Automatic Extraction of Subcategorization Frames for Czech*

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Abstract

We present some novel machine learning techniques for the identification of subcategorization information for verbs in Czech. We compare three different statistical techniques applied to this problem. We show how the learning algorithm can be used to discover previously unknown subcategorization frames from the Czech Prague Dependency Treebank. The algorithm can then be used to label dependents of a verb in the Czech treebank as either arguments or adjuncts. Using our techniques, we are able to achieve 88% precision on unseen parsed text.

1 Introduction

The subcategorization of verbs is an essential issue in parsing, because it helps disambiguate the attachment of arguments and recover the correct predicate-argument relations by a parser. (Carroll and Minnen, 1998; Carroll and Rooth, 1998) give several reasons why subcategorization information is important for a natural language parser. Machine-readable dictionaries are not comprehensive enough to provide this lexical information (Manning, 1993; Briscoe and Carroll, 1997). Furthermore, such dictionaries are available only for very few languages. We need some general method for the automatic extraction of subcategorization information from text corpora.

Several techniques and results have been reported on learning subcategorization frames (SFs) from text corpora (Webster and Marcus, 1989; Brent, 1991; Brent, 1993; Brent, 1994; Ushioda et al., 1993; Manning, 1993; Ersan and Charniak, 1996; Briscoe and Carroll, 1997; Carroll and Minnen, 1998; Carroll and Rooth, 1998). All of this work deals with English. In this paper we report on techniques that automatically extract SFs for Czech, which is a free word-order language, where verb complements have visible case marking.[1]

Apart from the choice of target language, this work also differs from previous work in other ways. Unlike all other previous work in this area, we do not assume that the set of SFs is known to us in advance. Also in contrast, we work with syntactically annotated data (the Prague Dependency Treebank, PDT (Hajič, 1998)) where the subcategorization information is *not* given; although this might be considered a simpler problem as compared to using raw text, we have discovered interesting problems that a user of a raw or tagged corpus is unlikely to face.

We first give a detailed description of the task of uncovering SFs and also point out those properties of Czech that have to be taken into account when searching for SFs. Then we discuss some differences from the other research efforts. We then present the three techniques that we use to learn SFs from the input data.

In the input data, many observed dependents of the verb are adjuncts. To treat this problem effectively, we describe a novel addition to the hypothesis testing technique that uses subset of observed frames to permit the learning algorithm to better distinguish arguments from adjuncts.

Using our techniques, we are able to achieve 88% precision in distinguishing arguments from adjuncts on unseen parsed text.

2 Task Description

In this section we describe precisely the proposed task. We also describe the input training material and the output produced by our algorithms.

2.1 Identifying subcategorization frames

In general, the problem of identifying subcategorization frames is to distinguish between arguments and adjuncts among the constituents modifying a

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[1] One of the anonymous reviewers pointed out that (Basili and Vindigni, 1998) presents a corpus-driven acquisition of subcategorization frames for Italian.

verb. e.g., in "John saw Mary yesterday at the station", only "John" and "Mary" are required arguments while the other constituents are optional (adjuncts). There is some controversy as to the *correct* subcategorization of a given verb and linguists often disagree as to what is the right set of SFs for a given verb. A machine learning approach such as the one followed in this paper sidesteps this issue altogether, since it is left to the algorithm to learn what is an appropriate SF for a verb.

Figure 1 shows a sample input sentence from the PDT annotated with dependencies which is used as training material for the techniques described in this paper. Each node in the tree contains a word, its part-of-speech tag (which includes morphological information) and its location in the sentence. We also use the functional tags which are part of the PDT annotation[2]. To make future discussion easier we define some terms here. Each daughter of a verb in the tree shown is called a *dependent* and the set of all dependents for that verb in that tree is called an *observed frame (OF)*. A *subcategorization frame (SF)* is a subset of the OF. For example the OF for the verb *mají (have)* in Figure 1 is { *N1, N4* } and its SF is the same as its OF. Note that which OF (or which part of it) is a true SF is not marked in the training data. After training on such examples, the algorithm takes as input parsed text and labels each daughter of each verb as either an argument or an adjunct. It does this by selecting the most likely SF for that verb given its OF.

2.2 Relevant properties of the Czech Data

Czech is a "free word-order" language. This means that the arguments of a verb do not have fixed positions and are not guaranteed to be in a particular configuration with respect to the verb.

The examples in (1) show that while Czech has a relatively free word-order some orders are still marked. The SVO, OVS, and SOV orders in (1)a, (1)b, (1)c respectively, differ in emphasis but have the same predicate-argument structure. The examples (1)d, (1)e can only be interpreted as a question. Such word orders require proper intonation in speech, or a question mark in text.

The example (1)f demonstrates how morphology is important in identifying the arguments of the verb. cf. (1)f with (1)b. The ending *-a* of *Martin* is the only difference between the two sentences. It however changes the morphological case of *Martin* and turns it from subject into object. Czech has 7 cases that can be distinguished morphologically.

[2]For those readers familiar with the PDT functional tags, it is important to note that the functional tag *Obj* does not always correspond to an argument. Similarly, the functional tag *Adv* does not always correspond to an adjunct. Approximately 50 verbs out of the total 2993 verbs require an adverbial argument.

(1) a. Martin otvírá soubor. (SVO: Martin opens the file)
b. Soubor otvírá Martin. (OVS: $\neq$ the file opens Martin)
c. Martin soubor otvírá.
d. #Otvírá Martin soubor.
e. #Otvírá soubor Martin.
f. Soubor otvírá Martina. (= the file opens Martin)

Almost all the existing techniques for extracting SFs exploit the relatively fixed word-order of English to collect features for their learning algorithms using fixed patterns or rules (see Table 2 for more details). Such a technique is not easily transported into a new language like Czech. Fully parsed training data can help here by supplying all dependents of a verb. The observed frames obtained this way have to be *normalized* with respect to the word order, e.g. by using an alphabetic ordering.

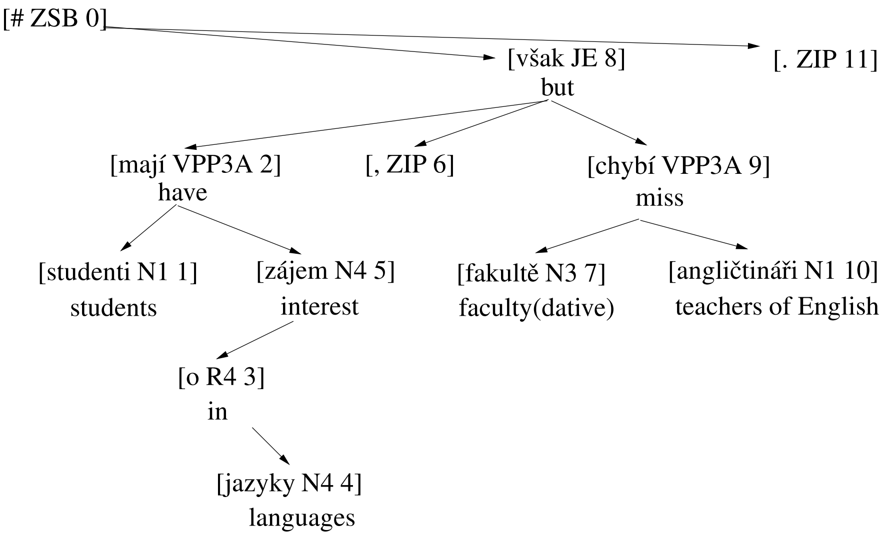
For extracting SFs, prepositions in Czech have to be handled carefully. In some SFs, a particular preposition is required by the verb, while in other cases it is a class of prepositions such as locative prepositions (e.g. *in, on, behind,* ...) that are required by the verb. In contrast, adjuncts can use a wider variety of prepositions. Prepositions specify the case of their noun phrase complements but a preposition can take complements with more than one case marking with a different meaning for each case. (e.g. *na mostě = on the bridge; na most = onto the bridge*). In general, verbs select not only for particular prepositions but also indicate the case marking for their noun phrase complements.

2.3 Argument types

We use the following set of labels as possible arguments for a verb in our corpus. They are derived from morphological tags and simplified from the original PDT definition (Hajič and Hladká, 1998; Hajič, 1998); the numeric attributes are the case marking identifiers. For prepositions and clause complementizers, we also save the lemma in parentheses.

- Noun phrases: N4, N3, N2, N7, N1
- Prepositional phrases: R2(bez), R3(k), R4(na), R6(na), R7(s), ...
- Reflexive pronouns *se*, *si*: PR4, PR3
- Clauses: S, JS(že), JS(zda)
- Infinitives (VINF)
- passive participles (VPAS)
- adverbs (DB)

We do not specify which SFs are possible since we aim to discover these (see Section 2.1).



The students are interested in languages but the faculty is missing teachers of English.

Figure 1: Example input to the algorithm from the Prague Dependency Treebank

3 Three methods for identifying subcategorization frames

We describe three methods that take as input a list of verbs and associated observed frames from the training data (see Section 2.1), and learn an association between verbs and possible SFs. We describe three methods that arrive at a numerical score for this association.

However, before we can apply any statistical methods to the training data, there is one aspect of using a treebank as input that has to be dealt with. A correct frame (verb + its arguments) is almost always accompanied by one or more adjuncts in a real sentence. Thus the *observed frame* will almost always contain noise. The approach offered by Brent and others counts all observed frames and then decides which of them do not associate strongly with a given verb. In our situation this approach will fail for most of the observed frames because we rarely see the correct frames isolated in the training data. For example, from the occurrences of the transitive verb *absolvovat* ("go through something") that occurred ten times in the corpus, no occurrence consisted of the verb-object pair alone. In other words, the correct SF constituted 0% of the observed situations. Nevertheless, for each observed frame, one of its subsets was the correct frame we sought for. Therefore, we considered all possible subsets of all observed frames. We used a technique which steps through the subsets of each observed frame from larger to smaller ones and records their frequency in data. Large infrequent subsets are suspected to contain adjuncts, so we replace them by more frequent smaller subsets. Small infrequent subsets may have elided some arguments and are rejected. Further details of this process are discussed in Section 3.3.

The methods we present here have a common structure. For each verb, we need to associate a score to the hypothesis that a particular set of dependents of the verb are arguments of that verb. In other words, we need to assign a value to the hypothesis that the observed frame under consideration is the verb's SF. Intuitively, we either want to test for independence of the observed frame and verb distributions in the data, or we want to test how likely is a frame to be observed with a particular verb without being a valid SF. We develop these intuitions with the following well-known statistical methods. For further background on these methods the reader is referred to (Bickel and Doksum, 1977; Dunning, 1993).

3.1 Likelihood ratio test

Let us take the hypothesis that the distribution of an observed frame f in the training data is independent of the distribution of a verb v. We can phrase this hypothesis as $p(f \mid v) = p(f \mid !v) = p(f)$, that is distribution of a frame f given that a verb v is present is the same as the distribution of f given that v is not present (written as $!v$). We use the log likelihood test statistic (Bickel and Doksum, 1977)(p.209) as a measure to discover particular frames and verbs that are highly associated in the training data.

$$\begin{aligned}
k_1 &= c(f, v) \\
n_1 &= c(v) = c(f, v) + c(!f, v) \\
k_2 &= c(f, !v) \\
n_2 &= c(!v) = c(f, !v) + c(!f, !v)
\end{aligned}$$

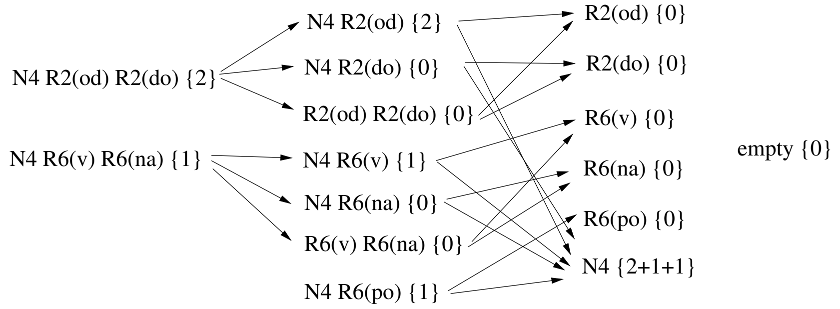


Figure 2: Computing the subsets of observed frames for the verb *absolvovat*. The counts for each frame are given within braces {}. In this example, the frames *N4 R2(od), N4 R6(v)* and *N4 R6(po)* have been observed with other verbs in the corpus. Note that the counts in this figure do not correspond to the real counts for the verb *absolvovat* in the training corpus.

where $c(\cdot)$ are counts in the training data. Using the values computed above:

$$\begin{aligned} p_1 &= \frac{k_1}{n_1} \\ p_2 &= \frac{k_2}{n_2} \\ p &= \frac{k_1+k_2}{n_1+n_2} \end{aligned}$$

Taking these probabilities to be binomially distributed, the log likelihood statistic (Dunning, 1993) is given by:

$$\begin{aligned} &-2\log\lambda = \\ &\quad 2[\log L(p_1,k_1,n_1) + \log L(p_2,k_2,n_2) - \\ &\quad \log L(p,k_1,n_2) - \log L(p,k_2,n_2)] \end{aligned}$$

where,

$$\log L(p,n,k) = k\log p + (n-k)\log(1-p)$$

According to this statistic, the greater the value of $-2\log\lambda$ for a particular pair of observed frame and verb, the more likely that frame is to be valid SF of the verb.

3.2 T-scores

Another statistic that has been used for hypothesis testing is the *t-score*. Using the definitions from Section 3.1 we can compute t-scores using the equation below and use its value to measure the association between a verb and a frame observed with it.

$$T = \frac{p_1 - p_2}{\sqrt{\sigma^2(n_1,p_1) + \sigma^2(n_2,p_2)}}$$

where,

$$\sigma(n,p) = np(1-p)$$

In particular, the hypothesis being tested using the t-score is whether the distributions p_1 and p_2 are *not* independent. If the value of T is greater than some threshold then the verb v should take the frame f as a SF.

3.3 Binomial Models of Miscue Probabilities

Once again assuming that the data is binomially distributed, we can look for frames that co-occur with a verb by exploiting the miscue probability: the probability of a frame co-occuring with a verb when it is not a valid SF. This is the method used by several earlier papers on SF extraction starting with (Brent, 1991; Brent, 1993; Brent, 1994).

Let us consider probability $p_{!f}$ which is the probability that a given verb is observed with a frame but this frame is not a valid SF for this verb. $p_{!f}$ is the error probability on identifying a SF for a verb. Let us consider a verb v which does *not* have as one of its valid SFs the frame f. How likely is it that v will be seen m or more times in the training data with frame f? If v has been seen a total of n times in the data, then $H^*(p_{!f};m,n)$ gives us this likelihood.

$$H^*(p_{!f};m,n) = \sum_{i=m}^{n} p_{!f}^{i}(1-p_{!f})^{n-i}\begin{pmatrix} n \\ i \end{pmatrix}$$

If $H^*(p;m,n)$ is less than or equal to some small threshold value then it is extremely unlikely that the hypothesis is true, and hence the frame f must be a SF of the verb v. Setting the threshold value to 0.05 gives us a 95% or better confidence value that the verb v has been observed often enough with a frame f for it to be a valid SF.

Initially, we consider only the observed frames (OFs) from the treebank. There is a chance that some are subsets of some others but now we count only the cases when the OFs were seen themselves. Let's assume the test statistic rejected the frame. Then it is not a real SF but there probably is a subset of it that is a real SF. So we select exactly one of the subsets whose length is one member less: this is the *successor* of the rejected frame and inherits its frequency. Of course one frame may be successor of several longer frames and it can have its own count as OF. This is how frequencies accumulate and frames become more likely to survive. The example shown in Figure 2 illustrates how the subsets and successors are selected.

An important point is the selection of the successor. We have to select only one of the n possible successors of a frame of length n, otherwise we would break the total frequency of the verb. Suppose there is m rejected frames of length n. This yields $m * n$ possible modifications to consider before selection of the successor. We implemented two methods for choosing a single successor frame:

1. Choose the one that results in the strongest preference for some frame (that is, the successor frame results in the lowest entropy across the corpus). This measure is sensitive to the frequency of this frame in the rest of corpus.

2. Random selection of the successor frame from the alternatives.

Random selection resulted in better precision (88% instead of 86%). It is not clear why a method that is sensitive to the frequency of each proposed successor frame does not perform better than random selection.

The technique described here may sometimes result in subset of a correct SF, discarding one or more of its members. Such frame can still help parsers because they can at least look for the dependents that have survived.

4 Evaluation

For the evaluation of the methods described above we used the Prague Dependency Treebank (PDT). We used 19,126 sentences of training data from the PDT (about 300K words). In this training set, there were 33,641 verb tokens with 2,993 verb types. There were a total of 28,765 *observed frames* (see Section 2.1 for explanation of these terms). There were 914 verb types seen 5 or more times.

Since there is no electronic valence dictionary for Czech, we evaluated our filtering technique on a set of 500 test sentences which were unseen and separate from the training data. These test sentences were used as a gold standard by distinguishing the arguments and adjuncts manually. We then compared the accuracy of our output set of items marked as either arguments or adjuncts against this gold standard.

First we describe the baseline methods. Baseline method 1: consider each dependent of a verb an adjunct. Baseline method 2: use just the longest known observed frame matching the test pattern. If no matching OF is known, find the longest partial match in the OFs seen in the training data. We exploit the functional and morphological tags while matching. No statistical filtering is applied in either baseline method.

A comparison between all three methods that were proposed in this paper is shown in Table 1.

The experiments showed that the method improved precision of this distinction from 57% to 88%. We were able to classify as many as 914 verbs which is a number outperformed only by Manning, with 10x more data (note that our results are for a different language).

Also, our method discovered 137 subcategorization frames from the data. The known upper bound of frames that the algorithm could have found (the total number of the *observed frame* types) was 450.

5 Comparison with related work

Preliminary work on SF extraction from corpora was done by (Brent, 1991; Brent, 1993; Brent, 1994) and (Webster and Marcus, 1989; Ushioda et al., 1993). Brent (Brent, 1993; Brent, 1994) uses the standard method of testing miscue probabilities for filtering frames observed with a verb. (Brent, 1994) presents a method for estimating $p_{!f}$. Brent applied his method to a small number of verbs and associated SF types. (Manning, 1993) applies Brent's method to parsed data and obtains a subcategorization dictionary for a larger set of verbs. (Briscoe and Carroll, 1997; Carroll and Minnen, 1998) differs from earlier work in that a substantially larger set of SF types are considered; (Carroll and Rooth, 1998) use an EM algorithm to learn subcategorization as a result of learning rule probabilities, and, in turn, to improve parsing accuracy by applying the verb SFs obtained. (Basili and Vindigni, 1998) use a conceptual clustering algorithm for acquiring subcategorization frames for Italian. They establish a partial order on partially overlapping OFs (similar to our OF subsets) which is then used to suggest a potential SF. A complete comparison of all the previous approaches with the current work is given in Table 2.

While these approaches differ in size and quality of training data, number of SF types (e.g. intransitive verbs, transitive verbs) and number of verbs processed, there are properties that all have in common. They all assume that they know the set of possible SF types in advance. Their task can be viewed as assigning one or more of the (known) SF types to a given verb. In addition, except for (Briscoe and Carroll, 1997; Carroll and Minnen, 1998), only a small number of SF types is considered.

	Baseline 1	Baseline 2	Lik. Ratio	T-scores	Hyp. Testing
Precision	55%	78%	82%	82%	88%
Recall:	55%	73%	77%	77%	74%
$F_{\beta=1}$	55%	75%	79%	79%	80%
% unknown	0%	6%	6%	6%	16%
Total verb nodes	1027	1027	1027	1027	1027
Total complements	2144	2144	2144	2144	2144
Nodes with known verbs	1027	981	981	981	907
Complements of known verbs	2144	2010	2010	2010	1812
Correct Suggestions	1187.5	1573.5	1642.5	1652.9	1596.5
True Arguments	956.5	910.5	910.5	910.5	834.5
Suggested Arguments	0	1122	974	1026	674
Incorrect arg suggestions	0	324	215.5	236.3	27.5
Incorrect adj suggestions	956.5	112.5	152	120.8	188

Table 1: Comparison between the baseline methods and the three methods proposed in this paper. Some of the values are not integers since for some difficult cases in the test data, the value for each argument/adjunct decision was set to a value between $[0, 1]$. *Recall* is computed as the number of known verb complements divided by the total number of complements. *Precision* is computed as the number of correct suggestions divided by the number of known verb complements. $F_{\beta=1} = (2 \times p \times r)/(p + r)$. *% unknown* represents the percent of test data not considered by a particular method.

Using a dependency treebank as input to our learning algorithm has both advantages and drawbacks. There are two main advantages of using a treebank:

- Access to more accurate data. Data is less noisy when compared with tagged or parsed input data. We can expect correct identification of verbs and their dependents.
- We can explore techniques (as we have done in this paper) that try and learn the set of SFs from the data itself, unlike other approaches where the set of SFs have to be set in advance.

Also, by using a treebank we can use verbs in different contexts which are problematic for previous approaches, e.g. we can use verbs that appear in relative clauses. However, there are two main drawbacks:

- Treebanks are expensive to build and so the techniques presented here have to work with less data.
- All the dependents of each verb are visible to the learning algorithm. This is contrasted with previous techniques that rely on finite-state extraction rules which ignore many dependents of the verb. Thus our technique has to deal with a different kind of data as compared to previous approaches.

We tackle the second problem by using the method of observed frame subsets described in Section 3.3.

6 Conclusion

We are currently incorporating the SF information produced by the methods described in this paper into a parser for Czech. We hope to duplicate the increase in performance shown by treebank-based parsers for English when they use SF information. Our methods can also be applied to improve the annotations in the original treebank that we use as training data. The automatic addition of subcategorization to the treebank can be exploited to add predicate-argument information to the treebank.

Also, techniques for extracting SF information from data can be used along with other research which aims to discover relationships between different SFs of a verb (Stevenson and Merlo, 1999; Lapata and Brew, 1999; Lapata, 1999; Stevenson et al., 1999).

The statistical models in this paper were based on the assumption that given a verb, different SFs occur independently. This assumption is used to justify the use of the binomial. Future work perhaps should look towards removing this assumption by modeling the dependence between different SFs for the same verb using a multinomial distribution.

To summarize: we have presented techniques that can be used to learn subcategorization information for verbs. We exploit a dependency treebank to learn this information, and moreover we discover the final set of valid subcategorization frames from the training data. We achieve upto 88% precision on unseen data.

We have also tried our methods on data which was automatically morphologically tagged which

Previous work	Data	#SFs	#verbs tested	Method	Miscue rate	Corpus
(Ushioda et al., 1993)	POS + FS rules	6	33	heuristics	NA	WSJ (300K)
(Brent, 1993)	raw + FS rules	6	193	Hypothesis testing	iterative estimation	Brown (1.1M)
(Manning, 1993)	POS + FS rules	19	3104	Hypothesis testing	hand	NYT (4.1M)
(Brent, 1994)	raw + heuristics	12	126	Hypothesis testing	non-iter estimation	CHILDES (32K)
(Ersan and Charniak, 1996)	Full parsing	16	30	Hypothesis testing	hand	WSJ (36M)
(Briscoe and Carroll, 1997)	Full parsing	160	14	Hypothesis testing	Dictionary estimation	various (70K)
(Carroll and Rooth, 1998)	Unlabeled	9+	3	Inside-outside	NA	BNC (5-30M)
Current Work	Fully Parsed	Learned 137	914	Subsets+ Hyp. testing	Estimate	PDT (300K)

Table 2: Comparison with previous work on automatic SF extraction from corpora

allowed us to use more data (82K sentences instead of 19K). The performance went up to 89% (a 1% improvement).

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