Generating Non-Projective Word Order in Statistical Linearization

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Abstract

We propose a technique to generate non-projective word orders in an efficient statistical linearization system. Our approach predicts *liftings* of edges in an unordered syntactic tree by means of a classifier, and uses a projective algorithm for tree linearization. We obtain statistically significant improvements on six typologically different languages: English, German, Dutch, Danish, Hungarian, and Czech.

1 Introduction

There is a growing interest in language-independent data-driven approaches to natural language generation (NLG). An important subtask of NLG is surface realization, which was recently addressed in the 2011 Shared Task on Surface Realisation (Belz et al., 2011). Here, the input is a linguistic representation, such as a syntactic dependency tree lacking all precedence information, and the task is to determine a natural, coherent linearization of the words.

The standard data-driven approach is to traverse the dependency tree deciding locally at each node on the relative order of the head and its children. The shared task results have proven this approach to be both effective and efficient when applied to English.

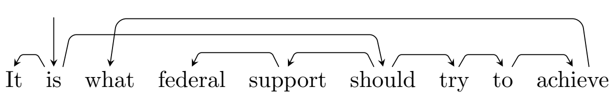

Figure 1: A non-projective example from the CoNLL 2009 Shared Task data set for parsing (Hajič et al., 2009).

However, the approach can only generate projective word orders (which can be drawn without any crossing edges). Figure 1 shows a non-projective word order: the edge connecting the extracted *wh*-pronoun with its head crosses another edge. Once *what* has been ordered relative to *achieve*, there are no ways of inserting intervening material. In this case, only ungrammatical linearizations can be produced from the unordered input tree:

(1) a. *It is federal support should try to what achieve
b. *It is federal support should try to achieve what
c. *It is try to achieve what federal support should

Although rather infrequent in English, non-projective word orders are quite common in languages with a less restrictive word order. In these languages, it is often possible to find a grammatically correct *projective* linearization for a given input tree, but discourse coherence, information structure, and stylistic factors will often make speakers prefer some non-projective word order.[1] Figure 2 shows an object fronting example from German where the edge between the subject and the finite verb crosses the edge between the object and the full verb. Various other constructions, such as extraposition of (relative) clauses or scrambling, can lead to non-projectivity. In languages where word order is driven to an even larger degree by information structure, such as Czech and Hungarian, non-projectivity can likewise result from various ordering decisions. These phenomena have been studied extensively in

[1] A categorization of non-projective edges in the Prague Dependency Treebank (Böhmová et al., 2000) is presented in Hajičová et al. (2004).

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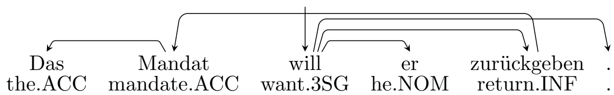
the linguistic literature, and for certain languages, work on rule-based generation has addressed certain aspects of the problem.



'He wants to return the mandate.'

Figure 2: German object fronting with complex verb introducing a non-projective edge.

In this paper, we aim for a general data-driven approach that can deal with various causes for non-projectivity and will work for typologically different languages. Our technique is inspired by work in data-driven multilingual parsing, where non-projectivity has received considerable attention. In pseudo-projective parsing (Kahane et al., 1998; Nivre and Nilsson, 2005), the parsing algorithm is restricted to projective structures, but the issue is side-stepped by converting non-projective structures to projective ones prior to training and application, and then restoring the original structure afterwards.

Similarly, we split the linearization task in two stages: initially, the input tree is modified by lifting certain edges in such a way that new orderings become possible even under a projectivity constraint; the second stage is the original, projective linearization step. In parsing, projectivization is a deterministic process that lifts edges based on the linear order of a sentence. Since the linear order is exactly what we aim to produce, this deterministic conversion cannot be applied before linearization. Therefore, we use a statistical classifier as our initial lifting component. This classifier has to be trained on suitable data, and it is an empirical question whether the projective linearizer can take advantage of this preceding lifting step.

We present experiments on six languages with varying degrees of non-projective structures: English, German, Dutch, Danish, Czech and Hungarian, which exhibit substantially different word order properties. Our approach achieves significant improvements on all six languages. On German, we also report results of a pilot human evaluation.

2 Related Work

An important concept for tree linearization are *word order domains* (Reape, 1989). The domains are bags of words (constituents) that are not allowed to be discontinuous. A straightforward method to obtain the word order domains from dependency trees and to order the words in the tree is to use each word and its children as domain and then to order the domains and contained words recursively. As outlined in the introduction, the direct mapping of syntactic trees to domains does not provide the possibility to obtain all possible correct word orders.

Linearization systems can be roughly distinguished as either rule-based or statistical systems. In the 2011 Shared Task on Surface Realisation (Belz et al., 2011), the top performing systems were all statistical dependency realizers (Bohnet et al., 2011; Guo et al., 2011; Stent, 2011).

Grammar-based approaches map dependency structures or phrase structures to a tree that represents the linear precedence. These approaches are mostly able to generate non-projective word orders. Early work was nearly exclusively applied to phrase structure grammars (e.g. (Kathol and Pollard, 1995; Rambow and Joshi, 1994; Langkilde and Knight, 1998)). Concerning dependency-based frameworks, Bröker (1998) used the concept of word order domains to separate surface realization from linear precedence trees. Similarly, Duchier and Debusmann (2001) differentiate Immediate Dominance trees (ID-trees) from Linear Precedence trees (LP-trees). Gerdes and Kahane (2001) apply a hierarchical topological model for generating German word order. Bohnet (2004) employs graph grammars to map between dependency trees and linear precedence trees represented as hierarchical graphs. In the frameworks of HPSG, LFG, and CCG, a grammar-based generator produces word order candidates that might be non-projective, and a ranker is used to select the best surface realization (Cahill et al., 2007; White and Rajkumar, 2009).

Statistical methods for linearization have recently become more popular (Langkilde and Knight, 1998; Ringger et al., 2004; Filippova and Strube, 2009; Wan et al., 2009; He et al., 2009; Bohnet et al., 2010; Guo et al., 2011). They typically work by traversing the syntactic structure either bottom-up (Filippova and Strube, 2007; Bohnet et al., 2010) or top-down (Guo et al., 2011; Bohnet et al., 2011). These linearizers are mostly applied to English and do not deal with non-projective word orders. An exception is Filippova and Strube (2007), who contribute a study on the treatment of preverbal and postverbal constituents for German focusing on constituent order at the sentence level. The work most similar to ours is that of Gamon et al. (2002). They use machine-learning techniques to lift edges in a preprocessing step to a surface realizer. Their objective is the same as ours: by lifting, they avoid crossing edges. However, contrary to our work, they use phrase-structure syntax and focus on a limited number of cases of crossing branches in German only.

3 Lifting Dependency Edges

In this section, we describe the first of the two stages in our approach, namely the classifier that lifts edges in dependency trees. The classifier we aim to train is meant to predict liftings on a given unordered dependency tree, yielding a tree that, with a perfect linearization, would not have any non-projective edges.

3.1 Preliminaries

The dependency trees we consider are of the form displayed in Figure 1. More precisely, all words (or nodes) form a rooted tree, where every node has exactly one parent (or *head*). Edges point from head to dependent, denoted in the text by $h \rightarrow d$, where h is the head and d the dependent. All nodes directly or transitively depend on an artificial root node (depicted in Figure 1 as the incoming edge to *is*).

We say that a node a *dominates* a node d if a is an ancestor of d. An edge $h \rightarrow d$ is *projective* iff h dominates all nodes in the linear span between h and d. Otherwise it is *non-projective*. Moreover, a dependency tree is projective iff all its edges are projective. Otherwise it is non-projective.

A *lifting* of an edge $h \rightarrow d$ (or simply of the node d) is an operation that replaces $h \rightarrow d$ with $g \rightarrow d$, given that there exists an edge $g \rightarrow h$ in the tree, and undefined otherwise (i.e. the dependent d is reattached to the head of its head).[2] When the lifting operation is applied n successive times to the same node, we say the node was lifted n *steps*.

[2]The undefined case occurs only when d depends on the root, and hence cannot be lifted further; but these edges are by definition projective, since the root dominates the entire tree.

3.2 Training

During training we make use of the projectivization algorithm described by Nivre and Nilsson (2005). It works by iteratively lifting the shortest non-projective edges until the tree is projective. Here, shortest edge refers to the edge spanning over the fewest number of words. Since finding the shortest edge relies on the linear order, instead of lifting the shortest edge, we lift non-projective edges ordered by depth in the tree, starting with the deepest nested edge. A lifted version of the tree from Figure 1 is shown in Figure 3. The edge of *what* has been lifted three steps (the original edge is dotted), and the tree is no longer non-projective.

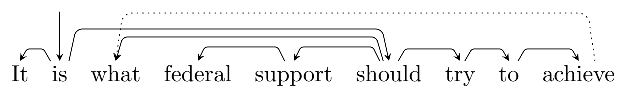


Figure 3: The sentence from Figure 1, where *what* has been assigned a new head (solid line). The original edge is dotted.

We model the edge lifting problem as a multi-class classification problem and consider nodes one at a time and ask the question "*How far should this edge be lifted?*", where classes correspond to lifting $0, 1, 2, ..., n$ steps. To create training instances we use the projectivization algorithm mentioned above. We traverse the nodes of the tree sorted by depth. For multiple nodes at the same depth, ties are broken by linear order, i.e. for multiple nodes at the same depth, the leftmost is visited first. When a node is visited, we create a training instance out of it. Its class is determined by the number of steps it would be lifted by the projectivization algorithm given the linear order (in most cases the class corresponds to no lifting, since most edges are projective). As we traverse the nodes, we also execute the liftings (if any) and update the tree on the fly.

The training instances derived are used to train a logistic regression classifier using the LIBLINEAR package (Fan et al., 2008). The features used for the lifting classifier are described in Table 1. Since we use linear classifiers, our feature set also contains conjunctions of atomic features. The features

Atomic features	
$\forall x \in \{w, w_p, w_{gp}, w_{ch}, w_s, w_{un}\}$	morph(x), label(x), lemma(x), PoS(x)
$\forall x \in \{w_{gc}, w_{ne}, w_{co}\}$	label(x), lemma(x), PoS(x)
Complex features	
$\forall x \in \{w, w_p, w_{gp}\}$	lemma(x)+PoS(x), label(x)+PoS(x), label(x)+lemma(x)
$\forall x \in \{w_{ch}, w_s, w_{un}\}, y = w$	lemma(x)+lemma(y), PoS(y)+lemma(x), PoS(y)+lemma(x)
$\forall x \in \{w, w_p, w_{gp}\}, y = \text{HEAD}(x)$	lemma(x)+lemma(y), lemma(x)+PoS(y), PoS(x)+lemma(y)
$\forall x \in \{w, w_p, w_{gp}\}, y = \text{HEAD}(x), z = \text{HEAD}(y)$	PoS(x)+PoS(y)+PoS(z), label(x)+label(y)+label(z)
$\forall x \in \{w_{ch}, w_s, w_{un}\}, y = \text{HEAD}(x), z = \text{HEAD}(y)$	PoS(x)+PoS(y)+PoS(z), label(x)+label(y)+label(z)
Non-binary features	
$\forall x \in \{w, w_p, w_{gp}\}$	SUBTREESIZE(x), RELSUBTREESIZE(x)

Table 1: Features used for lifting. w refers to the word (dependent) in question. And with respect to w, w_p is the parent; w_{gp} is the grandparent; w_{ch} are children; w_s are siblings; w_{un} are uncles (i.e. children of the grandparent, excluding the parent); w_{gc} are grandchildren; w_{ne} are nephews (i.e. grandchildren of the parent that are not children of w); w_{co} are cousins (i.e. grandchildren of the grandparent that are not w or siblings of w). The non-binary feature functions refer to: SUBTREESIZE – the absolute number of nodes below x, RELSUBTREESIZE – the relative size of the subtree rooted at x with respect to the whole tree.

involve the lemma, dependency edge label, part-of-speech tag, and morphological features of the node in question, and of several neighboring nodes in the dependency tree. We also have a few non-binary features that encode the size of the subtree headed by the node and its ancestors.

We ran preliminary experiments to determine the optimal architecture. First, other ways of modeling the liftings are conceivable. To find new reattachment points, Gamon et al. (2002) propose two other ways, both using a binary classifier: applying the classifier to each node x along the path to the root asking "*Should* d *be reattached to* x*?*"; or lifting one step at a time and applying the classifier iteratively until it says stop. They found that the latter outperformed the former. We tried this method, but found that it was inferior to the multi-class model and more frequently over- or underlifted.

Second, to avoid data sparseness for infrequent lifting distances, we introduce a maximum number of liftings. We found that a maximum of 3 gave the best performance. In the pseudocode below, we refer to this number as *maxsteps*.[3] This means that we are able to predict the correct lifting for most (but not all) of the non-projective edges in our data sets (cf. Table 3).

Third, as Nivre and Nilsson (2005) do for parsing, we experimented with marking edges that were lifted by indicating this on the edge labels. In the case of parsing, this step is necessary in order to reverse the liftings in the parser output. In our case, it could potentially be beneficial for both the lifting classifier, and for the linearizer. However, we found that marking liftings at best gave similar results as not marking, so we kept the original labels without marking.

3.3 Decoding

In the decoding stage, an unordered tree is given and the goal is to lift edges that would be non-projective with respect to the gold linear order. Similarly to how training instances are derived, the decoding algorithm traverses the tree bottom-up and visits every node once. Ties between nodes at the same depth are broken in an arbitrary but deterministic way. When a node is visited, the classifier is applied and the corresponding lifting is executed. Pseudocode is given in Algorithm 1.[4]

Different orderings of nodes at the same depth can lead to different lifts. The reason is that liftings are applied immediately and this influences the features when subsequent nodes are considered. For instance, consider two sibling nodes n_i and n_j. If n_i is visited before n_j, and n_i is lifted, this means

[3] During training, nodes that are lifted further than *maxsteps* are assigned to the class corresponding to *maxsteps*. This approach worked better than ignoring the training instance or treating it as a non-lifting (i.e. a lifting of 0 steps).

[4] The MIN function is used to guarantee that the edge is not lifted beyond the root node of the tree. This does not happen in practice though, since the feature set of the classifier include features that implicitly encode the proximity to the root node.

that at the time we visit n_j, n_i is no longer a sibling of n_j, but rather an uncle. An obvious extension of the decoding algorithm presented above is to apply beam search. This allows us to consider n_j both in the context where n_i has been lifted and when it has not been lifted.

```
N ← NODES(T)
SORT-BY-DEPTH-BREAK-TIES-ARBITRARILY(N, T)
foreach node ∈ N do
    feats ← EXTRACT-FEATURES(node, T)
    steps ← CLASSIFY(feats)
    steps ← MIN(steps, ROOT-DIST(node))
    LIFT(node, T, steps)
return T
```

Algorithm 1: Greedy decoding for lifting.

Pseudocode for the beam search decoder is given in Algorithm 2. The algorithm keeps an agenda of trees to explore as each node is visited. For every node, it clones the current tree and applies every possible lifting. Every tree also has an associated score, which is the sum of the scores of each lifting so far. The score of a lifting is defined to be the log probability returned from the logistic classifier. After exploring all trees in the agenda, the k-best new trees from the beam are extracted and put back into the agenda. When all nodes have been visited, the best tree in the agenda is returned. For the experiments the beam size (k in Algorithm 2) was set to 20.

```
N ← NODES(T)
SORT-BY-DEPTH-BREAK-TIES-ARBITRARILY(N, T)
T_score ← 0
Agenda ← {T}
foreach node ∈ N do
    Beam ← ∅
    foreach tree ∈ Agenda do
        feats ← EXTRACT-FEATURES(node, tree)
        m ← MIN(maxsteps, ROOT-DIST(node))
        foreach s ∈ 0 .. maxsteps do
            t ← CLONE(tree)
            score ← GET-LIFT-SCORE(feats, s)
            t_score = t_score + score
            LIFT(node, t, s)
            Beam ← Beam ∪ {t}
        Agenda ← EXTRACTKBEST(Beam, k)
return EXTRACTKBEST(Agenda, 1)
```

Algorithm 2: Beam decoding for lifting.

While beam search allows us to explore the search space somewhat more thoroughly, a large number of possibilities remain unaccounted for. Again, consider the sibling nodes n_i and n_j when n_i is visited before n_j. The beam allows us to consider n_j both when n_i is lifted and when it is not. However, the situation where n_j is visited *before* n_i is still never considered. Ideally, all permutations of nodes at the same depth should be explored before moving on. Unfortunately this leads to a combinatorial explosion of permutations, and exhaustive search is not tractable. As an approximation, we create two orderings and run the beam search twice. The difference between the orderings is that in the second one all ties are reversed. As this *bibeam* consistently improved over the beam in Algorithm 2, we only present these results in Section 5 (there denoted simply *Beam*).

4 Linearization

A linearizer searches for the optimal word order given an unordered dependency tree, where the optimal word order is defined as the single reference order of the dependency tree in the gold standard. We employ a statistical linearizer that is trained on a corpus of pairs consisting of unordered dependency trees and their corresponding sentences. The linearization method consists of the following steps:

Creating word order domains. In the first step, we build the word order domains d_h for all nodes $h \in y$ of a dependency tree y. A domain is defined as a node and all of its direct dependents. For example, the tree shown in Figure 3 has the following domains: {*it, be, should*}, {*what, support, should, try*}, {*federal, support*}, {*try, to*}, {*to, achieve*}

If an edge was lifted before the linearization, the lifted node will end up in the word order domain of its new head rather than in the domain of its original head. This way, the linearizer can deduce word orders that would result in non-projective structures in the non-lifted tree.

Ordering the words of the domains. In the second step, the linearizer orders the words of each domain. The position of a subtree is determined by the position of the head of the subtree in the enclosing domain. Algorithm 3 shows the tree linearization algorithm. In our implementation, the linearizer traverses the tree either top-down or bottom-up.

```
1  // T is the dependency tree with lifted nodes
2  beam-size ← 1000
3  for h ∈ T do
4      domain_h ← GET-DOMAIN(T,h)
5      // initialize the beam with a empty word list
6      Agenda_h ← (ϵ)
7      foreach w ∈ domain_h do
8          // beam for extending word order lists
9          Beam ← ()
10         foreach l ∈ Agenda_h do
11             // clone list l and append the word w
12             if w ∉ l then
13                 l′ ← APPEND(l,m)
14                 Beam ← Beam ⊕ l′
15                 score[l′] ← COMPUTE-SCORE(l′)
16         if | Beam | > beam-size then
17             SORT-LISTS-DESCENDING-TO-
               SCORE(Beam,score)
18             Agenda_h ← SUBLIST(0,beam-size,Beam)
19         else
20             Agenda_h ← Beam
21     foreach l ∈ Beam do
22         SCORE_g[l] ← SCORE[l] +
           GLOBAL-SCORE(l)
23     Agenda_h ← Beam
24 return Beam
```

Algorithm 3: Dependency Tree Linearization.

The linearization algorithm initializes the word order beam (*agenda*$_h$) with an empty order (ϵ) (line 6). It then iterates over the words of a domain (lines 7-20). In the first iteration, the algorithm clones and extends the empty word order list (ϵ) by each word of the sentence (line 12-15). If the beam (*beam*) exceeds a certain size (*beam-size*), it is sorted by score and pruned to maximum beam size (*beam-size*) (lines 16-20). The following example illustrates the extensions of the beam for the top domain shown in Figure 3.

Iter. agenda$_{be}$
0: (ϵ)
1: ((it) (be) (should))
2: ((it be) (it should) (be it) (be should) ...)

The beam enables us to apply features that encode information about the first tokens and the last token, which are important for generating, e.g. the word order of questions, i. e. if the last token is a question mark then the sentence should probably be a question (cf. feature set shown in Table 2). Furthermore, the beam enables us to generate alternative linearizations. For this, the algorithm iterates over the alternative word orders of the domains in order to assemble different word orders on the sentence level.[5] Finally, when traversing the tree bottom-up, the algorithm has to use the different orders of the already ordered subtrees as context, which also requires a search over alternative word orders of the domains.

Training of the Linearizer. We use MIRA (Crammer et al., 2006) for the training of the linearizer. The classifier provides a score that we use to rank the alternative word orders. Algorithm 3 calls two functions to compute the score: *compute-score* (line 15) for features based on pairs of words and trigrams and *compute-global-score* for features based on word patterns of a domain. Table 2 shows the feature set for the two functions. In the case that the linearization of a word order domain is incorrect the algorithm updates its weight vector w. The following equation shows the update function of the weight vector:

$$w = w + \tau_h(\phi(d_h, T, x_g) - \phi(d_h, T, x_p))$$

We update the weight vector w by adding the difference of the feature vector representation of the correct linearization x_g and the wrongly predicted linearization x_p, multiplied by τ. τ is the passive-aggressive update factor as defined below. The suffered $loss_h$ is $\phi(d_h, T, x_p) - \phi(d_h, T, x_g)$.

$$\tau = \frac{loss_h}{||\phi(d_h,T,x_g) - \phi(d_h,T,x_p)||^2}$$

Creating the word order of a sentence. The linearizer traverses the tree either top-down or bottom-up and assembles the results in the surface order. The bottom-up linearization algorithm can take into account features drawn from the already ordered subtrees while the top-down algorithm can employ as context only the unordered nodes. However, the bottom-up algorithm additionally has to carry out a search over the alternative linearization of the subdomains, as different orders of the subdomain provide different context features. This leads to a higher linearization time. We implemented both, but could only find a rather small accuracy difference. In the following, we therefore present results only for the top-down method.

[5] The beam also makes it possible to employ a generative language model to rerank alternative linearizations.

Atomic features		
For nodes $w \in domain_h$		lemma(w), label(w), PoS(w), num-children(w), num-grandchildren(w), label-children(w), PoS-children(w)
For domain $domain_h$		head(w_1,w_2), head(w_1,w_2,w_3), label($head$), PoS($head$), PoS(w_1), label(w_n), label(w_{n-1}), contains-?($domain_h$)
Complex features		
For bigrams $(w_1, w_2) \in domain_h$	feat$_2$:	label(w_1)+label(w_2), label(w_1)+lemma(w_2), lemma(w_1)+lemma(w_2), PoSw_1+PoSw_2
	feat$_3$:	label(w_1)+num-children(w_2)+num-children(w_1),PoS-child(w_1)+label(w_1)+label(w_2)
	feat$_4$:	label(w_1)+label(w_2)+lemma(w_2)+PoS(w_1), label(w_1)+label(w_2)+PoS($head$)+head(w_1,w_2)
	feat$_5$:	label(w_1)+label(w_2)+PoS($head$)+label($head$)+head(w_1,w_2)
For trigrams $(w_1, w_2, w_3) \in domain_h$	feat$_3$:	lemma(w_1)+lemma(w_2)+lemma(w_3)
	feat$_4$:	PoS(w_1)+PoS(w_2)+PoS(w_3)+head(w_1,w_2,w_3)
	feat$_5$:	label(w_1)+label(w_2)+label(w_3)+PoS(w_1)+head(w_1,w_2,w_3)
For sentence s	feat$_6$:	label(w_1)+label(w_{n-1})+lemma($head$)+lemma(w_1)+lemma(w_{n-1})
	feat$_7$:	PoS(w_1)+PoS(w_2)+PoS(w_3)+PoS(w_{n-1})+PoS(w_{n-2})+PoS(w_{n-3})+contains-?(s)

Table 2: Exemplified features used for scoring linearizations of a word order domain (see Algorithm 3). Atomic features which represent properties of a node or a domain are conjoined into feature vectors of different lengths. Linearizations are scored based on bigrams, trigrams, and global sentence-level features.

5 Experiments

We conduct experiments on six European languages with varying degrees of word order restrictions: While English word order is very restrictive, Czech and Hungarian exhibit few word order constraints. Danish, Dutch, and German (so-called V2, i. e. verb-second, languages) show a relatively free word order that is however more restrictive than in Hungarian or Czech. The English and the Czech data are from the CoNLL 2009 Shared Task data sets (Hajič et al., 2009). The Danish and the Dutch data are from the CoNLL 2006 Shared Task data sets (Buchholz and Marsi, 2006). For Hungarian, we use the Hungarian Dependency Treebank (Vincze et al., 2010), and for German, we use a dependency conversion by Seeker and Kuhn (2012).

	# sent's	np sent's	np edges	np $\leq$ 3 lifts
English	39,279	7.63 %	0.39%	98.39%
German	36,000	28.71%	2.34%	94.98%
Dutch	13,349	36.44%	5.42%	99.80%
Danish	5,190	15.62 %	1.00%	96.72%
Hungarian	61,034	15.81%	1.45%	99.82%
Czech	38,727	22.42%	1.86%	99.84%

Table 3: Size of training sets, percentage of non-projective (np) sentences and edges, percentage of np edges covered by 3 lifting steps.

Table 3 shows the sizes of the training corpora and the percentage of non-projective sentences and edges in the data. Note that the data sets for Danish and Dutch are quite small. English has the least percentage of non-projective edges. Czech, German, and Dutch show the highest percentage of non-projective edges. The last column shows the percentage of non-projective edges that can be made projective by at most 3 lifting steps.

5.1 Setup

In our two-stage approach, we first train the lifting classifier. The results for this classifier are reported in Section 5.2.

Second, we train the linearizer on the output of the lifting classifier. To assess the impact of the lifting technique on linearization, we built four systems on each language: (**a**) a linearizer trained on the original, non-lifted dependency structures (*No-lift*), two trained on the automatically lifted edges (comparing (**b**) the beam and (**c**) greedy decoding), (**d**) one trained on the oracle, i. e. gold-lifted structures, which gives us an upper bound for the lifting technique. The linearization results are reported in Section 5.3.

In this two-stage setup, we have the problem that, if we re-apply the lifting classifier on the data it was trained on, the input for the linearizer will be better during training than during testing. To provide realistic training data for the linearizer, we make a 10-fold cross-validation of the lifting classifier on the training set, and use this as training data for the linearizer. The lifting classifier that is applied to the test set is trained on the entire training set.

5.2 Lifting results

To evaluate the performance of the lifting classifier, we present precision, recall, and F-measure results for each language. We also compute the percentage of sentences that were handled perfectly by the lifting classifier. Precision and recall are defined the usual way in terms of true positives, false positives, and false negatives, where true positives are edges that should be lifted and were lifted correctly; false positives are edges that should not be lifted but were *and* edges that should be lifted and were lifted, but were reattached in the wrong place; false negatives are edges that should be lifted but were not.

The performance of both the greedy decoder and the bibeam decoder are shown in Table 4. The scores are taken on the cross-validation on the training set, as this provides more reliable figures. The scores are micro-averaged, i.e. all folds are concatenated and compared to the entire training set.

Although the major evaluation of the lifting is given by the performance of the linearizer, Table 4 gives us some clues about the lifting. We see that precision is generally much higher than recall. We believe this is related to the fact that some phenomena encoded by non-projective edges are more systematic and thus easier to learn than others (e. g. wh-extraction vs. relative clause extraposition). We also find that beam search consistently yields modest increases in performance.

	Greedy				Beam			
	P	R	F1	Perfect	P	R	F1	Perfect
Eng	77.31	50.45	61.05	95.76	78.85	50.63	61.66	95.83
Ger	72.33	63.59	67.68	81.91	72.05	64.41	68.02	81.97
Dut	76.66	74.89	75.77	79.28	78.07	76.49	77.27	80.34
Dan	85.90	58.55	69.64	92.76	85.90	58.55	69.64	92.74
Hun	72.60	61.61	66.66	88.46	73.06	64.77	68.67	88.73
Cze	77.79	55.00	64.44	86.28	77.31	55.68	64.74	86.33

Table 4: Precision, recall, F-measure and perfect projectivization results for the lifting classifier.

5.3 Linearization Results and Discussion

We evaluate the linearizer with standard metrics: n-gram overlap measures (BLEU, NIST), edit distance (Edit), and the proportion of exactly linearized sentences (Exact). As a means to assess the impact of lifting more precisely, we propose the word-based measure Exact$_{lift}$ which only looks at the words with an incoming lifted edge. The Exact$_{lift}$ score then corresponds to the percentage of these words that has been realized in the exact same position as in the original sentence.

Lang$_{Lift}$	BLEU	NIST	Edit	Exact	Exact$_{lift}$	N$_{lift}$
Eng$_{Nolift}$	0.911	15.09	0.922	56.40	0.00	0
Eng$_{Greedy}$	0.914	15.10	0.923	57.27	59.87	152
Eng$_{Beam}$	0.916	15.11	0.925	58.48	62.82	156
Eng$_{Oracle}$	0.923	15.14	0.928	60.73	70.42	240
Ger$_{Nolift}$	0.792	13.76	0.844	40.4	0.00	0
Ger$_{Greedy}$	0.811	13.86	0.864	42.9	55.21	480
Ger$_{Beam}$	0.813	13.86	0.866	43.3	56.47	487
Ger$_{Oracle}$	0.843	13.97	0.889	49.95	72.87	634
Dut$_{Nolift}$	0.743	11.31	0.796	30.05	0.00	0
Dut$_{Greedy}$	0.784	11.47	0.797	37.56	41.02	256
Dut$_{Beam}$	0.778	11.46	0.8	37.05	47.45	255
Dut$_{Oracle}$	0.825	11.63	0.848	44.82	70.55	292
Dan$_{Nolift}$	0.836	11.80	0.886	44.41	0.00	0
Dan$_{Greedy}$	0.852	11.88	0.90	45.96	67.65	34
Dan$_{Beam}$	0.858	11.90	0.90	48.76	67.65	34
Dan$_{Oracle}$	0.865	11.92	0.90	50.93	74.42	43
Hun$_{Nolift}$	0.755	15.70	0.839	30.71	0.00	0
Hun$_{Greedy}$	0.764	15.71	0.844	31.98	41,81	1,538
Hun$_{Beam}$	0.764	15.71	0.844	31.98	41.37	1,581
Hun$_{Oracle}$	0.777	15.79	0.849	34.30	57.53	1,933
Cze$_{Nolift}$	0.693	14.32	0.789	25.14	0.00	0
Cze$_{Greedy}$	0.711	14.45	0.797	26.85	42.04	923
Cze$_{Beam}$	0.712	14.45	0.795	26.37	41.34	941
Cze$_{Oracle}$	0.729	14.52	0.806	28.79	53.12	1,282

Table 5: Performance of linearizers using different liftings, Exact$_{lift}$ is the exact match for words with an incoming lifted edge, N$_{lift}$ is the total number of lifted edges.

The results are presented in Table 5. On each language, the predicted liftings significantly improve on the non-lifted baseline (except the greedy decoding in English).[6] The differences between the beam and the greedy decoding are not significant. The scores on the oracle liftings suggest that the impact of lifting on linearization is heavily language-dependent: It is highest on the V2-languages, and somewhat smaller on English, Hungarian, and Czech. This is not surprising since the V2-languages (especially German and Dutch) have the highest proportion of non-projective edges and sentences (see Table 3). On the other hand, English has a very small number of non-projective edges, such that the BLEU score (which captures the n-gram level) reflects the improvement by only

[6] We used a t-test, with $\alpha = 0.01$.

a small increase. However, note that, on the sentence level, the percentage of exactly regenerated sentences increases by 2 points which suggests that a non-negligible amount of non-projective sentences can now be generated more fluently.

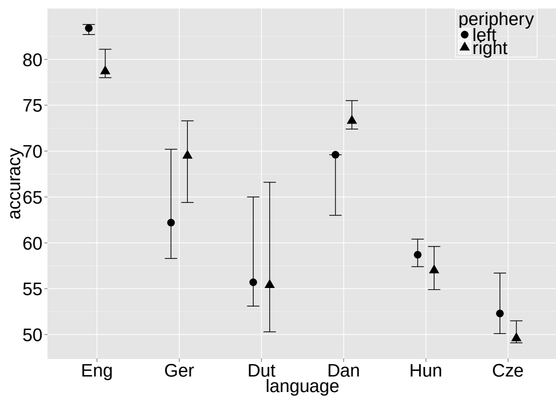


Figure 4: Accuracy for the linearization of the sentences' left and right periphery, the bars are upper and lower bounds of the non-lifted and the gold-lifted baseline.

The Exact_{lift} measure refines this picture: The linearization of the non-projective edges is relatively exact in English, and much less precise in Hungarian and Czech where Exact_{lift} is even low on the gold-lifted edges. The linearization quality is also quite moderate on Dutch where the lifting leads to considerable improvements. These tendencies point to some important underlying distinctions in the non-projective word order phenomena over which we are generalizing: In certain cases, the linearization seems to systematically follow from the fact that the edge has to be lifted, such as *wh*-extraction in English (Figure 1). In other cases, the non-projective linearization is just an alternative to other grammatical, but maybe less appropriate, realizations, such as the *prefield*-occupation in German (Figure 2).

Since a lot of non-projective word orders affect the clause-initial or clause-final position, we evaluate the exact match of the left periphery (first three words) and the right periphery (last three words) of the sentence. The accuracies obtained are plotted in Figure 4, where the lower and upper bars correspond to the lower and upper bound from the non-lifted and the gold-lifted baseline. It clearly emerges from this figure that the range of improvements obtainable from lifting is closely tied to the general linearization quality, and also to word order properties of the languages. Thus, the range of sentences affected by the lifting is clearly largest for the V2-languages. The accuracies are high, but the ranges are small for English, whereas the accuracies are low and the ranges quite small for Czech and Hungarian.

System	BLEU	NIST
(Bohnet et al., 2011) (ranked 1st)	0.896	13.93
(Guo et al., 2011) (ranked 2nd)	0.862	13.68
Baseline-Non-Lifted + LM	0.896	13.94
Beam-Lifted + LM	0.901	13.96

Table 6: Results on the development set of the 2011 Shared Task on Surface Realisation data, (the test set was not officially released).

We also evaluated our linearizer on the data of 2011 Shared Task on Surface Realisation, which is based on the English CoNLL 2009 data (like our previous evaluations) but excludes information on morphological realization. For training and evaluation, we used the exact set up of the Shared Task. For the morphological realization, we used the morphological realizer of Bohnet et al. (2010) that predicts the word form using shortest edit scripts. For the language model (LM), we use a 5-gram model with Kneser-Ney (Kneser and Ney, 1995) smoothing derived from 11 million sentences of the Wikipedia.

In Table 6, we compare our two linearizers (with and without lifting) to the two top systems of the 2011 Shared Task on Surface Realisation, (Bohnet et al., 2011) and (Guo et al., 2011). Without the lifting, our system reaches a score comparable to the top-ranked system in the Shared Task. With the lifting, we get a small[7] but statistically significant improvement in BLEU such that our system reaches a higher score than the top ranked systems. This shows that the improvements we obtain from the lifting carry over to more complex generation tasks which include morphological realization.

5.4 Human Evaluation

We have carried out a pilot human evaluation on the German data in order to see whether human judges prefer word orders obtained from the lifting-based

[7]Remember that English has the least percentage of non-projective edges in our data sets, which are however important to linearize correctly (see Figure 1).

linearizer. In particular, we wanted to check whether the lifting-based linearizer produces more natural word orders for sentences that had a non-projective tree in the corpus, and maybe less natural word orders on originally projective sentences. Therefore, we divided the evaluated items into originally projective and non-projective sentences.

We asked four annotators to judge 60 sentence pairs comparing the lifting-based against the non-lifted linearizer using the toolkit by Kow and Belz (2012). All annotators are students, two of them have a background in linguistics. The items were randomly sampled from the subset of the development set containing those sentences where the linearizers produced different surface realizations. The items are subdivided into 30 originally projective and 30 originally non-projective sentences.

For each item, we presented the original context sentence from the corpus and the pair of automatically produced linearizations for the current sentence. The annotators had to decide on two criteria: (i) which sentence do they prefer? (ii) how fluent is that sentence? In both cases, we used continuous sliders as rating tools, since humans seem to prefer them (Belz and Kow, 2011). For the first criterion, the slider positions were mapped to values from -50 (preference for left sentence) to 50 (preference for right sentence). If the slider position is zero, both sentences are equally preferred. For the second criterion, the slider positions were mapped to values from 0 (absolutely broken sentence) to 100 (perfectly fluent sentence).

Sentences	Scores	Equal	Lifted	Non-lifted
All	% selected	44.58%	35.0%	20.42%
	Fluency	56.14	75.77	72.78
	Preference	0	34.75	31.06
Non-Proj.	% selected	29.63%	58.33%	12.04%
	Fluency	43.06	76.27	68.85
	Preference	0	37.52	24.46
Proj.	% selected	56.82%	15.91%	27.27%
	Fluency	61.72	74.29	74.19
	Preference	0	26.43	33.44

Table 7: Results from human evaluation.

Table 7 presents the results averaged over all sentences, as well as for the subsets of non-projective and projective sentences. We report the percentage of items where the judges selected both, the lifted, or non-lifted sentence, alongside with the average fluency score (0-100) and preference strength (0-50).

On the entire set of items, the judges selected both sentences in almost half of the cases. However, on the subset of non-projective sentences, the lifted version is clearly preferred and has a higher average fluency and preference strength. The percentage of zero preference items is much higher on the subset of projective sentences. Moreover, the average fluency of the zero preference items is remarkably higher on the projective sentences than on the non-projective subset. We conclude that humans have a strong preference for lifting-based linearizations on non-projective sentences. We attribute the low fluency score on the non-projective zero preference items to cases where the linearizer did not get a correct lifting or could not linearize the lifting correctly such that the lifted and the non-lifted version were not appropriate. On the other hand, incorrect liftings on projective sentences do not necessarily seem to result in deprecated linearizations, which leads to the high percentage of zero preferences with a good average fluency on this subset.

6 Conclusion

We have presented a novel technique to linearize sentences for a range of languages that exhibit non-projective word order. Our approach deals with non-projectivity by lifting edges in an unordered input tree which can then be linearized by a standard projective linearization algorithm.

We obtain significant improvements for the lifting-based linearization on English, German, Dutch, Danish, Czech and Hungarian, and show that lifting has the largest impact on the V2-languages. In a human evaluation carried out on German we also show that human judges clearly prefer lifting-based linearizations on originally non-projective sentences, and, on the other hand, that incorrect liftings do not necessarily result in bad realizations of the sentence.

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