Coreference Systems based on Kernels Methods

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Abstract

Various types of structural information - e.g., about the type of constructions in which binding constraints apply, or about the structure of names - play a central role in coreference resolution, often in combination with lexical information (as in expletive detection). Kernel functions appear to be a promising candidate to capture structure-sensitive similarities and complex feature combinations, but care is required to ensure they are exploited in the best possible fashion. In this paper we propose kernel functions for three subtasks of coreference resolution - binding constraint detection, expletive identification, and aliasing - together with an architecture to integrate them within the standard framework for coreference resolution.

1 Introduction

Information about coreference relations - i.e., which noun phrases are mentions of the same entity - has been shown to be beneficial in a great number of NLP tasks, including information extraction (McCarthy and Lehnert 1995), text planning (Barzilay and Lapata 2005) and summarization (Steinberger et al. 2007). However, the performance of coreference resolvers on unrestricted text is still quite low. One reason for this is that coreference resolution requires a great deal of information, ranging from string matching to syntactic constraints to semantic knowledge to discourse salience information to full common sense reasoning (Sidner 1979; Hobbs 1978, 1979; Grosz et al. 1995; Vieira and Poesio 2000; Mitkov 2002). Much of this information won’t be available to robust coreference resolvers until better methods are found to represent and encode common sense knowledge; but part of the problem is also the need for better methods to encode information that is in part structural, in part lexical. Enforcing binding constraints - e.g., ruling out Peter as antecedent of him in (1a) requires recognizing that the anaphor occurs in a particular type of construction (Chomsky 1981; Lappin and Leass 1994; Yang et al. 2006) whose exact definition however has not yet been agreed upon by linguists (indeed, it may only be definable in a graded sense (Sturt 2003; Yang et al. 2006)), witness examples like (1b). Parallelism effects are a good example of structural information inducing preferences rather than constraints. Recognizing that It in examples such as (1c,d) are expletives requires a combination of structural information and lexical information (Lappin and Leass 1994; Evans 2001). But some sort of structure also underlies our interpretation of other types of coreference: e.g., knowledge about the structure of names certainly plays a role in recognizing that BJ Habibie is a possible antecedent for Mr. Habibie.

(1) a. John thinks that Peter hates him.
    b. John hopes that Jane is speaking only to himself.
    c. It’s lonely here.
    d. It had been raining all day.

The need to capture such information suggests a role for kernel methods (Vapnik 1995) in coreference resolution. Kernel functions make it possible to capture the similarity between structures...
without explicitly enumerating all the substruc-
tures, and have therefore been shown to be a vi-
able approach to feature engineering for natural
language processing for any task in which struc-
tural information plays a role, e.g. (Collins and
Duffy 2002; Zelenko et al. 2003; Giuglea and Mos-
chitti 2006; Zanzotto and Moschitti 2006; Mos-
chitti et al. 2007). Indeed, they have already been
used in NLP to encode the type of structural in-
formation that plays a role in binding constraints
(Yang et al. 2006); however, the methods used in
this previous work do not make it possible to ex-

ploit the full power of kernel functions. In this
work, we extend the use of kernel functions for
coreference by designing and testing kernels for
three subtasks of the coreference task:

- Binding constraints
- Expletive detection
- Aliasing

and developing distinct classifiers for each of these
tasks. We show that our developed kernels produce
high accuracy for both distinct classifiers for these
subtasks as well as for the complete coreference

system.

In the remainder: Section 2, briefly describes
the basic kernel functions that we used; Section
3 illustrates our new kernels for expletive, binding
and name alias detection along with a coreference
context kernel; Section 4 reports the experiments
on individual classifiers on expletives, binding and
names whereas Section 5 shows the results on the
complete coreference task; Finally, Section 6 de-

rives the conclusions.

2 Kernel for Structured Data

We used three kernel functions in this work: the
String Kernel (SK) proposed in Shawe-Taylor and
Cristianini (2004) to evaluate the number of sub-
sequences between two sequences, the Syntactic
Tree Kernel (STK; see Collins and Duffy 2002)
which computes the number of syntactic tree frag-
ments and the Partial Tree Kernel (PTK; see Mos-
chitti 2006) which provides a more general represen-
tation of trees in terms of tree fragments. We

discuss each in turn.

2.1 String Kernels (SK)

The string kernels that we consider count the num-
ber of substrings shared by two sequences contain-
ging gaps, i.e. some of the characters of the original

string are skipped. Gaps penalize the weight asso-
ciated with the matched substrings. More in detail,
(a) longer subsequences receive lower weights.
(b) Valid substrings are sequences of the original
string with some characters omitted, i.e. gaps. (c)
Gaps are accounted by weighting functions and (d)
symbols of a string can also be whole words, i.e.
the word sequence kernel Cancedda et al. (2003).

2.2 Tree Kernels

The main idea underlying tree kernels is to com-
pute the number of common tree fragments be-

tween two trees without explicitly considering the
whole fragment space. The type of fragments char-
acterize different kernel functions. We consider
syntactic tree fragments (STFs) and partial tree
fragments (PTFs)

2.2.1 Syntactic Tree Kernels (STK)

An STF is a connected subset of the nodes and
edges of the original tree, with the constraint that
any node must have all or none of its children. This
is equivalent to stating that the production rules
contained in the STF cannot be partial. For ex-
ample, Figure 1 shows a tree with its STFs: [VP [V
NP]] is an STF, [VP [V]] or [VP [NP]] are not STFs.

2.2.2 Partial Tree Kernel (PTK)

If we relax the production rule constraint over
the STFs, we obtain a more general substructure
type, i.e. PTF, generated by the application of par-
tial production rules, e.g. Figure 2 shows that [VP
[NP[D]] is indeed a valid fragment. Note that
PTK can be seen as a STK applied to all possible
child sequences of the tree nodes, i.e. a string ker-

nel combined with a STK.

2.3 Kernel Engineering

The Kernels of previous section are basic functions
that can be applied to feature vectors, strings and
trees. In order to make them effective for a specific task, e.g. for coreference resolution: (a) we can combine them with additive or multiplicative operators and (b) we can design specific data objects (vectors, sequences and tree structures) for the target tasks.

It is worth noting that a basic kernel applied to an innovative view of a structure yields a new kernel (e.g. Moschitti and Bejan (2004); Moschitti et al. (2006)), as we show below:

Let $K(t_1, t_2) = \phi(t_1) \cdot \phi(t_2)$ be a basic kernel, where $t_1$ and $t_2$ are two trees. If we map $t_1$ and $t_2$ into two new structures $s_1$ and $s_2$ with a mapping $\phi_M(\cdot)$, we obtain: $K(s_1, s_2) = \phi(s_1) \cdot \phi(s_2) = \phi(\phi_M(t_1)) \cdot \phi(\phi_M(t_2)) = \phi'(t_1) \cdot \phi'(t_2) = K'(t_1, t_2)$, which is a noticeably different kernel induced by the mapping $\phi' = \phi \circ \phi_M$.

3 Kernels for Coreference Resolution

In this paper we follow the standard learning approach to coreference developed by Soon et al. (2001) and also used the few variants in Ng and Cardie (2002). In this framework, training and testing instances consist of a pair (anaphor, antecedent). During training, a positive instance is created for each anaphor encountered by pairing the anaphor with its closest antecedent; each of the non-coreferential mentions between anaphor and antecedent is used to produce a negative instance. During resolution, every mention to be resolved is paired with each preceding antecedent candidate to form a testing instance. This instance is presented to the classifier which then returns a class label with a confidence value indicating the likelihood that the candidate is the antecedent.

The nearest candidate with a positive classification will be selected as the antecedent of the possible anaphor. The crucial point is that in this approach, the classifier is trained to identify positive and negative instances of the resolution process. In previous work on using kernel functions for coreference (Yang et al. 2006), structural information in the form of tree features was included in the instances. This approach is appropriate for identifying contexts in which the binding constraints apply, but not, for instance, to recognize expletives. In this work we adopted therefore a more general approach, in which separate classifiers are used to recognize each relevant configuration, and their output is then used as an input to the coreference classifier. In this section we discuss the types of structures and kernel functions we used for three different kinds of classifiers: expletive, binding and alias classifiers. We then present the results of these classifiers, and finally the results with the coreference resolver as a whole.

3.1 Expletive Kernels

In written text, about a third of the occurrences of the pronoun it are not coreferent to a previous mention, but either refer to a general discourse topic (it’s a shame) or do not refer at all, as in the case of extraposed subjects (it is thought that . . . ) or weather verbs (it’s raining). It is desirable to minimize the impact that these non-anaphoric pronouns have on the accuracy of a anaphora resolution: Lappin and Leass (1994), for example, use several heuristics to filter out expletive pronouns, including a check for patterns including modal adjectives (it is good/necessary/ . . . that . . . ), and cognitive verbs (it is thought/believed/ . . . that . . . ).

Newer approaches to the problem use machine-learning on hand-annotated examples: Evans (2001) compares a shallow approach based on surrounding lemmas, part-of-speech tags, and the presence of certain elements such as modal adjectives and cognitive verbs, trained on 3171 examples from Susanne and the BNC to a reimplementation of a pattern-based approach due to Paice and Husk (1987) and finds that the shallower machine-learning approach compares favorably to it. Boyd et al. (2005) use an approach that combines some of Evans’ shallow features with hand-crafted patterns in a memory based learning approach and find that the more informative features are beneficial for the system’s performance (88% accuracy against 71% for their reimplementation using Evans’ shallow features).

Evans’ study also mentions that incorporating the expletive classifier as a filter for a pronoun resolver gives a gain between 2.86% (for manually determined weights) and 1% (for automatically optimized weights).

Tree kernels are a good fit for expletive classification since they can naturally represent the lexical and structural context around a word. Our final classifier uses the combination of an unmodified tree (UT) (where the embedding clause or verb phrase of the pronoun is used as a tree), and a tree that only preserves the most salient structural features (ST).

The reduced representation prunes all nodes that
would not be seen as indicative in a pattern approach, essentially keeping verb argument structure and important lexical items, such as the governing verb and, in the case of copula constructions, the predicate. For example, the phrase

\[
(S \ (NP \ (PRP \ It)))
\]

\[
(VP \ (VBZ \ has))
\]

\[
(NP \ (NP \ (DT \ no) \ (NN \ bearing)))
\]

\[
(PP \ (IN \ on))
\]

\[
(NP \ (NP \ (PRP\$ \ our))
\]

\[
(\text{AN})
\]

\[
(\text{PRP\$ \ force})
\]

\[
(NP \ (\text{NN \ today})))
\]

\[
(\text{AN})
\]

would be reduced to the ST:

\[
(S-I \ (NP-I \ (PRP-I \ It)))
\]

\[
(VP \ (VBX \ have))
\]

\[
(NP)
\]

\[
(\text{AN})
\]

or, in a similar fashion,

\[
(S \ (NP \ (PRP \ it)))
\]

\[
(VP \ (VBZ \ 's))
\]

\[
(NP \ (NP \ (NN \ time)))
\]

\[
(PP \ (IN \ for))
\]

\[
(NP \ (PRP\$ \ their))
\]

\[
(JJ \ biannual)
\]

\[
(\text{AN})
\]

\[
(\text{PRP}\$ \ NN \ powwow)))))
\]

would just be represented as the ST:

\[
(S-I \ (NP-I \ (PRP-I \ it)))
\]

\[
(VP \ (BE \ VBZ))
\]

\[
(NP-PRD \ (NN \ time)))
\]

3.2 Binding Kernels

The resolution of pronominal anaphora heavily relies on the syntactic information and relationships between the anaphor and the antecedent candidates, including binding and other constraints, but also context-induced preferences in sub-clauses.

Some researchers (Lappin and Leass 1994; Kennedy and Boguraev 1996) use manually designed rules to take into account the grammatical role of the antecedent candidates as well as the governing relations between the candidate and the pronoun, while others use features determined over the parse tree in a machine-learning approach (Aone and Bennett 1995; Yang et al. 2004; Luo and Zitouni 2005). However, such a solution has limitations, since the syntactic features have to be selected and defined manually, and it is still partly an open question which syntactic properties should be considered in anaphora resolution.

We follow (Yang et al. 2006; Iida et al. 2006) in using a tree kernel to represent structural information using the subtree that covers a pronoun and its antecedent candidate. Given a sentence like “The man in the room saw him,” we represent the syntactic relation between “The man” and “him”, by the shortest node path connecting the pronoun and the candidate, along with the first-level of the node children in the path.

Figure 3 graphically shows such tree highlighted with dash lines. More in detail we operate the following tree transformation:

(a) To distinguish from other words, we explicitly mark up in the structured feature the pronoun and the antecedent candidate under consideration, by appending a string tag “ANA” and “CANDI” in their respective nodes, i.e. “NN-CANDI” for “man” and “PRP-ANA” for “him”.

(b) To reduce the data sparseness, the leaf nodes representing the words are not incorporated in the feature, except that the word is the word node of the “DET” type (this is to indicate the lexical properties of an expression, e.g., whether it is a definite, indefinite or bare NP).

(c) If the pronoun and the candidate are not in the same sentence, we do not include the nodes denoting the sentences (i.e., “S” nodes) before the candidate or after the pronoun.

The above tree structures will be jointly used with the basic STK which extracts tree fragments able to characterize the following information: (a) the candidate is post-modified by a preposition phrase, (the node “PP” for “in the room” is included), (b) the candidate is a definite noun phrase (the article word “the” is included), (c) the candidate is in a subject position (NP-S-VP structure), (d) the anaphor is an object of a verb (the node “VB” for “saw” is included) and (e) the candidate is c-commanding the anaphor (the parent of the NP node for “the man in the room” is dominating the anaphor (“him”), which are important for reference determination in the pronoun resolution.

Figure 3: The structure for binding detection for the instance inst(“the man”, “him”) in the sentence “the man in the room saw him”
### 3.3 Encoding Context via Word Sequence Kernel

The previous structures aim at describing the interaction between one referential and one referent; if such interaction is observed on another mention pair, an automatic algorithm can establish if they corefer or not. This kind of information is the most useful to characterize the target problem, however, the context in which such interaction takes place is also very important. Indeed, natural language proposes many exceptions to linguistic rules and these can only be detect by looking at the context. To be able to represent context words or phrases, we use context word windows around the mentions and the subsequence kernel function (see section 2.1) to extract many features from it.

For example, in the context of “and so Bill Gates says that”, a string kernel would extract features including: \textit{Bill}, \textit{Gates says that}, \textit{says that}, \textit{Gates}, \textit{Gates says that}, \textit{Bill says that}, \textit{so Gates says that}, \textit{and so that} and so on.

| Name         | Alias       |
|--------------|-------------|
| DJ Habibie   | Mr. Habibie |
| Federal Express | FedEx     |
| Ju Rong Zhi | Ju          |

| Table 1: Examples of coreferent named entities (aliases) taken from the MUC 6 corpus. |

### 3.4 Kernels for Alias Resolution

Most methods currently employed by coreference resolution (CR) systems for identifying coreferent named entities, i.e. aliases, are fairly simplistic in nature, relying on simple surface features such as the edit distance between two strings representing names. We investigate the potential of using the structure contained within names. This can be very useful to solve complex cases like those shown in Table 1, taken from the MUC 6 corpus (Chinchor and Sundheim 2003). For this purpose, we add syntactic information to the feature set by tagging the parts of a name (e.g. first name, last name, etc.) as illustrated in Figure 4.

To automatically extract such structure we used the High Accuracy Parsing of Name Internal Structure (HAPNIS) script\(^1\). HAPNIS takes a name as input and returns a tagged name like what is shown in Figure 4. It uses a series of heuristics in making its classifications based on information such as the serial positions of tokens in a name, the total number of tokens, the presence of meaningful punctuation such as periods and dashes, as well as a library of common first names which can be arbitrarily extended to any size. The tag set consists of the following: \textit{surname}, \textit{forename}, \textit{middle}, \textit{link}, \textit{role}, and \textit{suffix}\(^2\).

Once the structure for a name has been derived, we can apply tree kernels to represent it in the learning algorithms thus avoiding the manual feature design. Such structures are not based on any particular grammar, therefore, any tree subpart may be relevant. In this case the most suitable kernel is PTK, which extracts any tree subpart. It is worth to note that the name tree structure can be improved by inserting a separate node for each name character and exploiting the string matching approximation carried out by PTK. For example, \textit{Microsoft Inc.} will have a large match with \textit{Microsoft Incorporated} whereas the standard string matching would be null.

### 4 Experiments with Coreference Subtask Classifiers

In these experiments we test the kernels devised for expletive (see Section 3.1), binding (see Section 3.2) and alias detection (see Section 3.4), to study the level of accuracy reachable by our kernel-based classifiers. The baseline framework is constituted by SVMs along with a polynomial kernel over the Soon et al.’s features.

#### 4.1 Experiments on Expletive Classification

We used the BBN Pronoun corpus\(^3\) as a source of examples, with the training set consisting of sections 00-19, yielding more than 5800 instances of

\(^1\)Daumé reports a 99.1% accuracy rate on his test data set. We therefore concluded that it was sufficient for our purposes.

\(^2\)Ralph Weischedel and Ada Brunstein (2005): BBN Pronoun Coreference and Entity Type Corpus, LDC2005T33

\(^3\)Ralph Weischedel and Ada Brunstein (2005): BBN Pronoun Coreference and Entity Type Corpus, LDC2005T33
it, with the testing set consisting of sections 20 and 21, using the corresponding parses from the Penn Treebank for the parse trees. Additionally, we report on the performance of the classifier learnt on only the first 1000 instances to verify that our approach also works for small datasets. The results in Table 2 show that full tree (UT) achieves good results whereas the salient tree (ST) leads to a better ability to generalize, and the combination approach outperforms both individual trees.

|                | Prec  | Recl  | Acc   | Prec  | Recl  | Acc   |
|----------------|-------|-------|-------|-------|-------|-------|
| UT             | 83.87 | 61.54 | 84.35 | 78.76 | 52.66 | 80.85 |
| ST             | 78.08 | 67.46 | 83.98 | 77.61 | 61.54 | 82.50 |
| UT+ST          | 81.12 | 68.64 | 85.27 | 80.74 | 64.50 | 84.16 |

Table 2: Results for kernel-based expletive detection (using STK)

Note that the accuracy we get by training on 1000 examples (84% accuracy; see the small column in Table 2) is better than Boyd’s replication of Evans (76% accuracy) or their decision tree classifier (81% accuracy) even though Boyd et al.’s dataset is three times bigger. On the other hand, Boyd et al.’s full system, which uses substantial hand-crafted knowledge, gets a still better result (88% accuracy), which is also higher than the accuracy of our classifier even when trained on the full 5800 instances.

|                | Prec  | Recl  | F     |
|----------------|-------|-------|-------|
| Soon et al.    | 51.25 | 55.51 | 53.29 |
| STK            | 71.93 | 55.41 | 62.59 |

Table 3: Binding classifier: coreference classification on same-sentence pronouns

### 4.2 Experiments with the Binding Classifier

To assess the effect of the binding classifier on same-sentence pronoun links, we extracted 1398 mention pairs from the MUC-6 training data where both mentions were in the same sentence and at least one item of the pair included a pronoun, using the first 1000 for training and the remaining 398 examples for testing. The results (see Table 3) show that the syntactic tree kernel (STK) considerably improves the precision of classification of the Soon et al.’s features.

### 4.3 Experiments on Alias Classification

For our preliminary experiments, we extracted only pairs in the MUC 6 testing set in which both mentions were proper names, as determined by the coreference resolver’s named entity recognizer. This set of proper names contained about 37,000 pairs of proper names of which about 600 were positive instances. About 5,500 pairs were randomly selected as test instances and the rest were used for training.

In the first experiment, we trained a decision tree classifier to detect if two names are aliases. For this task, we used either the string kernel score over the sequence of characters or the edit distance. The results in Table 4 show that the string kernel score performs better by 21.6 percentage points in F-measure.

In the second experiments we used SVMs trained with the string kernel over the name-character sequences and with PTK, which takes into account the structure of names. The results in Table 5 show that the structure improves alias detection by almost 5 absolute percent points. This suggests that an effective coreference system should embed PTK and name structures in the coreference pair representation.

|                | Recall | Precision | F-measure |
|----------------|--------|-----------|-----------|
| String kernel  | 49.5%  | 60.8%     | 54.6%     |
| Edit distance  | 23.9%  | 53.1%     | 33.0%     |

Table 4: Decision-tree based classification of name aliases using string kernels and edit distance.

|                | Recall | Precision | F-measure |
|----------------|--------|-----------|-----------|
| String kernel  | 58.4%  | 67.5%     | 62.6%     |
| PTK            | 64.8%  | 70.0%     | 67.3%     |

Table 5: SVM-based classification of name aliases using string kernels and tree-based feature.

### 5 Experiments on Coreference Systems

In this section we evaluate the contribution in the whole coreference task of the expletive classifier and the binding kernel. The predictions of the former are used as a feature of our basic coreference system whereas the latter is used directly in the coreference classifier by adding it to the polynomial kernel of the basic system.

Our basic system is based on the standard learning approach to coreference developed by Soon et al. (2001). It uses the features from Soon et al’s work, including lexical properties, morphologic type, distance, salience, parallelism, grammatical role and so on. The main difference with
Soon et al. (2001) is the use of SVMs along with a polynomial kernel.

|          | MUC-6 |            |            |
|----------|-------|------------|------------|
|          | Prec  | Recl       | F          |
| plain    | 65.2  | 66.9       | 66.0       |
| plain+expletive | 66.1  | 66.9       | 66.5       |
| upper limit | 70.0  | 66.9       | 68.4       |

Table 6: Expletive classification: influence on pronoun resolution

5.1 Influence of Expletive classification

To see how useful a classifier for expletives can be, we conducted experiments using the expletive classifier learned on the BBN pronoun corpus on the MUC-6 corpus. Preliminary experiments indicated that perfect detection of expletives (i.e. using gold standard annotation) could raise the precision of pronoun resolution from 65.2% to 70.0%, yielding a 2.4% improvement in the F-score for pronoun resolution alone, or 0.6% improvement in the overall coreference F-score (see Table 6).

For a more realistic assessment, we used the classifier learned on the BBN pronoun corpus examples as an additional feature to gauge the improvement that could be achieved using it. While the gain in precision is small even in comparison to the achievable error reduction, we need to keep in mind that our baseline is in fact a well-tuned system.

Table 7 lists the results for the pronoun resolution. We used $PK$ on the Soon et al.’s features as the baseline. On MUC-6, the system achieves a recall of 64.3% and precision 63.1% and an overall F-measure of 63.7%. On ACE02-BNews, the recall is lower 58.9% but the precision is higher, i.e. 68.1%, for a resulting F-measure of 63.1%. In contrast, adding the binding kernel ($PK+STK$) leads to a significant improvement in 17% precision for MUC-6 with a small gain (1%) in recall, whereas on the ACE data set, it also helps to increase the recall by 7%. Overall, we can see an increase in F-measure of around 8% for MUC and 4.5% for ACE02-BNews. These results suggest that the structured feature is very effective for pronoun resolution.

Table 8 lists the results on the coreference resolution. We note that adding the structured feature to the polynomial kernel, i.e. using the model $PK+STK$, improves the recall of 1.9% for MUC-6 and 1.8% for ACE-02-BNews and keeps invariant the precision. Compared to pronoun resolution, the improvement of the overall F-measure is smaller (about 1%). This occurs since the resolution of non-pronouns case does not require a massive use of syntactic knowledge as in the pronoun resolution problem. WSK further improves the system’s F1 suggesting that adding structured features of different types helps in solving the coreference task.

6 Conclusions

We presented four examples of using kernel-based methods to take advantage of a structured representation for learning problems that arise in coreference systems, presenting high-accuracy classifiers for expletive detection, binding constraints and same-sentence pronoun resolution, and name alias matching. We have shown the accuracy of the individual classifiers for the above tasks and the impact of expletives and binding classifiers/kernels in the complete coreference resolution system. The improvement over the individual and complete tasks suggests that kernel methods
are a promising research direction to achieve state-of-the-art coreference resolution systems.

Future work is devoted on making the use of kernels for coreference more efficient since the size of the ACE-2 corpora prevented us to directly use the combination of all kernels that we designed. In this paper, we have also studied a solution which relates to factoring out decisions into separate classifiers and using the decisions as binary features. However, this solution shows some loss in terms of accuracy. We are currently investigating methods that allow us to combine the accuracy and flexibility of the integrated approach with the speed of the separate classifier approach.

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