Using DOP for transformations

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Abstract

In this paper, we investigate transformations with Data-Oriented Translation (DOT), based on the existing formalisms of Data-Oriented Parsing, synchronous grammar, and the Goodman Reduction. The goal is to define and evaluate a general formalism for learning arbitrary transformations composed of movement and insertions based on annotated exemplars. Parsing a sentence should result in a pair of trees corresponding to the original and a transformed sentence. This stochastic approach contrasts with purely rule-based formalisms such as transformational grammar, in which abstract representations are manipulated with *a priori* specified operations. The test case will be declarative versus interrogative sentences.

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1 Introduction

Data Oriented Parsing (DOP) has proven to be a successful framework for the parsing of natural language and several other applications in computational linguistics. In this paper, we will explore options of using a Data-Oriented method to be able to perform frequently occurring transformations in natural language. The main application of such transformations will be that between declarative and interrogative sentences in English, but the developed framework should be generalizable to other transformations, such as:

- Transformations between affirmative and negative sentences.
- The transformation between the 'main clause' and 'auxiliary clause' sentence order in Dutch.
- Active versus passive sentences, focus, wh-fronting, etc.

For this project, we make use of a number of existing frameworks that may prove useful to us. In particular, these include:

- Synchronous grammars, as developed by Chiang (2006).
- Data Oriented Translation framework by Poutsma (2000b;a).
- The Goodman-reduction, as developed by Goodman (2003).

In section 2, these underlying frameworks (as well as their relevance to our project) will be explained in a somewhat more detailed fashioned; then in section 3, our own approach will be described more comprehensively; in section 4, further details regarding our implementation will be given, and in section 5 some preliminary results will be presented.

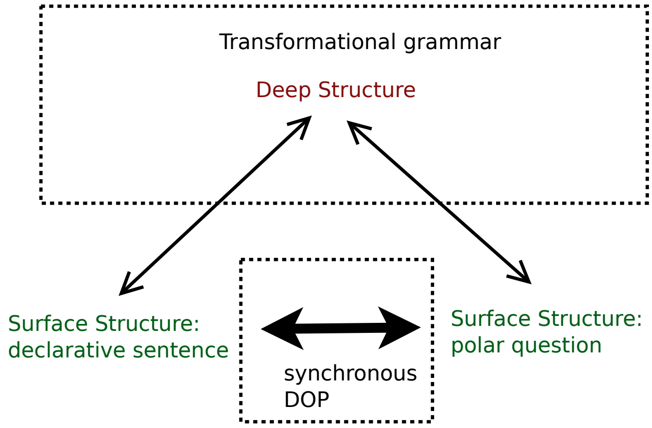


Figure 1: Overview of transformations: the orthodox approach (transformational grammar), contrasted with our data-oriented approach

2 Theoretical framework

We will use a data-oriented approach. This is opposed to the abstract, rule-based formalisms such as transformational grammar, which assume abstract structures in addition to realizations of surface structures. See figure 2 for a diagrammatic overview showing the relation of our project to the traditional, generative approach.

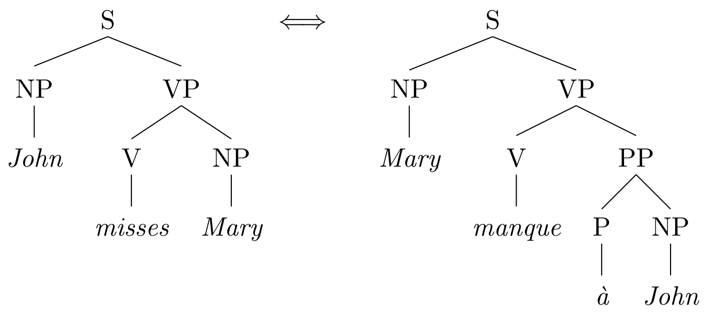
2.1 Synchronous grammars

In Chiang (2006), the concept of a synchronous grammar is introduced, as a tool to easily extend the notion of a (P)CFG into the domains of translation and transformation. The main idea, here, is that instead of single CFG-rules with a left and right hand side, every rule now has a pair of right-hand sides – one corresponding to the source language, and the other corresponding to the target language. Moreover, there has to be a bijective function between the nonterminal symbols on both right-hand sides.

Parsing and translating using synchronous grammars is just as easy as it is for regular PCFGs: to translate, we simply parse using the right-hand sides corresponding to the source language. By reading off the right-hand sides corresponding to the target language, of the rules used in the derivation, the translation is immediately obtained.

Some problems with synchronous grammars are also mentioned in Chiang (2006). One of these problems is that, in reality, tree structures often do not coincide between the original language and the translated language. For example:

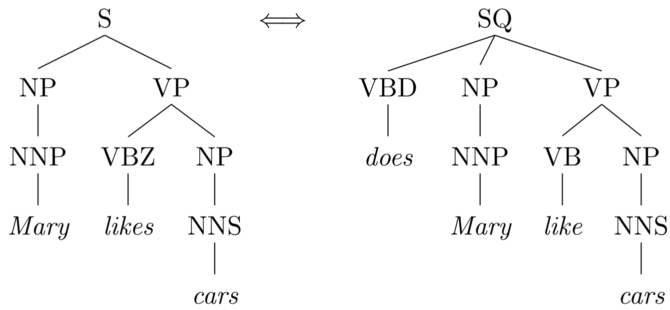
(1)



A common analysis of (1) is problematic under the original framework of synchronous grammars, because of the mismatch in the tree structures.

Similarly, when looking at transformations between declarative and interrogative sentences, and basing ourselves on standard analyses of the Stanford parser (which are based on the annotation of the Penn treebank), we encounter the following pairs of trees:

(2)



Again, we here are faced with a pair of sentences, where the tree structures are rather different from each other.

As a solution to the problem of a mismatch, the notion of flattening is named. In this case, several CFG-rules are collapsed into a single rule, so that the mismatch between the trees is resolved.

2.2 DOP for translations

In Poutsma (2000b;a), synchronous grammars are extended from plain PCFGs to the DOP framework: instead of looking at rules with two right-hand sides and a corresponding set of non-terminals, we now consider pairs subtrees with identical top nodes, and corresponding non-terminal leaf nodes.

These linked subtrees are then combined into a bag of linked subtree pairs, which can then be used as a grammar for translations and transformations. Just like in the case of synchronous PCFGs, we can simply parse new sentences using the source 'side' of the grammar, and derive the corresponding target side immediately.

Formally, in Poutsma (2000a), linked subtree pairs are defined as follows:

Definition 2.1. Given a pair of linked trees $\langle T_1, T_2 \rangle$, a *linked subtree pair* consists of two connected and linked subgraphs $\langle t_1, t_2 \rangle$ such that:

1. for every pair of linked nodes in $\langle t_1, t_2 \rangle$, it holds that
   (a) both nodes in $\langle t_1, t_2 \rangle$ have either zero daughter nodes, or
   (b) both nodes have all the daughter nodes of the corresponding node in $\langle T_1, T_2 \rangle$
2. every non-linked node in either t_1 (or t_2) has all the daughter nodes of the corresponding node in T_1 (or T_2), and
3. both t_1 and t_2 consist of more than one node.

Then, the *bag of linked subtree pairs* is defined as follows: given a corpus of linked trees C, the *bag of linked subtree pairs* of C is the bag in which linked subtree pairs occur exactly as often as they can be identified in C.

An important contrast with the earlier synchronous grammars for PCFGs, is that in the framework of Poutsma (2000a), we are not necessarily dependent on strong similarities between the tree structures on both sides (although, ultimatlely, a strong similarity may still be a prerequisite for good performance). This would make translations and transformations, such as in the examples given in section 2.1, possible.

Of course, it should be noted that, in this framework, it is unlikely that *all* subtrees on the source side are linked to subtrees on the target side: especially in the (far from unlikely) case where the total number of subtree differs, this has to be trivially false.

A problem with the DOT model, as described in Poutsma (2000a), consists of the fact that the complexity of parsing new sentences can be quite huge, as the number of subtrees can be (at worst) exponential in the number of nodes. For standard DOP-based parsing the Goodman reduction, which will be described in the next section, has been found to resolve such issues: however, because we do not have a complete set of subtrees available to use, it is impossible to use this reduction right away. This question of finding a suitable reduction for the DOT model as described in Poutsma (2000b;a), will be addressed at a later stage in this report.

2.3 Goodman reduction

A significant problem with DOP parsing, is the fact that the number of subtrees that have to be included is exponential in the size of the tree. In Goodman (2003), a solution to this problem is presented, that is able to yield equivalent parse probabilities (but not equivalent derivation probabilities) to regular DOP parsing, while limiting the number of rules to a number that is linear in the number of tree nodes.

Here, the subtrees are replaced by a set of PCFG-rules, where nodes can be either 'addressed' or 'non-addressed': in every tree, every node has a unique address, and the addressed nodes only match with that specific address, whereas the non-addressed nodes match with any node of the type.

It is proven in Goodman (2003) that the PCFG resulting from the Goodman reduction leads to equivalent parse probabilities as the underlying STSG:

Theorem 2.2. *This construction [the Goodman-reduction] produces PCFG trees homomorphic to the STSG trees with equal probability.*

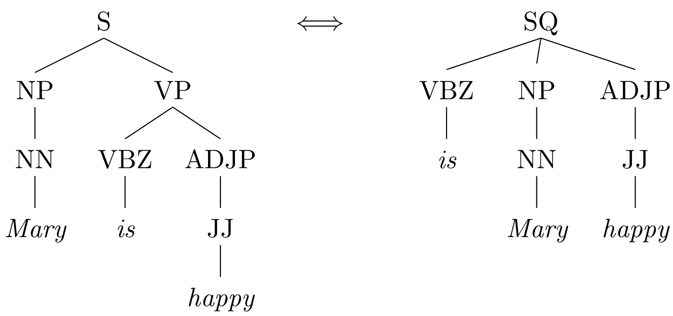
3 Approach

3.1 Definition of DOP model

We will assume a parallel corpus of pairs of trees with declarative and interrogative versions of sentences. This assumption lies on the extreme end of supervised parsing; other options are a bag of unrelated sentences marked as declarative or interrogative in their root node. Whether the assumption of a parallel corpus is cognitively plausible in terms of language acquisition is irrelevant because the point is to learn transformations from exemplars alone, without relying on built in primitives for movement and insertions, or on a common, abstract representation for sentences such as Deep Structures or Logical Form in generative grammar.

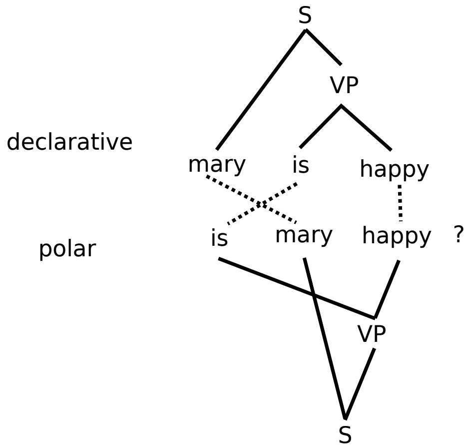
Assuming ordered pairs of trees, $\langle T_s, T_t \rangle$, may be enough to learn transformations from data alone. Naturally the word forms will often coincide, so words are implicitly linked (although this may be problematic with multiple occurrences in the same sentence). Further annotation could add indices for each constituent, but this implies labor-intensive annotation. More difficult than the linking problem is the problem of structure mismatch. Consider the following example:

(3)



In the phrase-structure annotation of the interrogative of (3) (as produced by the Stanford parser), the VP constituent has arguably become a discontinuous constituent (Harman, 1963), but due to a strong, pragmatically motivated preference for orthodox phrase-structures in computational linguistics (as well as a completely indefensible Anglocentrism), such information is sacrificed by collapsing the phrase-structure. This means that the phrase-structure no longer encodes the connection of the verb and its direct object. A more elaborate representation such as employed in the discontinuous constituent phrase-structure grammar of Harman (1963) would make it possible to streamline the annotation of sentences so that less configurational and more relational information can be preserved. Note that discontinuous constituents are only a minor step in the spectrum of constituency versus dependency. While a discontinuous constituent violates the canonical definition of a tree, it is still word order which determines constituency (e.g., in the example a fronted auxiliary verb signifies VSO order), and it is not obvious that a free word-order language could be profitably described by such a representation. When (3) is represented using discontinuous constituents, the tree could look like this:

(4)

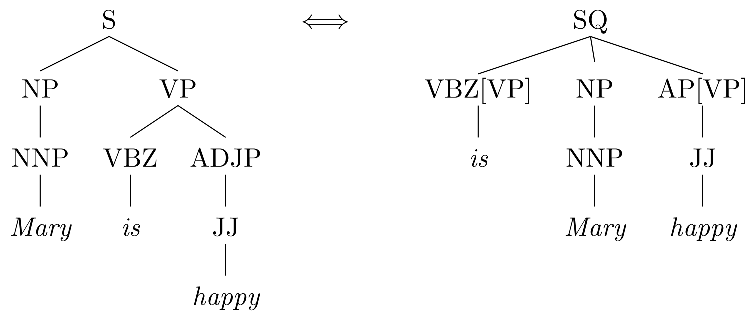


It is clear that this kind of representation provides a way to avoid structure mismatch as a result of movement completely (ie., the bag of non-terminals will be equivalent for both structures). The absence of the auxiliary 'did' in the declarative such as in (2) can be represented by trace elements; an even simpler strategy would be to allow structure mismatch as long as one of the trees is a proper subtree of the other. The reason that it may be worthwhile to avoid structure mismatch is that it maximizes the number of parallel subtrees, which minimizes the violation of the DOP hypothesis stating that all fragments should count in order to fully exploit the data at hand. It may turn out that without isomorphic phrase-structures, the generalizing power of synchronous DOP is not sufficient to handle complex, novel sentences (long constituents, relative or embedded clauses, etc.).

The same definition for subtrees and fragments can be applied to discontinuous structures, it is basically a matter of annotation and implementation to employ them, not formalism. Whether it will be necessary or worthwhile to adopt discontinuous constituents will have to be determined emprically. Initially we will attempt to use the standard PTB phrase-structure annotation and see how well it works; this has the obvious advantage of the availability of large corpora such as the WSJ, which can complement a small, hand-annotated parallel treebank.

As a compromise between the impoverished PTB annotation and the rich but non-standard discontinuous annotation, we could consider labelling POS tags with (former) parent annotations, e.g.:

(5)



As operations we will restrict ourselves to the standard substitution operation. While it may seem obvious to extend the DOP framework with movement and adjunction operations, that has the downside of having to adapt the existing, well-defined formalisms, including their probability models. On top of that we set out to induce transformations from data alone, so making such things part of the formalism means smuggling in *a priori* expectations (albeit only in a very general sense).

As estimation method we will employ the standard DOP1 estimator, but DOP* (Zollmann and Sima'an, 2005) or backoff-DOP (Sima'an and Buratto, 2003; Prescher et al., 2004) can be considered as well. Although sparsity of evidence is claimed to be an insurmountable problem for non-nativist theories by generativists (cf. MacWhinney (2004) for a discussion), for example the transformation of aux-fronting seems simple enough given elaborate information such as phrase structures; e.g. Bod (2007) shows that auxiliary fronting is learnable from positive evidence from Childes data annotated with dependency structures. For this reason it would seem that DOP1 should be adequate.

3.2 A reduction for synchronous DOP

As an instantiation of the previously mentioned assumptions, we will apply Data-Oriented Translation to transformations. For implementation efficiency we would like to use the Goodman reduction.

We are now faced with the situation, that we cannot simply apply the Goodman reduction, reducing subtree pairs to PCFG rules, because of the reason that not every subtree will always be a part of a subtree pair. In particular, the PCFG-rules themselves, the 'building blocks' of the Goodman reduction, may not be a part of a subtree pair. This leads us to wonder whether it is possible to, in some way or another, still perform a Goodman-like reduction on the bag of linked subtree pairs.

It turns out that, indeed, a reduction is possible over the bag of linked subtree pairs. For this, consider the notion of a *minimal linked subtree pair*:

Definition 3.1. For a pair of linked trees $\langle T_1, T_2 \rangle$, a *minimal linked subtree pair* is a linked subtree pair $\langle t_1, t_2 \rangle$, s.t. $t_1 \subseteq T_1$, $t_2 \subseteq T_2$, such that there is no other linked pair $\langle s_1, s_2 \rangle$ where $s_1 \subsetneq t_1$ and $s_2 \subsetneq t_2$.

Theorem 3.2. *Every pair of linked trees can be reconstructed from the minimal linked subtree pairs derived from it.*

Proof. Assume (towards a contradiction) that there is a pair of linked trees $\langle T_1, T_2 \rangle$ for which this is not possible, given a certain bag of linked subtree pairs. Then there has to be some linked pair of subtrees $\langle t_1, t_2 \rangle$ for which:

1. It is not possible to construct $\langle t_1, t_2 \rangle$ from minimal linked subtree pairs.
2. All pairs of subtrees $\langle s_1, s_2 \rangle \subsetneq \langle t_1, t_2 \rangle$ can be constructed from minimal subtree linked pairs.

It is impossible that this pair of subtrees is itself minimal: if it were, it could trivially be constructed from linked minimal subtree pairs. So, for this case to hold, the linked subtree pair $\langle t_1, t_2 \rangle$ must have a proper linked subtree pair $\langle s_1, s_2 \rangle$. When 'removing' $\langle s_1, s_2 \rangle$ from the linked subtree pairs, we are left with a set of linked subtree pairs (zero or one corresponding to the root nodes of $\langle s_1, s_2 \rangle$, and zero or one corresponding to each frontier node of $\langle s_1, s_2 \rangle$), from which the linked subtree pair $\langle t_1, t_2 \rangle$ can be reconstructed.

So we are now, at least, able to construct the subtree pair $\langle t_1, t_2 \rangle$ from smaller linked subtree pairs. By assumption, all subtrees of $\langle t_1, t_2 \rangle$ can be constructed from minimal subtree pairs. However, this implies that $\langle t_1, t_2 \rangle$ can also be constructed from minimal subtree pairs – providing the contradiction to the assumption, and thus completing the proof. □

In other words: just like the PCFG rules can be used as 'building blocks' for the Goodman reduction, the minimal linked subtree pairs as defined above can be used as the 'building blocks' for a similar reduction. It should be noted that, for all means and purposes, such minimal subtrees can be worked with, as if they were simple CFG-rules, that just happen to have an additional internal structure (which is ignored by the parser).

Like in the Goodman-reduction, we replace every elementary tree-pair (i.e. every minimal linked subtree pair) with $2^{(k+1)}$ partially annotated minimal linked subtree pairs, where k is the number of nonterminals occurring as frontier nodes (which has to be equal on the left and right hand sides). For the root node, and for every nonterminal node, either an 'addressed' version or a 'non-addressed' version can occur.

The probability of a partially annotated minimal linked subtree pair, with a root node (either addressed or non-addressed) R, and addressed frontier nodes $X_1, \ldots X_n$, will be

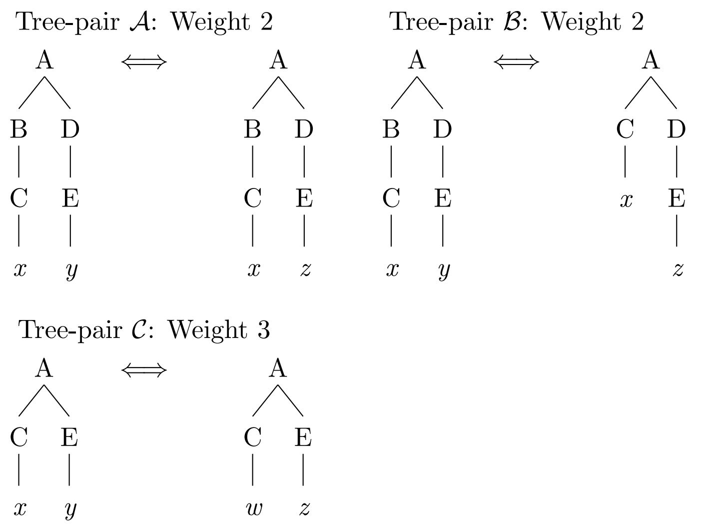
$$\frac{n(X_1) \cdot \ldots \cdot n(X_n)}{n(R)}$$

where $n(K)$ is the number of linked subtree pairs headed by the node K. (In the case of addressed nodes K, this is the number of lined subtree pairs headed by that specific node, whereas in the case of a non-addressed root-node R, this is the number of all linked subtree pairs headed by nodes with the label R.)

3.3 (Joint) parse and derivation probabilities

An important difference, between the Data Oriented Translation/Transformation framework, and ordinary DOP, is that a 'derivation' does not just consist of the building blocks of a single tree, but rather of the combined building blocks of a pair of trees. It is, furthermore, possible that a left-side tree may be the most occuring tree in the set of derivations, but not be the left-side of the most probable joint parse. Take for example the following (abstract) situation:

(6)



Here the left side of tree-pairs $\mathcal{A}$ and $\mathcal{B}$ is, by itself, the most probable left-hand side parse, but the tree pair $\mathcal{C}$ here is the most probable joint parse.

So, instead of simply looking at the most probable parses and derivations (as we would do in the case of ordinary DOP, with or without Goodman reduction), we can now look at the most probable *joint* derivations and parses. Whether we are, ultimately, most interested in the most probable joint parses, the most probable left hand side parses, or the most probable right hand side parses, can be subject to discussion. It may be argued that, ultimately, we are most interested in the most probable parse on the target side – or perhaps even in the most probable *sentence* on the target side. For now, the outcome of this discussion is not important to us: we simply use the equivalence between joint parse probabilities as a base case, from which the equivalence between left and right hand side probabilities, and target side sentence probabilities can be easily derived.

Theorem 3.3. *A 'Goodman-like' reduction based on minimal linked subtree pairs leads to equivalent joint parse probabilities (but not equivalent joint derivation probabilities) as those of the original synchronous DOP (DOT) model.*

Proof. The proof of this theorem is exactly analagous to those of Theorem 1 and 2 in Goodman (2003), with the exception that Theorem 1 has to be generalized for situations with n frontier nodes, rather than the 2 from Goodman's paper. □

Corollary 3.4. *The 'Goodman-like' reduction leads to the same left hand side and right hand side parse probabilities as those of the original synchronous DOP model.*

Proof. The probability of a left (or right) hand side parse is simply the sum of all joint parse probabilities with that left (or right) hand side. Because the joint parse probabilities are invariant, so are the left (and right) hand side parse probabilities. □

Corollary 3.5. *The 'Goodman-like' reduction leads to the same target side sentence probabilities as those of the original synchronous DOP model.*

Proof. This follows from the fact that the sentence probability of a sentence s is simply the sum of all joint parse probabilities of tree pairs which, on the target side, yield s. $\square$

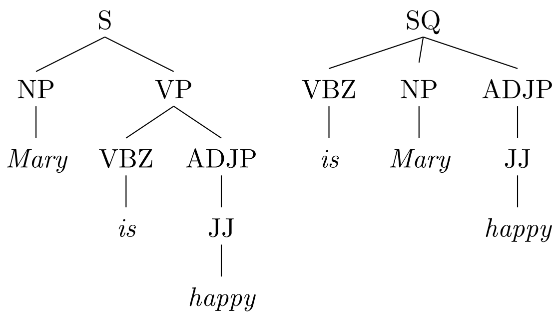
4 Implementation

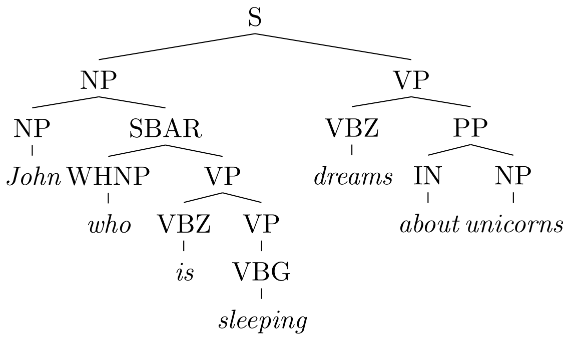
In order to discover the subtrees in pairs of exemplars, we use a simple algorithm to automaticallly discover links. At each step the largest subtree which occurs on both sides is sought, and removed from the tree pair after noting the link. This process is repeated until the trees can no longer be decomposed, after which the last fragment containing a top production remains. To increase the number of links that can be found, lemmatization of verbs has been added.

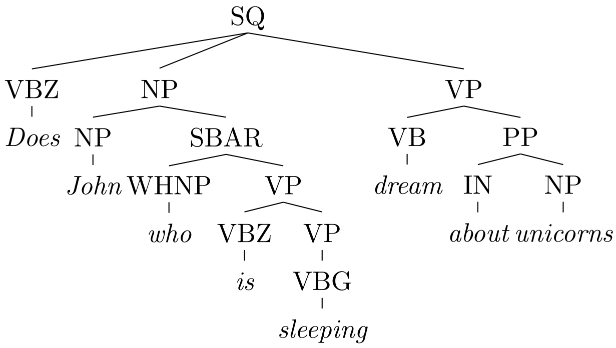
To approximate the most probable joint parse we use the 1000 most probable viterbi derivations, summing equivalent trees. Next all possible translations of each tree are produced; this step can produce multiple translations for each derivation. Again we sum over equivalent trees, but this time only after first removing the node addresses added by the Goodman-like reduction. The translation with the highest joint probability is then selected by multiplying the derivation and translation probability for each tree. The probabilities during translation are stored as log probabilities to avoid underflow.

5 Evaluation

To test the soundness of the approach, the model was first applied to a toy corpus. This corpus is meant to show that so-called complex declaratives can be transformed without problem.





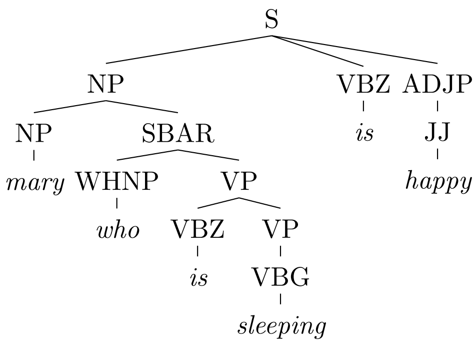


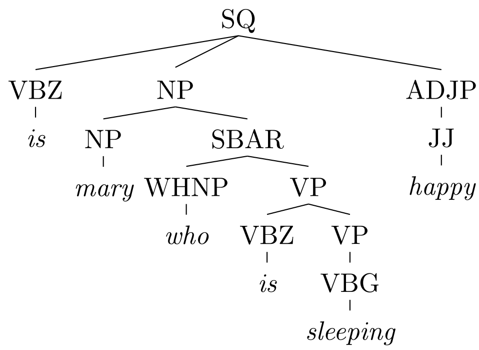
Using this corpus, we can transform the following novel sentence:

(7) Mary who is sleeping is happy $\Longleftrightarrow$ Is Mary who is sleeping happy

This is the paradigm case of a syntactic phenomenon that is claimed to be unlearnable from data. Children are said to have no reason to prefer movement of the second occurrence of 'is,' rather than the first. However, with these two exemplars we can already transform this sentence with two occurrences of 'is' correctly, thus accounting for auxiliary fronting.

As the transformations can be modelled in both directions, both of the following trees can be produced, when the words of the other are provided:





The corpus we evaluate on consists of 185 exemplars of declarative sentences paired with interrogative sentences. Roughly half of these were interrogative sentences found in the Wall Street Journal (WSJ) corpus, and the other half declarative sentences from the same corpus. It is noteworthy that nearly all of the polar questions in the WSJ were included. These sentences were transformed by hand, and fed to the Stanford parser to obtain parse trees. The resulting parse trees were manually 'corrected' so as to conform to the corresponding trees from the WSJ.

The corpus has 32 types of (top-level) S productions, and 81 types of SQ productions. Especially the latter is problematic, as these 81 productions include 58 productions occurring only once. If any of these 58 occur in the test set then the model doesn't stand a chance, because the smallest fragment in a DOP model is a CFG rule. This gives us an expected minimum error rate of $58/185 = 31\%$.

For the S productions the hapaxes were all attributable to punctuation (e.g., S $\rightarrow$ " FRAG , " NP VP .). The hapaxes for SQ were more varied, such as SQ $\rightarrow$ CC VBD NP VP . In effect, for every type of S production an SQ production is generated for every kind of top-level VP production, since the VP is flattened in case of aux-fronting. This is a form of sparsity that is dictated by the formalism of context-free phrase-structures.

Evaluation is done on the resulting surface forms, after lemmatizing verbs and expanding contractions. Words and POS tags of the test set were added to the training corpus to avoid problems with unseen words. The following table shows the results of ten-fold testing (with test sets of 20 sentences):

	original trees	right branching
decl $\rightarrow$ inter	45.0 %	62.0 %
inter $\rightarrow$ decl	46.0 %	54.0 %

To increase the coverage, a number of modifications were tried:

- Smoothing: when during translation any structure is not found, it is assumed that it is equal to its translation, with a count of 1. Also, when none of the target trees can be used during translation (in case of an incompatible label blocking substitution), the same smoothing is applied.
- Annotating the POS tags of 'to be,' 'to have' and their parent nodes with an AUX feature, to distinguish them from regular verbs.
- Binarization, both left and right branching, with and without markings.
- Folding labels of constituents other than TOP, S, SQ, VP and NP, by relabeling them to X.

6 Conclusion

We have presented a reduction of Data-Oriented Translation inspired by Goodman's reduction of DOP. While the application to the transformation of interrogative questions to declarative sentence suffers from the sparsity of questions in the Penn treebank, it is evident that the approach can generalize productively by recombining exemplars.

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