A Dependency Edge-based Transfer Model for Statistical Machine Translation

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Abstract

Previous models in syntax-based statistical machine translation usually resort to some kinds of synchronous procedures, few of these works are based on the analysis-transfer-generation methodology. In this paper, we present a statistical implementation of the analysis-transfer-generation methodology in rule-based translation. The procedures of syntax analysis, syntax transfer and language generation are modeled independently in order to break the synchronous constraint, resorting to dependency structures with dependency edges as atomic manipulating units. Large-scale experiments on Chinese to English translation show that our model exhibits state-of-the-art performance by significantly outperforming the phrase-based model. The statistical transfer-generation method results in significantly better performance with much smaller models.

1 Introduction

Researches in statistical machine translation have been flourishing in recent years. Statistical translation methods can be divided into word-based (Brown et al., 1993), phrase-based (Marcu and Wong, 2002; Koehn et al., 2003) and syntax-based models (Yamada and Knight, 2001; Graehl and Knight, 2004; Chiang, 2005; Liu et al., 2006; Mi et al., 2008; Huang et al., 2006; Lin, 2004; Ding and Palmer, 2004; Quirk et al., 2005; Shen et al., 2008; Xie et al., 2011; Meng et al., 2013). Compared with word-based and phrase-based methods, syntax-based models perform better in long distance reordering and enjoy higher generalization capability by leveraging the hierarchical structures in natural languages, and achieve the state-of-the-art performance in these years.

Most syntax-based models (except for Lin (2004) ) utilize some kinds of synchronous generation procedures which directly model the structural correspondence between two languages. In contrast, the analysis-transfer-generation methodology in rule-based translation solves the machine translation problem in a more divided scheme, where the processing procedures of analysis, structural transfer and language generation are modeled separately. The analysis-transfer-generation strategy can tolerate higher non-isomorphism between languages if with a more general transformation unit and it can facilitate elaborating engineering of each processing procedure, however, there isn’t a statistical transfer model that shows the comparable performance with the current state-of-the-art SMT model so far.

In this paper, we propose a novel statistical analysis-transfer-generation model for machine translation, to integrate the advantages of the transfer-generation scheme and the statistical modeling. The procedures of transfer and generation are modeled on dependency structures with dependency edges as atomic manipulating units. First, the source sentence is parsed by a dependency parser. Then, the source dependency structure is transferred into a target structure by translation rules, which composed of the source and target edges. Last, the target sentence is finally generated from the target edges which are used as intermediate syntactic structures. By directly modeling the edge, the most basic unit in the dependency tree, which definitely describe the modifying relationship and positional relation between words, our model alleviates the non-isomorphic problem and shows the flexibility of reordering.
The rest of the paper is organized as follows, we first describe the dependency edge-based transfer model (Section 2). Then, we present our rule acquisition algorithm (Section 3), the decoding and target sentence generation process (Section 4). Finally, large-scale experiments (Section 5) on Chinese-to-English translation show that our edge-based transfer model gains state-of-the-art performance by significantly outperforming the phrase-based model (Koehn et al., 2003) by averaged +1.34 BLEU points on three test sets. To the best of our knowledge, this is the first transfer-generation-based statistical machine translation model that achieves the state-of-the-art performance.

2 Dependency Edge-based Transfer Model

2.1 Edges in Dependency Trees

Given a sentence, its dependency tree is a directed acyclic graph with words in the sentence as nodes. An example dependency tree is shown in Figure 1 (a). An edge in the tree represents a dependency relationship between a pair of words, a head and a dependent. When a nominal dependent acts as a subject and modifies a verbal head, they usually have a fixed relative position. In Figure 1 (a), “àobāmǎ” modifies “fābù”. The grammatical relation label nsubj (Chang et al., 2009) between them denotes that a noun phrase acts as the subject of a clause. “àobāmǎ” is on the left of “fābù”.

Based on the above observations, we take the edge as the elementary structure of a dependency tree and regard a dependency tree to be a set of edges.

**Definition 1.** An source side edge is a 4-tuple \( e = (H, D, P, R) \), where \( H \) is the head, \( D \) is the dependent, \( P \) denotes the relative position between \( H \) and \( D \), left or right, \( R \) is the grammatical relation label.

In Figure 1 (b), the upper sides of transfer rules are source side edges extracted from the dependency tree.
2.2 Transfer Rules

A transfer rule of our model represents the reordering and relative positions of edges between language pairs. For example, in Figure 1 (b), the first rule shows that when a nominal subject modifies a verb, the target side keeps the same position relations. “obama” is also on the left of “issue”, the same with the source side relative position. The 5-th and 6-th rules show the inversion relations between the source and the target. Formally, a transfer rule can be defined as a triple $\langle e, f, \sim \rangle$, where $e$ is an edge extracted from the source dependency tree, $f$ is a target edge. $\sim$ denotes one-to-one correspondence between variables in $e$ and $f$.

Figure 1 (b) are part of transfer rules extracted from the word aligned sentence in Figure 1 (a). The target edge denotes whether the target dependent is on the left or the right side of the target head, the
label on the edge indicates whether the target head and the target dependent are adjacent or not. If
the dependent is an internal node (contrast with the leaf nodes in the dependency tree), then it will be
regarded as a substitution node. The dependent in the 4-th transfer rule is an internal node and the its
corresponding target side is a substitution variable.

Figure 2 shows a partial transfer-generation of our model which involves three phases. First, analysis.
Given a source language sentence, we obtain its dependency tree using a dependency parser. We assume
that the sub-tree of the substitution node has been translated. Second, transfer. For each internal node,
we transfer the source side edges between the head and all its dependents into the target sides. In the
second block of Figure 2, we transfer four edges into the target sides. Third, generation, corresponding
to the third block of Figure 2. We generate the target sentence with the target side edges starting from the
target head, “issue”. We first try to concatenate the edges to the left. First, we select a target side edge
that is on the left side of “issue” and adjacent to it to form a consecutive phrase. Edge 3 is selected and “to
issue” is generated. Then, we enumerate all possible left concatenations of the other edges that are not
adjacent to “issue”. The two sequences (1,2,3 and 2,1,3) of the edges are generated, corresponding to the
two hypotheses. After that, we extend the two hypotheses to the right. The internal node “shèngmíng” is
a substitution node, so the candidate translation of the sub-tree rooted at “shèngmíng” is concatenated to
the two hypotheses. Finally, we generate the two candidate translations of the input sentence.

3 Acquisition of Transfer Rules

Transfer rules can be extracted automatically from a word-aligned corpus, which is a set of triples
\((T, S, A)\), where \(T\) is a source dependency tree, \(S\) is a target side sentence and \(A\) is an alignment relation
between \(T\) and \(S\). Following the dependency-to-string model (Xie et al., 2011), we extract transfer rules
from each triple \((T, S, A)\) by three steps:

1. Tree Annotation: Label each node in the dependency tree with the alignment information
2. Edges Identification: Identify acceptable edges from the annotated dependency tree
3. Rule induction: Induce a set of lexicalized and un-lexicalized transfer rules from the acceptable
edges.

3.1 Tree Annotation

Given a triple \((T, S, A)\) as Figure 3 shows, we define two attributes for every node in \(T\): node span and
sub-tree span:

Definition 2. Given a node \(n\), its node span \(nsp(n)\) is a set of consecutive indexes of the target words
aligned with the node \(n\).

For example, \(nsp(ānquán)=\{7-8\}\), which corresponds to the target word “of” and “security”.

Definition 3. A node span \(nsp(n)\) is consistent if for any other node \(n'\) in the dependency tree, \(nsp(n)\)
and \(nsp(n')\) are not overlapping.

For example, \(nsp(zhànluè)=\{3\}\) is consistent, while \(nsp(ānquán)=\{1\}\) is not consistent for it corresponds to the
same word “of” with \(nsp(shèngmíng)\).

Definition 4. Given a sub-tree \(T'\) rooted at \(n\), the sub-tree span \(tsp(n)\) of \(n\) is a consecutive target word
indexes from the lower bound of the \(nsp\) of all the nodes in \(T'\) to the upper bound of those spans.

For example, \(tsp(shèngmíng)=\{5-9\}\), which corresponds to the target phrase “a statement of security
strategy”.

Definition 5. A sub-tree span \(tsp(n)\) is consistent if for any other node \(n'\) that is not in the sub-tree
rooted at \(n\) in the dependency tree, \(tsp(n)\) and \(nsp(n')\) are not overlapping.

For example, \(tsp(shèngmíng)=\{5-9\}\) is consistent, even though \(nsp(shèngmíng)\) is not consistent, while
\(tsp(ānquán)=\{1\}\) is not consistent for “shèngmíng” is not a node in sub-tree rooted at “ānquán” and “ānquán”
corresponds to the same word “of” with \(nsp(shèngmíng)\).
3.2 Acceptable Edges Identification

We identify the edges from the annotated dependency tree that are acceptable for rule induction. For an acceptable edge, its node span of the head $nsp(\text{head})$ and the sub-tree span of the dependent $tsp(\text{dependent})$ satisfy the following properties:

1. $nsp(\text{head})$ and $tsp(\text{dependent})$ are consistent.
2. $nsp(\text{head})$ and $tsp(\text{dependent})$ are non-overlapping.

For example, $tsp(\text{ānquán})$ and $nsp(\text{shēngmíng})$ are neither consistent nor non-overlapping. So the gray edge between head “shēngmíng” and dependent “ānquán” is not an acceptable edge. $nsp(\text{fābù})$ and $tsp(\text{shēngmíng})$ are consistent and the two spans are non-overlapping. Thus, the edge between head “fābù” and dependent “shēngmíng” is an acceptable edge.

3.3 Transfer Rule Induction

From each acceptable source side edge, we induce a set of lexicalized and un-lexicalized transfer rules. We induce a lexicalized transfer rule from an acceptable edge by the following procedures:

1. extract the source side edge and mark the internal nodes as substitution sites. This form the input of a transfer rule.
2. extract the position information according to $nsp(\text{head})$ and $tsp(\text{dependent})$, whether they are adjacent or not and whether $tsp(\text{dependent})$ is on the left side or the right side of $nsp(\text{head})$.

In Figure 4, the first transfer rule is lexicalized rule, it is induced from the edge between “fābù” and “àobāmā”.

In addition to the lexicalized rules described above, we also generalized the rules by replacing the word in an source side edge with a wild card and the part of speech of the word. For example, the rule in Figure 4 can be generalized in two ways. The generalized versions of the rule apply to “àobāmā” modifying any verb and “fābù” modifying any noun, respectively. The generalized rules are also called
un-lexicalized rules for the loss of word information. The single node translations of the generalized words are also extracted. The unaligned words of the target side is handled by extending \text{nsp}(head) and \text{tsp}(dependent) on both left and right directions. We do this process similar with the method of Och and Ney (2004). We might obtain \(m(m \geq 1)\) extended rules from an acceptable edge. The frequency of each rule is divided by \(m\). We take the extracted rule set as observed data and make use of relative frequency estimator to obtain the translation probabilities \(P(t|s)\) and \(P(s|t)\).

4 Decoding and Generation

We follow Och and Ney (2002), using a general log-linear model to score the sentence generated by each concatenation of the target edges. Let \(c\) be concatenations that concatenate the target edges to generate the target sentence \(e\). The probability of \(e\) is defined as:

\[
P(e) \propto \prod_i \phi_i(c)^{\lambda_i}
\]  

where \(\phi_i(c)\) are features defined on concatenations and \(\lambda_i\) are feature weights. In our experiments of this paper, thirteen features are used as follows:

- Transfer rules translation probabilities \(P(t|s)\) and \(P(s|t)\), and lexical translation probabilities \(P_{lex}(t|s)\) and \(P_{lex}(s|t)\);
- Bilingual phrases probabilities \(P_{bp}(t|s)\) and \(P_{bp}(s|t)\), and bilingual phrases lexical translation probabilities \(P_{bplex}(t|s)\) and \(P_{bplex}(s|t)\);
- Transfer rule penalty \(\exp(-1)\);
- Bilingual phrase penalty \(\exp(-1)\);
- Pseudo translation rule penalty \(\exp(-1)\);
- Target word penalty \(\exp(|e|)\);
- Language model \(P_{lm}(e)\).

Our decoder is based on a bottom-up chart-based beam-search algorithm. We regard the decoding process as the composition of the target side edges. For a given source language sentence, we obtain its
dependency tree $T$ with an external dependency parser. Each node in $T$ is traversed in post-order. For each internal node and root node $n$, we do the transfer-generation translation as the following procedures:

1. Extract all the source side edges including the lexicalized and generalized edges between $n$ and all its dependents using the same way we extract the source side edges of the transfer rules.

2. Transfer the source side edges into target side edges. For a generalized rule, we restore it to a lexicalized rule by combining it with the single word translation. For no matched edges, we construct the pseudo translation rule according to the word order of the source head-dependent relation.

3. Generate the target sentence by bi-directional extension from an adjacent target edge. We first group all the target edges by their heads. For each group, we generate translation hypotheses with the following procedures:
   (a) Select an adjacent target edge as the starting position;
   (b) Extend to the left side and enumerate all possible permutations of the target edges directing left;
   (c) Extend to the right side and enumerate all possible permutations of the target edges directing right.

Considering that in dependency trees, a head may relate to more than 4 edges which results in massive search space. We reduce the time complexity by using the maximum distortion limit. The distortion is defined as $(a_i - b_{i-1} - 1)$, where $a_i$ denotes the start position of the source side edge that is translated into the $i$th target side edge and $b_{i-1}$ denotes the end position of the source side edge translated into the $(i - 1)$th target side edge.

When we reach the root node, the candidate translations of the input sentence are generated.

In our model, only the adjacent target edge of a transfer rule can be regarded as a consecutive phrase and its corresponding source side length is only 2. As we start extending the target sentence from the target head, it is quite natural to incorporate the bilingual phrases to make the target sentences be extended from the phrases as well as the single target head word. Due to the flexibility of our model, we can incorporate not only the syntactic phrases which are phrases covering a whole sub-tree, but also the non-syntactic phrases as the fixed dependency structures in Shen et al. (2008) which are consecutive phrases covering the head. Figure 5 shows two examples of the phrases incorporated in our model.

We prune the search space in several ways. First, beam threshold $\beta$, items with a score worse than $\beta$ times of the best score in the same span will be discarded; second, beam size $b$, items with a score worse than the $b$th best item will be discarded. For our experiments, we set $\beta = 10^{-3}$ and $b = 300$; Third, we also prune rules for the same edge with a fixed rule limit ($r = 200$), which denotes the maximum number of rules we keep.

5 Experiments

In this section, the performance of our model is evaluated by comparing with phrase-based model (Koehn et al., 2003), on the NIST Chinese-to-English translation tasks. We also present the influence of the
maximum distortion limit to our model. We take open source phrase-based system Moses (with default configuration)\(^1\) as our baseline system.

5.1 Experimental Setting

Our training corpus consists of 1.25M sentence pairs from LDC data, including LDC2002E18, LDC2003E07, LDC2003E14, Hansards portion of LDC2004T07, LDC2004T08 and LDC2005T06.

To obtain the dependency trees of the source side, we parse the source sentences with Stanford Parser (Klein and Manning, 2003) into projective dependency structures with nodes annotated by POS tags and edges by dependency labels.

To obtain the word alignments, we run GIZA++ (Och and Ney, 2003) on the corpus in both directions and apply “grow-diag-and” refinement (Koehn et al., 2003). We extract the phrases covering no more than 10 nodes of the fixed structures.

We use SRILM (Stolcke, 2002) to train a 4-gram language model with modified Kneser-Ney smoothing on the Xinhua portion of the Gigaword corpus.

We use NIST MT Evaluation test set 2002 as our development set, 2003-2005 NIST datasets as test sets. The quality of translations is evaluated by the case insensitive NIST BLEU-4 metric\(^2\).

We make use of the minimum error rate training algorithm (Och, 2003) in order to maximize the BLEU score of the development set.

The statistical significance test is performed by sign-test (Collins et al., 2005).

5.2 Influence of Maximum Distortion Limit

Figure 6 gives the performance of our system with different maximum distortion limits in terms of uncased BLEU of three NIST test sets. The performance of different distortion limit are consistent on both development set and three test sets. Maximum distortion limit 2 gets the best performances. A low distortion limit may cause the target sentence been translated more close to the sequence of the source, especially when the distortion limit equals to 0, none of the reordering is allowed, while a high distortion limit may lead the good translations be flooded by too many ambiguities when enumerating the possible sequences of the target non-adjacent dependents. We choose 2 as the maximum distortion limit in the next experiments.

\(^1\)http://www.statmt.org/moses/
\(^2\)ftp://jaguar.ncsl.nist.gov/mt/resources/mteval-v11b.pl.
| System | Rule # | MT03 | MT04 | MT05 | Average |
|--------|--------|------|------|------|---------|
| Moses  | 44.49M | 32.03| 32.83| 31.81| 32.22   |
| DEBT   | 30.7M  | **32.7** | **35.4** | **32.59** | **33.56** |

Table 1: Statistics of the extracted rules on training data and the BLEU scores (%) on the test sets. “DEBT” denotes our edge-based transfer model. The “*” denotes that the results are significantly better than the baseline system (p<0.01).

5.3 Performance of Our Model

Table 1 illustrates the translation results of our experiments. We (DEBT) surpass the baseline over +1.34 BLEU points on average. Our model significant outperforms the baseline phrase-based model, with \( p < 0.01 \) on statistical significance test sign-test (Collins et al., 2005).

We also list the statistical number of rules extracted from the training corpus. The number of our transfer rules is only 69.0% of the rules extracted by Moses, thus, the total rules in our model is 31% smaller than Moses.

6 Related Work

Transfer-based MT systems usually take a parse tree in the source language and translate it into a parse tree in the target language with transfer rules. Both our model and some of those previous works acquired transfer rules automatically from word-aligned corpus (Richardson et al., 2001; Carbonell et al., 2002; Lavoie et al., 2002; Lin, 2004). Gimpel and Smith (2009) and Gimpel and Smith (2014) used quasi-synchronous dependency grammar for MT and they are similar to our idea of doing transfer of dependency syntax in a non-synchronous setting. They do the translation as monolingual lattice parsing.

As dependency-based system, Lin (2004) used path as the transfer unit and regarded the translation problem with minimal path covering. Quirk et al. (2005) and Xiong et al. (2007) used treelets to model the source dependency tree using synchronous grammars. Quirk et al. (2005) projected the source dependency structure into target side by word alignment and faced the problem of non-isomorphism between languages. Xiong et al. (2007) directly modeled the treelet to the corresponding target string to alleviate the problem. Xie et al. (2011) directly specified the ordering information in head-dependents rules that represent the source side as head-dependents relations and the target side as string.

Differently, our model uses a much simpler elementary structure, edge, which consist of only a head and a dependent. As a transfer-generation model, we transfer an edge in the source dependency tree into target side and incorporate the position information on the target edge, which alleviate non-isomorphism problem and incorporate ordering among different target edges simultaneously. Moreover, our decoding method is quite different from previous dependency tree-based works. After parsing a given source language sentence, we transfer and generate the target sentence fragments recursively on each internal node of the dependency tree bottom-up.

7 Conclusions and Future Work

In this paper, we present a novel dependency edge-based transfer model using dependency trees on the source side for machine translation. We directly transfer the edges in source dependency tree into the target sides and then generate the target sentences by beam-search. With the concise transfer rules, our model is compatible with both the syntactic and non-syntactic phrases. Although the generation process of our model seems relatively simple, it still exhibits a good performance and outperforms the phrase-based model on large scale experiments. For the first time, a statistical transfer model shows a comparable performance with the state-of-the-art translation models.

Since the translation procedure is divided into three phases and each phase can be modeled independently, we would like to take further steps focusing on modeling the target language generation process specifically to ensure a better grammatical translation with the help of natural language generation methods.
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