Yuqing Guo
Toshiba Research and Development Center
5/F., Tower W2, Oriental Plaza,
Dongcheng District, Beijing, China
guoyuqing@rdc.toshiba.com.cn

Deirdre Hogan and Josef van Genabith
NCLT/CNGL, School of Computing,
Dublin City University,
Glasnevin, Dublin 9, Ireland.
dhogan,josef@computing.dcu.ie

Abstract

In this paper we describe our system and experimental results on the development set of the Surface Realisation Shared Task. DCU submitted 1-best outputs for the Shallow sub-task of the shared task, using a surface realisation technique based on dependency-based n-gram models. The surface realiser achieved BLEU and NIST scores of 0.8615 and 13.6841 respectively on the SR development set.

1 Introduction

DCU submitted outputs for SR-Shallow, the shallow sub-task of the surface realisation shared task, using a surface realisation technique based on dependency-based n-gram models, described in some detail in (Guo et al., 2010).

The generation method captures the mapping between the surface form sentences and the unordered syntactic representations of the shallow representation by linearising a set of dependencies directly, rather than via the application of grammar rules as in more traditional chart-style or unification-based generators (White, 2004; Nakanishi et al., 2005; Cahill and van Genabith, 2006; Hogan et al., 2007; White and Rajkumar, 2009). In contrast to conventional n-gram language models over surface word forms (Langkilde-Geary, 2002), we exploit structural information and various linguistic features inherent in the dependency representations to constrain the generation space and improve the generation quality.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{dependency_tree.png}
\caption{Unordered dependency tree for the input of the sentence: the young athlete ran fast}
\end{figure}

2 Dependency-based N-gram Models

The shallow input representation takes the form of an unordered dependency tree. The basic approach of the surface realisation method is to traverse the input tree ordering the nodes at each sub-tree based on local information. For each sub-tree the nodes are ordered according to a combination of n-gram models of increasing specificity. At the most general level, for a particular sub-tree, the n-gram model simply models the grammatical relations (including the predicate/head) of the sub-tree. Take for example the sub-tree rooted at node $I$ from Figure 1. The realiser linearises the lemmas at nodes $I$, $J$ and $K$ by learning the correct order of the syntactic relations (in this case $subj \prec pred \prec mnr$).

Formally, in our most basic model, for a lo-
cal sub-tree \( t_i \) containing \( m \) grammatical relations (GRs) (including \( \text{pred} \)), generating a surface string \( S_1^m = s_1...s_m \) expressed by \( t_i \) is equivalent to linearising all the GRs present at \( t_i \). The dependency n-gram (DN-gram) model calculates probabilities for all permutations \( \text{GR}^m_i = \text{GR}_1...\text{GR}_m \), and searches for the best surface sequence that maximises the probability \( P(S^m_1) \) in terms of maximising \( P(\text{GR}^m_i) \). Applying the chain rule and the Markov assumption, the probability of the surface realisation is computed according to Eq. (1).

\[
P(S_1^m) = P(\text{GR}_1^m) = P(\text{GR}_1...\text{GR}_m) = \prod_{k=1}^{m} P(\text{GR}_k | \text{GR}_{k-1}^m) = \prod_{k=1}^{m} P_{\text{DF}_k}(s_k | s_{k-1}^{m})
\]

(1)

The basic dependency n-gram model over bare GRs is not a good probability estimator as it only makes use of a few dozen grammatical function roles. For example, for the input dependency tree of sentence \( I \) from Figure 1 the model learns: \( \text{subj(athlete)} \prec \text{pred(run)} \prec \text{mngr(fast)} \). Log-linear interpolations (LLI) are used to combine the estimates from the different DN-gram models:

\[
P_{\text{LLI}}(S_1^m) = \prod_{i} P_i(S_1^m) = \prod_{k=1}^{m} P(\text{GR}_k | \text{GR}_{k-1}^m)
\]

(2)

3 The Realisation Algorithm

In order to generate the surface lexical form corresponding to an input lemma, morphological alternation has to be determined. From the training corpus, we use the grammatical properties like number, part-of-speech tag, tense, and participle feature which are encoded in the input nodes, to learn a mapping from lemma to the appropriate word form in the surface realisation.

The generation process proceeds as follows: Given an input tree \( T \) consisting of unordered projective\(^1\) dependencies, the generation algorithm recursively traverses \( T \) in a bottom-up fashion and at each sub-tree \( t_i \):

1. instantiates the local predicate \( \text{pred}_i \) at \( t_i \) and performs morphological inflections if necessary
2. calculates DN-gram probabilities of possible GR permutations licensed by \( t_i \)
3. finds the most probable GR sequence among all possibilities by Viterbi search
4. generates the surface string \( s_i \) according to the best GR sequence as a realisation of \( t_i \)
5. propagates \( s_i \) up to the parent sub-tree.

4 Experimental Results

Results of the surface generator on the SR development set, trained exclusively on the SR training set, are displayed in Table 1.

| BLEU-4 | NIST    | METEOR |
|--------|---------|--------|
| 0.8615 | 13.6841 | 0.8925 |

Table 1: Results on the development set

References

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\(^1\)The algorithm assumes all dependencies are projective and therefore has a somewhat inadequate handling of the non-projective dependencies that do exist in the SR data. For example, for the input dependency tree of sentence \( \text{Why, they wonder, should it belong to the EC?} \) (training set sentId=32553) the algorithm can not generate the original word order. A further pre-processing step is needed to make all dependencies projective.
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