridge (2007)-style) models of coreference. Corry relies on a rich linguistically motivated feature set, which has, however, been manually reduced to 64 features for efficiency reasons. Three runs have been submitted for the SemEval task 1 on Coreference Resolution, optimizing Corry’s performance for BLANC, MUC and CEAF. The runs differ with respect to the model (local for BLANC, global for MUC and CEAF) and the definition of mention types.

1 Introduction

Corry is a system for coreference resolution in English. It supports both local (Soon et al. (2001)-style) and global (ILP, Denis and Baldridge (2007)-style) models of coreference. The backbone of the system is a family of SVM classifiers for pairs of mentions: each mention type receives its own classifier. A separate anaphoricity classifier is learned for the ILP setting. Corry relies on a rich linguistically motivated feature set, which has, however, been manually reduced to 64 features for efficiency reasons.

Corry has only participated in the “open” setting, as it has already a number of preprocessing modules integrated into the system: the Stanford NLP toolkit for parsing (Klein and Manning, 2003) and NE-tagging (Finkel et al., 2005), Wordnet for semantic classes and the U.S. census data for assigning gender values to person names.

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2 Preprocessing and Mention Extraction

In our previous study (Uryupina, 2008) we have shown that up to 35% recall and 20% precision errors in coreference resolution for MUC corpora are due to inaccurate mention detection. We have therefore invested substantial efforts into our mention detection module.

Most state-of-the-art coreference resolution systems operate either on gold markables or on the output of an ACE-style mention detection module. We are not aware of extensive studies on mention extraction algorithms for such datasets as SemEval (OntoNotes) where mentions are complex NPs not constrained with respect to their semantic types.

We rely on the Stanford NLP toolkit for extracting named entities (Finkel et al., 2005) and parse trees for each sentence (Klein and Manning, 2003). We then merge the output of the NE-tagger and the parser to create a list of mentions in the following way:

1. Named entities are considered mentions if they correspond to a sequence of parsing constraints.
2. Pronouns are considered mentions if they are not a part of an NE-mention.
3. NPs are considered “candidate mentions” if they are not a part of an NE-mention. The set of
candidate mentions is then filtered to eliminate pairs of NPs with the same head noun (coordinate NPs receive unique artificial heads). For possessive NPs we adjust the boundaries and the head to exclude the “’s” token. The remaining candidates are aligned with NE-mentions—if an NE and an NP have the same last word, they are considered the same mention of a special type. Finally, the list of candidates is optionally filtered using a small stop-list (for example, all the “there” NPs in “There is ..” are discarded).

We rely on the Stanford NLP toolkit, WordNet and the U.S. census data to assign numerous properties to our mentions: semantic type, number, gender and others.

3 Features

Corry relies on two SVM\(^1\) classifiers for coreference and anaphoricity. The former determines whether two given mentions \(M_i\) and \(M_j\) are coreferent or not. The latter determines whether a given mention \(M_i\) is anaphoric or discourse new. In Section 4 we show how these classifiers help us build coreference chains. We use the SVM-Light package (Joachims, 1999) for learning our classifiers.

The strength of our system lies in its rich feature set for the coreference classifier. In our previous studies (Uryupina, 2006; 2007) we have tested up to 351 nominal/continuous (1096 boolean/continuous) features showing significant improvements over basic feature sets advocated in the literature. For the SemEval task 1, we have reduced our rich feature set to 64 nominal/continuous features for efficiency reasons: on the one hand, our new set is large enough to cover complex linguistic patterns of coreference, on the other hand, it allows us to test different settings and investigate possibilities for global modeling.

Our anaphoricity classifier is used by the ILP model. It relies on 26 boolean/continuous features. More details on the classifier itself can be found in (Uryupina, 2003).

\(^1\)Corry supports a number of machine learning algorithms: C4.5, TiMBL, Ripper, MaxEnt and SVM. See Uryupina (2006) for a comparison of Corry’s performance with different learners.

4 Modeling

Corry supports both global and local views of coreference. Our evaluation experiments (cf. Section 5) show that the choice of a particular model should be motivated by the desired scoring metric.

Our local model of coreference is a reimplementation of the algorithm, proposed by Soon et al. (2001) with an extended feature set. The core of Soon et al.’s (2001) approach is a link-based classifier: it determines whether a given pair of markables are coreferent or not. During testing, a greedy clustering algorithm (link-first) is next used to build coreference chains on the output of the classifier.

We have slightly extended this model to allow separate classifiers for different mention types: each candidate anaphor receives a type (e.g. “pronoun”) and is processed with a corresponding classifier. We, thus, rely on a family of classifiers, with the same feature set and the same machine learner. The exact definition of mention types is a parameter to be determined empirically on the development set.

Our global model is largely motivated by Denis and Baldridge (2007; 2008) and Finkel and Manning (2008). Following these studies, we use Integer Linear Programming to find the most globally optimal solution, given the decisions made by our coreference and anaphoricty classifiers.

In general, an ILP problem is determined by an objective function to be maximized (or minimized) and a set of task-specific constraints. The function is defined by costs \(\text{link}_{<i,j>}\), and \(\text{dnew}_j\) reflecting potential gains and losses for committing to specific variable assignments. We assume that costs can be positive (for pairs of markables that are likely to be coreferent) or negative (for pairs of markables that are unlikely to be coreferent). The costs are computed by an external module (such as a family of local classifiers described above). The objective function then takes the form:

\[
\text{max} \left( \sum_{<i,j>} \text{link}_{<i,j>} \ast L_{<i,j>} - \sum_j \text{dnew}_j \ast D_j \right)
\]

(1)

Binary variables \(L_{<i,j>}\) indicate that two markables \(M_i\) and \(M_j\) are coreferent in the output assignment. Binary variables \(D_j\) indicate that the markable \(M_j\) is considered anaphoric in the output assignment. The ILP solver thus assigns values to...
We refer the reader to the above-mentioned papers for detailed discussions of these constraints and their impact on coreference resolution. As we show in Section 5 below, the usability of a particular constraint should be determined experimentally based on the desired system behaviour.

5 Evaluation

5.1 Development

Corry has participated in the gold and regular open settings for English. We have collected a number of runs on the development data to optimize the performance level for a particular score: BLANC (Recasens and Hovy, in prep), MUC (Vilain et al., 1995) or CEAF (Luo, 2005). The runs differ with respect to the model (local vs. global with varying sets of constraints) and the definition of mention types. We deliberately left the B-CUBE score (Bagga and Baldwin, 1998) completely out of our preliminary experiments. The official SemEval scorer was used for these experiments.

Our experiments on the development set show that no configuration is able to produce equally reliable scores according to all the metrics (note, for example, that on the test set the BLANC difference between Corry-M and Corry-B in the gold setting is almost 10%). We believe that it is a challenging point for future research.

We have selected the best configurations for each score and submitted them as separate runs. The Corry-C system, optimized for CEAF-\(\phi_4\), is a global model with the \(L, D\) and \(A\) constraints. For the gold setting, mention types are defined as pronouns and non-pronouns. For the regular setting, the system distinguishes between “speech” pronouns, 3rd person pronouns, names and nominals.

Finally, Corry-B, optimized for BLANC, is a local model that distinguishes between pronouns, nominals and names. The fact that such a simple model is able to outperform much more complex versions of Corry strengthens the importance of feature engineering.

5.2 Testing

Table 1 shows the SemEval task 1 scores for the gold/regular open setting. Corry has shown reliable performance for both mention detection and coreference resolution. For mention detection, Corry’s F-score is 4% higher than the one of the competing approach. For coreference, all the Corry runs yielded the best performance level for a score under optimization.

Finally, for the B-CUBE metric that had not been optimized at all, Corry lost only marginally to the RelaxCor system in the gold setting and came first in the regular setting.

6 Conclusion

We have presented Corry – a system for coreference resolution in English. Our plans include extending it to cover multiple languages. However, as the main strength of Corry lies in its rich linguistically motivated feature set, this remains an issue.
Table 1: System scores for the gold/regular open setting. The best F-score for each metric shown in bold.

| Mention detection | CEAF | MUC | Bʼ | BLANC |
|-------------------|------|-----|----|-------|
|                   | R    | P   | F1 | R    | P   | F1 | R    | P   | F1 | R    | P   | F1 | R    | P   | F1 | Bʼ   | BLANC |
| Corry-B           | 100  | 100 | 77.5 | 77.5 | 56.1 | 57.5 | 56.8 | 82.6 | 85.7 | 84.1 | 69.3 | 75.3 | 71.8 |
| Corry-C           | 100  | 100 | 77.7 | 77.7 | 57.4 | 58.3 | 57.9 | 83.1 | 84.7 | 83.9 | 71.3 | 71.6 | 71.5 |
| Corry-M           | 100  | 100 | 73.8 | 73.8 | 62.5 | 56.2 | 59.2 | 85.5 | 78.6 | 81.9 | 76.2 | 58.8 | 62.7 |
| RelaxCor          | 100  | 100 | 75.8 | 75.8 | 72.6 | 70.5 | 34.2 | 75.2 | 96.7 | 84.6 | 58.0 | 83.8 | 62.7 |
| BART              | 76.1 | 69.8 | 72.8 | 70.1 | 64.3 | 67.1 | 62.8 | 52.4 | 57.1 | 74.9 | 67.7 | 71.1 | 55.3 | 73.2 | 57.7 |
| Corry-B           | 79.8 | 76.4 | 78.1 | 70.4 | 67.4 | 68.9 | 55.0 | 54.2 | 54.6 | 73.7 | 74.1 | 73.9 | 57.1 | 75.7 | 60.6 |
| Corry-C           | 79.8 | 76.4 | 78.1 | 70.9 | 67.9 | 69.4 | 54.7 | 55.5 | 55.1 | 73.8 | 73.1 | 73.5 | 57.4 | 63.8 | 59.4 |
| Corry-M           | 79.8 | 76.4 | 78.1 | 66.3 | 63.5 | 64.8 | 61.5 | 53.4 | 57.2 | 76.8 | 66.5 | 71.3 | 58.5 | 56.2 | 57.1 |

An important advantage of Corry is its flexibility: the system allows for a number of modeling solutions that can be tested on the development set to optimize the performance level for a particular objective. Our SemEval task 1 results confirm that a system might benefit a lot from a direct optimization for a given performance metric.

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