Abstract

We present a simple, two-steps supervised strategy for the identification and classification of thematic roles in natural language texts. We employ no external source of information but automatic parse trees of the input sentences. We use a few attribute-value features and tree kernel functions applied to specialized structured features. The resulting system has an F$_1$ of 75.44 on the SemEval2007 closed task on semantic role labeling.

1 Introduction

In this paper we present a system for the labeling of semantic roles that produces VerbNet (Kipper et al., 2000) like annotations of free text sentences using only full syntactic parses of the input sentences. The labeling process is modeled as a cascade of two distinct classification steps: (1) boundary detection (BD), in which the word sequences that encode a thematic role for a given predicate are recognized, and (2) role classification (RC), in which the type of thematic role with respect to the predicate is assigned. After role classification, a set of simple heuristics are applied in order to ensure that only well formed annotations are output.

We designed our system on a per-predicate basis, training one boundary classifier and a battery of role classifiers for each predicate word. We clustered all the senses of the same verb together and ended up with 50 distinct boundary classifiers (one for each target predicate word) and 619 role classifiers to recognize the 47 distinct role labels that appear in the training set.

The remainder of this paper is structured as follows: Section 2 describes in some detail the architecture of our labeling system; Section 3 describes the features that we use to represent the classifier examples; Section 4 describes the experimental setting and reports the accuracy of the system on the SemEval2007 semantic role labeling closed task; finally, Section 5 discusses the results and presents our conclusions.

2 System Description

Given a target predicate word in a natural language sentence, a SRL system is meant to correctly identify all the arguments of the predicate. This problem is usually divided in two sub-tasks: (a) the detection of the boundaries (i.e. the word span) of each argument and (b) the classification of the argument type, e.g. Arg0 or ArgM in PropBank or Agent and Goal in FrameNet or VerbNet.

The standard approach to learn both the detection and the classification of predicate arguments is summarized by the following steps:

1 Given a sentence from the training-set, generate a full syntactic parse-tree;
2 let $\mathcal{P}$ and $\mathcal{A}$ be the set of predicates and the set of parse-tree nodes (i.e. the potential arguments), respectively;
3 for each pair $\langle p, a \rangle \in \mathcal{P} \times \mathcal{A}$:

3.1 extract the feature representation set, $F_{p,a}$;
3.2 if the sub-tree rooted in $a$ covers exactly the words of one argument of $p$, put $F_{p,a}$ in $T^+$ (positive examples), otherwise put it in $T^-$ (negative examples).

For instance, in Figure 1.a, for each combination of the predicate approve with any other tree node $a$
that does not overlap with the predicate, a classifier example \( F_{\text{approve},a} \) is generated. If \( a \) exactly covers one of the predicate arguments (in this case: "The charter", "by the EC Commission" or "on Sept. 21") it is regarded as a positive instance, otherwise it will be a negative one, e.g. \( F_{\text{approve},(\text{NN charter})}\).

The \( T^+ \) and \( T^- \) sets are used to train the boundary classifier. To train the role multi-class classifier, \( T^+ \) can be reorganized as positive \( T^+_{\text{arg}_i} \) and negative \( T^-_{\text{arg}_i} \) examples for each argument \( i \). In this way, an individual ONE-vs-ALL classifier for each argument \( i \) can be trained. We adopted this solution, according to (Pradhan et al., 2005), since it is simple and effective. In the classification phase, given an unseen sentence, all its \( F_{p,a} \) are generated and classified by each individual role classifier. The role label associated with the maximum among the scores provided by the individual classifiers is eventually selected.

To make the annotations consistent with the underlying linguistic model, we employ a few simple heuristics to resolve the overlap situations that may occur, e.g. both “charter” and “the charter” in Figure 1 may be assigned a role:

- if more than two nodes are involved, i.e. a node \( d \) and two or more of its descendants \( n_i \) are classified as arguments, then assume that \( d \) is not an argument. This choice is justified by previous studies (Moschitti et al., 2006b) showing that the accuracy of classification is higher for lower nodes;

- if only two nodes are involved, i.e. they dominate each other, then keep the one with the highest classification score.

### 3 Features for Semantic Role Labeling

We explicitly represent as attribute-value pairs the following features of each \( F_{p,a} \) pair:

- **Phrase Type**, **Predicate Word**, **Head Word**, **Position** and **Voice** as defined in (Gildea and Jurafsky, 2002);

- **Partial Path**, **No Direction Path**, **Head Word POS**, **First and Last Word/POS in Constituent** and **SubCategorization** as proposed in (Pradhan et al., 2005);

- **Syntactic Frame** as designed in (Xue and Palmer, 2004).

We also employ structured features derived by the full parses in an attempt to capture relevant aspects that may not be emphasized by the explicit feature representation. (Moschitti et al., 2006a) and (Moschitti et al., 2006b) defined several classes of structured features that were successfully employed with tree kernels for the different stages of an SRL process. Figure 1 shows an example of the \( \text{AST}^m \) structures that we used for both the boundary detection and the role classification stages.

### 4 Experiments

In this section we discuss the setup and the results of the experiments carried out on the dataset of the SemEval2007 closed task on SRL.
Table 2: SRL accuracy on the development test for the boundary detection (BD) and the complete SRL task (BD+RC) using the polynomial kernel alone (poly) or combined with a tree kernel function (poly + TK).

4.1 Setup

The training set comprises 15,838\textsuperscript{1} training annotations organized on a per-verb basis. In order to build a development set (Dev), we sampled about one tenth, i.e. 1,606 annotations, of the original training set. For the final evaluation on the test set (Test), consisting of 3,094 annotations, we trained our classifiers on the whole training data. Statistics on the dataset composition are shown in Table 1.

The evaluations were carried out with the SVM-Light-TK\textsuperscript{2} software (Moschitti, 2004) which extends the SVM-Light package (Joachims, 1999) with tree kernel functions. We used the default polynomial kernel (degree=3) for the linear features and a SubSet Tree (SST) kernel (Collins and Duffy, 2002) for the comparison of AST\textsuperscript{3} structured features. The kernels are normalized and summed by assigning a weight of 0.3 to the TK contribution.

Training all the 50 boundary classifiers and the 619 role classifiers on the whole dataset took about 4 hours on a 64 bits machine (2.2GHz, 1GB RAM).\textsuperscript{3}

4.2 Evaluation

All the evaluations were carried out using the CoNLL2005 evaluator tool available at http://www.lsi.upc.es/~srlconll/soft.html.

Table 2 shows the aggregate results on boundary detection (BD) and the complete SRL task (BD+RC) on the development set using the polynomial kernel alone (poly) or in conjunction with the tree kernels and structured features (poly+TK). For both tasks, tree kernel functions do trigger automatic feature selection and improve the polynomial kernel by 2.46 and 1.39 F\textsubscript{1} points, respectively.

The SRL accuracy for each one of the 47 distinct role labels is shown in Table 3. Column 2 lists

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|}
\hline
Task & Kernel(s) & Precision & Recall & F\textsubscript{1}\beta=1 \\
\hline
BD & poly & 94.34\% & 71.26\% & 81.19\% \\
& poly + TK & 92.89\% & 76.09\% & 83.65\% \\
BD + RC & poly & 88.72\% & 68.76\% & 77.47\% \\
& poly + TK & 86.60\% & 72.40\% & 78.86\% \\
\hline
\end{tabular}
\caption{SRL accuracy on the development test for the boundary detection (BD) and the complete SRL task (BD+RC) using the polynomial kernel alone (poly) or combined with a tree kernel function (poly + TK).}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|}
\hline
Role & #TI & Precision & Recall & F\textsubscript{1} \\
\hline
Ov(BD) & 6931 & 87.09\% & 72.96\% & 79.40\% \\
Ov(BD+RC) & 70.16\% & 75.44\% & 71.30\% \\
\hline
ARG2 & 4 & 100.00\% & 25.00\% & 40.00\% \\
ARG3 & 17 & 61.11\% & 64.71\% & 62.86\% \\
ARG4 & 4 & 0.00\% & 0.00\% & 0.00\% \\
ARGM-ADV & 188 & 55.14\% & 31.38\% & 40.00\% \\
ARGM-CAU & 13 & 50.00\% & 23.08\% & 31.58\% \\
ARGM-DIR & 4 & 100.00\% & 25.00\% & 40.00\% \\
ARGM-EXT & 3 & 0.00\% & 0.00\% & 0.00\% \\
ARGM-LOC & 151 & 51.66\% & 51.66\% & 51.66\% \\
ARGM-MNR & 85 & 41.94\% & 15.29\% & 22.41\% \\
ARGM-PNC & 28 & 38.46\% & 17.86\% & 24.39\% \\
ARGM-PRD & 9 & 83.33\% & 55.56\% & 66.67\% \\
ARGM-REC & 1 & 0.00\% & 0.00\% & 0.00\% \\
ARGM-TMP & 386 & 55.65\% & 35.75\% & 43.53\% \\
Actor1 & 12 & 85.71\% & 50.00\% & 63.16\% \\
Actor2 & 1 & 100.00\% & 100.00\% & 100.00\% \\
Agent & 2551 & 91.38\% & 77.34\% & 83.78\% \\
Asset & 21 & 42.42\% & 66.67\% & 51.85\% \\
Attribute & 17 & 60.00\% & 70.59\% & 64.86\% \\
Beneficiary & 24 & 65.00\% & 54.17\% & 59.09\% \\
Cause & 48 & 75.56\% & 70.83\% & 73.12\% \\
Experimenter & 132 & 86.49\% & 72.73\% & 79.01\% \\
Location & 12 & 83.33\% & 41.67\% & 55.56\% \\
Material & 7 & 100.00\% & 14.29\% & 25.00\% \\
Patient & 37 & 76.67\% & 62.16\% & 68.66\% \\
Patient1 & 20 & 72.73\% & 40.00\% & 51.61\% \\
Predicate & 181 & 63.75\% & 56.35\% & 59.82\% \\
Product & 106 & 70.79\% & 59.43\% & 64.62\% \\
R-ARGM-LOC & 2 & 0.00\% & 0.00\% & 0.00\% \\
R-ARGM-MNR & 2 & 0.00\% & 0.00\% & 0.00\% \\
R-ARGM-TMP & 4 & 0.00\% & 0.00\% & 0.00\% \\
R-Agent & 74 & 70.15\% & 63.51\% & 66.67\% \\
R-Experimenter & 5 & 100.00\% & 20.00\% & 33.33\% \\
R-Patient & 1 & 0.00\% & 0.00\% & 0.00\% \\
R-Predicate & 1 & 0.00\% & 0.00\% & 0.00\% \\
R-Product & 2 & 0.00\% & 0.00\% & 0.00\% \\
R-Recipient & 8 & 100.00\% & 87.50\% & 93.33\% \\
R-Theme & 7 & 75.00\% & 42.86\% & 54.55\% \\
R-Theme1 & 7 & 100.00\% & 85.71\% & 92.31\% \\
R-Theme2 & 1 & 50.00\% & 100.00\% & 66.67\% \\
R-Topic & 14 & 66.67\% & 42.86\% & 52.17\% \\
Recipient & 48 & 75.51\% & 77.08\% & 76.29\% \\
Source & 25 & 65.22\% & 60.00\% & 62.50\% \\
Stimulus & 21 & 33.33\% & 19.05\% & 24.24\% \\
Theme & 650 & 79.22\% & 68.62\% & 73.54\% \\
Theme1 & 69 & 77.42\% & 69.57\% & 73.28\% \\
Theme2 & 60 & 74.55\% & 68.33\% & 71.30\% \\
Topic & 1867 & 84.26\% & 82.27\% & 83.25\% \\
\hline
\end{tabular}
\caption{Evaluation of the semantic role labeling accuracy on the SemEval2007 - Task 17 test set using the poly + TK kernel. Column #TI reports the number of instances of each role label in the test set. Rows Ov(BD) and Ov(BD + RC) show the overall accuracy on the boundary detection and the complete SRL task, respectively.}
\end{table}

\textsuperscript{1}A bunch of unaligned annotations were removed from the dataset.

\textsuperscript{2}http://ai-nlp.info.uniroma2.it/moschitti/

\textsuperscript{3}In order to have a faster development cycle, we only used 60k training examples to train the boundary classifier of the verb say. The accuracy on this relation is still very high, as we measured an overall F\textsubscript{1} of 87.18 on the development set and of 85.13 on the test set.
the number of instances of each role in the test set. Many roles have very few positive examples both in
the training and the test sets, and therefore have little
or no impact on the overall accuracy which is domi-
nated by the few roles which are very frequent, such as Theme, Agent, Topic and ARGMTMP which ac-
count for almost 80% of all the test roles.

5 Final Remarks

In this paper we presented a system that employs
tree kernels and a basic set of flat features for the classification of thematic roles.

We adopted a very simple approach that is meant
to be as general and fast as possible. The issue of
generality is addressed by training the bound-
ary and role classifiers on a per-predicate basis and
by employing tree kernel and structured features in
the learning algorithm. The resulting architecture

Splitting the learning problem also has the clear
advantage of noticeably improving the efficiency of the
classifiers, thus reducing training and classification
time. On the other hand, this split results in
some classifiers having too few training instances
and therefore being very inaccurate. This is es-
specially true for the boundary classifiers, which con-
versely need to be very accurate in order to posi-
tively support the following stages of the SRL pro-
cess. The solution of a monolithic boundary classifier
that we previously employed (Moschitti et al.,
2006b) is noticeably more accurate though much
less efficient, especially for training. Indeed, after
the SemEval2007 evaluation period was over, we
ran another experiment using a monolithic boundary
classifier. On the test set, we measured F1 values of
82.09 vs 79.40 and 77.17 vs 75.44 for the boundary
detection and the complete SRL tasks, respectively.

Although it was provided as part of both the train-
ing and test data, we chose not to use the verb sense
information. This choice is motivated by our in-
tention to depend on as less external resources as
possible in order to be able to port our SRL system
to other linguistic models and languages, for which
such resources may not exist. Still, identifying the
predicate sense is a key issue especially for role clas-
sification, as the argument structure of a predicate is
largely determined by its sense. In the near feature
we plan to use larger structured features, i.e. span-
ing all the potential arguments of a predicate, to
improve the accuracy of our role classifiers.

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\(^4\)http://www.prestospace.org