Doubling DOP*

A comparison of Double-DOP and DOP*

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Abstract

This paper investigates two existing estimators in the Data Oriented Parsing approach to natural language syntax. We assess the theoretical and practical differences between these estimators by comparing the grammars they derive.

1 Introduction

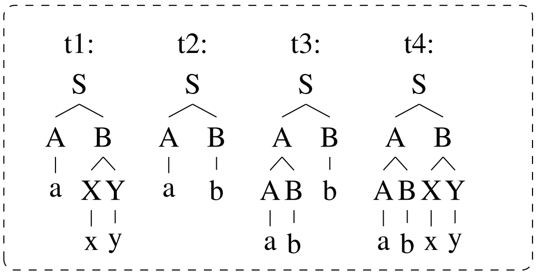


Figure 1: A toy treebank

A common approach to natural language syntax, is to view the structure of sentences as constituent trees. An artificial example of a treebank is given in figure 1. Constituent trees can be described by a *Context Free Grammars* (CFGs), such that all trees are built up from rules that each describe the production (children nodes) of a single node (parent) in the tree. When building an empirical model of observed parse trees, these rules are extended with probabilities to form a *probabilistic CFG* (PCFG). This gives the trees that are 'generated' by these rules their own probability, which makes it a statistical model of a distribution over natural language syntax.

The simple rules of a CFG cannot describe all linguistic phenomena, such as long distance dependencies. Grammars can be enriched (e.g. by Markovisation), to include deeper levels in the tree.

1.1 DOP

Data-Oriented Parsing (DOP), as first introduced in (Scha, 1990), takes a different approach. It models the language with a *Probabilistic Tree Substitution Grammar* (PTSG). The trees in the treebank are taken apart, which results in *fragments* of arbitrary depth[1]. A fragment is a connected subgraph of a tree such that it corresponds to context-free productions in that tree, i.e. each node must have either have children with the same labels as in the original tree, or no children at all. This is illustrated in figure 2. Note that a level-one fragment corresponds to a CFG rule. The *symbolic grammar* refers to the set of fragments (that receive a non-zero weight) in a grammar.

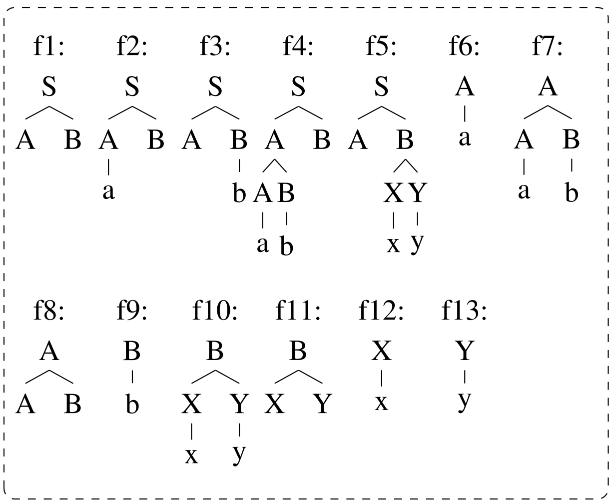


Figure 2: All extracted fragments

Fragments can be combined in a *derivation* to build syntactic structures. A step in a derivation is a composition, denoted by the symbol $\circ$. For instance, tree t_1 can be derived as $t_1 = f_2 \circ f_{10}$. We follow the convention to only allow left-most

[1]Fragments are sometimes referred to as 'subtrees' or 'elementary trees' in literature

derivations. This means that the left-most non-terminal node in a fragment f_1 must correspond to the root node of f_2 in order to derive $f_3 = f_1 \circ f_2$

For each fragment, a weight is assessed. This can be done by counting how often it occurs in the treebank compared to others with the same root, yielding the *relative frequency estimate*. The probability of a derivation is the product of the probability of the fragments it uses. Note that a single tree can be the result of different derivations. Therefore probability of a tree is the sum of the probabilities of all its derivations.

1.2 Theoretical issues

It has been argued that DOP (in its original formulation) is biased and inconsistent (Johnson, 2002), which are both assumed to be bad properties of an estimator in general. As we will see, bias is not necessarily a bad thing. In fact, Zollman proves in (Zollmann and Sima'an, 2005) that any non-overfitting estimator is biased. Furthermore, he shows that it is possible to define a DOP-estimator that is consistent.

1.3 Practical issues

In its original formulation, DOP takes the trees apart in all possible ways. The number of fragments is exponential in the length of the sentences, thus the size of the symbolic grammar would be far too huge to be computationally feasible. Different approaches have been taken to reduce the symbolic grammar, e.g. by sampling or by applying a smart algorithm. This appears to be far from trivial.

1.4 Outlook

Section 2 elaborates the notions of consistency and bias and their relation to overfitting. In section 3, we outline two approaches that tackle the reduction of the symbolic grammars: Double-DOP and DOP*. This report focuses on a comparison of these approaches. Section 4 offers a detailed comparison as well as a description of the experiments we conduct. Theoretically, they differ in that DOP*, unlike Double-DOP, has been proven to be consistent (Zollmann and Sima'an, 2005). We investigate the differences between the grammars produced by Double-DOP DOP*. The algorithms can be decomposed into two parts. We also analyze the impact of the partial choices by mutually using these parts.

In section 5, we present our findings and provide an analysis.

2 Statistics: Consistency and Bias

Linguistic studies of syntax mostly concern *competence* models, which describe the which structures appear in a language. In contrast, a *performance* model of language is an estimate of the probability of observing a parse tree in language use. It treats language as a statistical distribution over syntactic structures.

Let Ω be the set of all possible parse trees. The distribution P_Ω then describes the language, where $P_\Omega(t)$ is the probability of observing a tree $t \in \Omega$. Using a sample of parse trees from the language, an *estimator* EST builds a statistical model. A parser then uses that statistical model to predict the correct parse tree of sentences. A sample $X \in \Omega^n$ from the language is called a *corpus* or *treebank* of size n, which makes $\text{EST}(X)$ an estimator trained on a sample. If $\mathcal{M}$ is the set of probability distributions over Ω, then $P_\Omega \in \mathcal{M}$ and $\text{EST}(X) \in \mathcal{M}$.

In theory, an estimator should make exactly the right estimations of probabilities if it's given an infinite amount of data. That is to say, it should *converge* to the true distribution. If an estimator converges in the limit, that estimator is *consistent*. However, given a finite amount of data, the estimator will probably not generate the correct distribution. The distance between the true distribution P^* and an estimate P is called the *loss* of that estimate. The loss can be defined in different ways, but the most popular is the *mean squared difference*:

$$\mathcal{L}(P, P^*) = \sum_{t \in \Omega} P^*(t)(P^*(t) - P(t))^2$$

From a true distribution, it's possible to calculate the expected loss of an estimator trained on a treebank of a certain size. This is the *risk* or *error* of that estimator given a sample size and a distribution. With these definitions, it is possible to define estimator consistency when sampling $X \in \Omega^n$ from P_Ω:

$$\lim_{n \to \infty} \mathbf{E}[\mathcal{L}(\text{EST}(X), P_\Omega)] = 0$$

In its original formulation, DOP was defined using a *relative frequency estimate*, by counting how often it occurs in the treebank compared to others with the same root. However, it has been shown () that in this case, the RF estimator is inconsistent.

Another possible property of an estimator is its *bias*, which is defined as the difference between the true probability and the expected estimate. It has been proven that any unbiased DOP estimator will overfit a treebank by assigning zero-probabilites to trees outside the corpus. To prevent overfitting, it is therefore necessary to introduce a bias that assigns a non-zero probability to unseen trees. By maximizing the probability of a corpus different from the one from which the fragments are extracted, we will see that it is possible to minimize overfitting.

3 Existing Models: Double-DOP and DOP*

In this section, we outline two approaches to constrain the extraction of fragments: Double-DOP and DOP*. Furthermore, we discuss the similarities and dissimilarities for these two approaches.

3.1 Double-DOP

In the following, we discuss Double-DOP as it was presented in (Sangati and Zuidema, 2011). In this model, no unique fragments are extracted from the dataset: if a construction occurs in one tree only, it is probably not representative for the language. This is carried out by a dynamic algorithm using tree-kernels. It iterates over pairs of trees in the treebank, looking for fragments they have in common. In fact, only the largest shared fragment is stored.

The symbolic grammar that is the output of this algorithm is not guaranteed to derive each tree in the training corpus. Therefore all one-level fragments, constituting the set of PCFG-productions, are also added.

The emphasis of Double-DOP is on the extraction method for determining the symbolic grammar. However, it was also implemented with different estimators. The estimation is done in a second pass over the treebank, gathering frequency counts for the fragments in the grammar.

The best maximizing objective appears to be MCP (max constituent parse), which maximizes a weighted average of expected labeled recall and precision. The latter cannot be maximized directly, but is approximated by minimizing the mistake rate. Parameter λ that rules the linear interpolation was empirically found to be optimal at 1.15. Efficient calculation of MPC is possible with dynamic programming, but it can also be approximated with a list of k-best derivations.

In addition, empirical results show that the relative frequency estimate outperforms the other estimates tested, i.e. Equal Weights Estimate (first adjust counts proportional to the size of the symbolic grammar, then make this value proportional to fragments with the same root), and Maximum Likelihood (optimizing to maximum likelihood for the training data with an Inside-Outside algorithm).

3.2 DOP*

In DOP* (Zollmann and Sima'an, 2005), a rather different approach is taken called held-out estimation. The treebank is split in two parts, the *extraction corpus* (EC) and a *held-out corpus* (HC). An initial set of fragments is extracted from the EC, containing all the fragments from its trees. The weights are then determined so as to to maximize the likelihood of HC, under the assumption that this is equivalent to maximizing the joint probability of the *shortest derivations* of the trees in HC.

The weight of a fragment is its relative frequency of occurring in a shortest derivation, and all fragments that do not occur in such a derivation are removed from the symbolic grammar. Note that some trees in HC may not be derivable at all. Furthermore, a tree could have several shortest derivations. The probability mass is divided over the fragments taking parts in the different derivations in that case.

Consistency and bias DOP* was claimed to be the first consistent (non-trivial) DOP-estimator. Zollmann provides a consistency proof in (Zollmann and Sima'an, 2005). On the other hand DOP* is biased, but Zollmann shows how bias actually arises from generalization: no non-overfitting DOP estimator could be unbiased. Bias is therefore not prohibited but on the contrary a desirable property of an estimator.

In (Zuidema, 2006) it is argued that there is a problem with the consistency proof given for DOP*, as well as the non-consistency proof for other DOP-estimators by (Johnson, 2002). Zuidema points out that these proofs use a frequency-distribution test, whereas for DOP a weight-distribution test would be more appropriate.

4 Comparison

DOP* and Double-DOP differ both in the set of fragments they extract and their estimation of the weights. To investigate the exact differences, we will view both steps separately.

Extraction Double-DOP uses tree kernels to find the maximal overlapping fragments of pairs of trees, which are added to the symbolic grammar. We will call this the *maximal-overlap* method. DOP* iteratively finds the shortest derivation of one tree given all the fragments of a set of trees, hereafter the *shortest-derivation* method.

It is easy to see that the*shortest-derivation* extraction in itself does not depend on the corpus split: we can also try to find the shortest possible derivation using fragments from all the other trees. Likewise Double-DOP could be implemented using a split, comparing only those pairs that consist of a tree from each part of the corpus.

Estimation Double-DOP determines the weights of the fragments in the symbolic grammar in a separate run over the treebank, to obtain exact counts. We use the relative frequency estimate to assign weights to the fragments. DOP* on the other hand counts the occurrence in shortest derivations of the fragments, and normalizes relative to counts of fragments with the same rout.

Example This example clarifies how the grammars that result from Double-DOP and DOP* can actually differ. Recall our toy treebank from figure 1 and the fragments in figure 2. Applying the maximal overlap extraction and shortest derivation extraction in a 1 vs the rest manner to this treebank, yields the weights in table 1. Note that in the maximal overlap case, all context-free productions are added as well. The weight estimates are the relative frequencies of the fragments in the treebank(Sangati and Zuidema, 2011):

$$p(f) = \frac{count(f)}{\sum_{f' \in F_{root}(f)} count(f')} \quad (1)$$

As for the shortest derivation extraction, the weights are determined as the relative frequency of occurring in shortest derivations(Zollmann and Sima'an, 2005):

$$p(f) = \frac{r_c}{\sum_{k \in \{1 \dots N\}: root(f_k) = root(f_j)} r_k} \quad (2)$$

Note the remarkable differences in the weight distributions. For example, f_1 gets a weight of 0.5 in the maximal overlap approach, and zero in the shortest derivation case. Of course, the sparsity of the data contributes much to these extreme variations. However, the observed differences encourage us to investigate these two approaches into more depth.

	Maximal overlap	weight	Shortest deriv.[2]	weight
f1	(t1,t3),(t2,t4)	4/12	-	0
f2	(t1,t2)	2/12	1b, 2a	1/4
f3	(t2,t3)	2/12	2b, 3b	1/4
f4	(t3,t4)	2/12	3a, 4b	1/4
f5	(t1,t4)	2/12	1a, 4a	1/4
f6	(t1,t3),(t1,t4), (t2,t3),(t2,t4)	4/6	1a, 2b	1/2
f7	-	0	3b, 4a	1/2
f8	CFG rule	2/6	-	0
f9	(t2,t3),(t2,t4), (t3,t4)	4/6	2a, 3a	1/2
f10	-	0	1b, 4b	1/2
f11	CFG rule	2/6	-	0
f12	CFG rule	2/2	-	0
f13	CFG rule	2/2	-	0

Table 1: The weights assignment according to both methods in a one vs. the rest manner

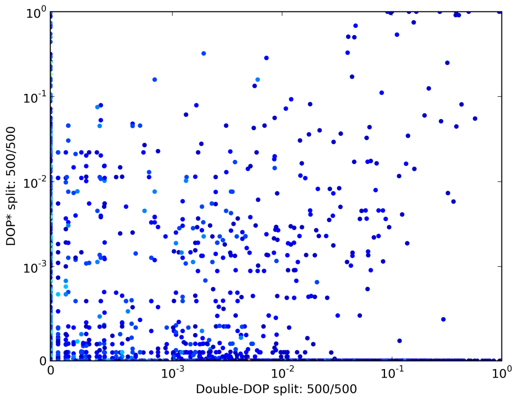
4.1 Experiments

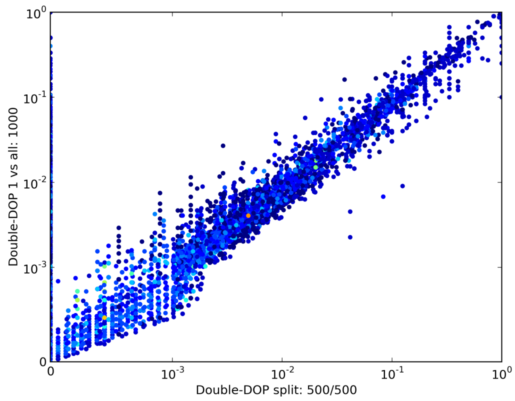
We compare the maximal overlap and shortest derivation extraction by using either a split or the whole set of trees for both estimators. We will plot the fragments according to the weights assigned by the estimators, such that the differences can stand out. In the same way, we compare the split and one vs. the rest estimation or the same estimator.

Furthermore, we can compare the grammars by having them parse a test set and determine their performance, e.g. the F1-score for correctly predicted parses.

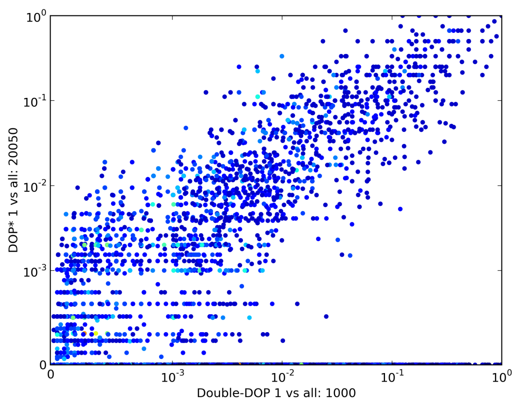
Data We use the *Wall Street Journal* (WSJ) treebank for our experiments. DOP* has only been applied to the Dutch OVIS corpus in (Zollmann and Sima'an, 2005), which contains relatively small and (therefore) easy sentences. Therefore we are curious about its performance on the WSJ.

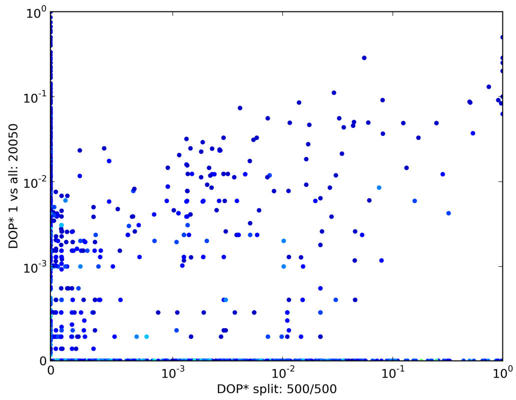
[2]For this dataset, two shortest derivations exist for each tree. We refer to them with the following variables: 1a = f5, f6; 1b = f2, f9; 2a = f2, f8; 2b = f3, f6; 3a = f4, f8; 3b = f3, f7; 4a = f5, f7; 4b = f4, f9





5 Results





6 Conclusion

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