Fast BTG-Forest-Based Hierarchical Sub-sentential Alignment

Hao Wang and Yves Lepage
Graduate School of Information, Production and Systems, Waseda University
{oko_ips@ruri., yves.lepage@waseda.jp}

Abstract
In this paper, we propose a novel BTG-forest-based alignment method. Based on a fast unsupervised initialization of parameters using variational IBM models, we synchronously parse parallel sentences top-down and align hierarchically under the constraint of BTG. Our two-step method can achieve the same run-time and comparable translation performance as fast_align while it yields smaller phrase tables. Final SMT results show that our method even outperforms in the experiment of distantly related languages, e.g., English–Japanese.

1 Introduction
Bracketing transduction grammars (BTGs) (Wu, 1997) are known to produce high quality, phrase-friendly alignments (Xiong et al., 2010; Wang et al., 2007) for phrase-based statistical machine translation (SMT) (Koehn et al., 2003) or syntax-based machine translation (Chiang, 2007).

Differing from generative methods (Och and Ney, 2003; Liang et al., 2006) that the complexity of word alignment grows exponentially with the length of the source and the target sentences, e.g., IBM models (Brown et al., 1993) and HMM-based model (Vogel et al., 1996), BTG provides a natural, polynomial-time, alternative method to reduce the search space in aligning. It also eliminates the need for any of the conventional heuristics.

Since BTG is effective to restrict the exploration of the possible permutations and alignments, there has been some interest in using BTGs for the purpose of alignment (Wu, 1995; Zhang and Gildea, 2005; Wang et al., 2007; Xiong et al., 2010; Neubig et al., 2011, 2012).

In particular, Cherry and Lin (2007) presented a phrasal BTG to the joint phrasal translation model and reported the results on word alignment. Haghghi et al. (2009); Riesa and Marcu (2010) showed that BTG, which captures structural coherence between parallel sentences, helps in word alignment. (Saers et al., 2009) explored approximate BTG parsing and probabilistic induction for word alignment. Neubig et al. (2011) incorporated a Gibbs sampling into joint phrase alignment and extraction framework. Kamigaito et al. (2016) modified the bidirectional agreement constraints and applied a more complex version (BTG-style agreement) to train the BTG model jointly.

However, state-of-the-art BTG-based alignment methods are considered much time-consuming than the simplified generative model (Dyer et al., 2013). The biggest barrier to applying BTG for alignment is the time complexity of naïve CYK parsing (\(O(n^6)\)), which makes it hard to deal with long sentences or large grammars in practice. Most of the previous research attempts to reduce the computational complexity of BTG parsing with some pruning methods. Zhang and Gildea (2005) propose tic-tac-toe pruning by extending BTG with the additional lexical information based on IBM model 1 Viterbi probability. Haghghi et al. (2009) investigate pruning based on the posterior predictions from two joint estimated models. Li et al. (2012) present a simple beam search algorithm for searching the Viterbi BTG alignments.

In this paper, we propose a novel and fast BTG-parsing based word alignment method, which works as a heuristic to explore probable alignments in a given alignment matrix. It can be regarded as a hybridization of BTG parsing and IBM. We improved (Lardilleux et al., 2012) with k-best beam search and introduced several new fast ways to build soft matrices using IBM models.
Our aligner works as a top-down parser to generate hierarchical many-to-many symmetric alignments directly. We compare it with state-of-the-art methods and prove that it can lead to higher quality output for SMT.

2 From Viterbi Alignment to Bipartite Graph Bipartitioning

Given a source sentence \( F \) and a target sentence \( E \), alignment associations between the bilingual sentences can be represented as a contingency matrix, which we note as \( M(F, E) \) (Matusov et al., 2004; Liu et al., 2009).

Given this adjacent matrix, there exist a number of methods to extract \( 1 \)-to-1 alignments or directly extract \( \)many-to-many\ alignments from it. For example, Liu et al. (2010) propose a linear model to score the word alignments for searching the best one. These supervised approaches work using a large number of features (Haghighi et al., 2009; Liu et al., 2010). We focus on simple unsupervised alignment. Other works are trying to induce BTGs with supervised (Haghighi et al., 2009; Burkett et al., 2010) or unsupervised (Wu, 1997; Zhang and Gildea, 2005) training, but they have a common disadvantage: they are time-consuming. In fact, BTG parsing is as simple as what we will discuss in the following.

Consider a bipartite graph \( G(U, V, E) \) with representing the matrix \( M \), with \( \{U, V\} \) two independent subsets of vertices and \( E \) a set of edges. Each pair of nodes \( (f, e) \) is connected with a weighted edge. With the constraints of BTGs, synchronously parsing a sentence pair \( (F, E) \) is a top-down processing that is equivalent to recursively bi-partitioning the graph \( G \) into two disjoint sets of words \( U \) and \( V \) across languages. For example, assume splitting the source sentence \( F = \{X, \bar{X}\} \) (splitting at index \( j \), between \( f_j \) and \( f_{j+1} \)) and the target sentence \( E = \{Y, \bar{Y}\} \) (splitting at index \( i \), between \( e_i \) and \( e_{i+1} \)) in a dichotomous way, i.e., \( \)straight \( \{U : XY, V : \bar{X}Y\} \) or \( \)inverted \( \{U : \bar{X}Y, V : XY\} \). Recursively bi-partitioning in \( G \) will finally derive a BTG parse tree in which each leaf stands for a word-to-word correspondence. In this explanation, applying BTG parsing to a sentence pair can be regarded as trying to find the most reasonable splitting points \( (i, j) \) in \( F \) and \( E \) at the same time. In the case of \( \)straight\, the optimal partition of such a graph is to find the minimum of the risk when reducing \( G(U, V, E) \) to two subgraphs \( G(X, Y, E_{XY}) \) and \( G(\bar{X}, \bar{Y}, E_{\bar{X}\bar{Y}}) \) with applying BTG rule at \( (i, j) \), at which the risk of reducing (cutting) \( \)cut\( (U, V) \) (or \( \)cut\( (i, j) \)) can be computed as total weight of the removed edges as:

\[
\begin{align*}
\text{cut}(i, j|\gamma) &= \begin{cases} 
\text{asso}(X, Y) + \text{asso}(\bar{X}, Y), & \gamma = \text{straight} \\
\text{asso}(X, Y) + \text{asso}(\bar{X}, Y), & \gamma = \text{inverted}
\end{cases} \\
\text{asso}(X, Y) &= \sum_{f \in X} \sum_{e \in Y} w(f, e)
\end{align*}
\]

(1)

However, the minimum cut criterion favors cutting small sets of isolated nodes in the graph. To solve this problem, Shi and Malik (2000) propose a \( \)normalized cut\ (Ncut) to compute the cost as a fraction of the total edge connections to all the nodes in the graph. Following (Vilar, 2005), Lardilleux et al. (2012) use Ncut for sub-sentential alignment, with a naïve assumption that words in a language are independent from each other as:

\[
Ncut(i, j|\gamma) = \frac{\text{cut}(i, j|\gamma)}{\text{cut}(i, j)} + 2 \times \text{cut}_{\text{left}}(i, j|\gamma)
\]

(3)

\( \gamma \) is just the opposite of \( \)\( \gamma \). The ideal criterion Ncut for a recursive partitioning algorithm should minimize the disassociation between the unaligned blocks while maximizing the association within the aligned blocks at the same time. The time complexity of such a top-down algorithm is \( O(m \times n \times \log \min(m, n)) \), better than an exhaustive BTG bi-parsing algorithm which is known to be in \( O(m^3 \times n^3) \).

3 Forest-based BTG Alignment

Lardilleux et al. (2012) employs best-1 parsing to find the optimal \( \)Ncut\, which is intended to minimize. They binary segment the alignment matrix recursively to compute BTG-like alignments based on word level association scores but have not reported the alignment performance independently. While experimentally, we found that this strategy does not ensure the best global derivation. Different from that, we propose a BTG-forest-based parsing/alignment method with a beam search. Firstly, we define a scoring function \( \)Score\( () \) aiming to find the best derivation \( \tilde{D} \) with the minimal value:

\[
\tilde{D} = \arg \min_{D} \text{Score}(D_{\text{Ncut}}|M)
\]

(4)
Algorithm 1 Top-Down Parsing

1: function TopDownParsing($F, E, \tau$)  
2: $M \leftarrow \text{initializeSoftMatrix}(F, E, \tau)$  
3: $S_0 \leftarrow \{\text{initializeState}(0, |F|, 0, |E|)\}$  
4: $S_{final} \leftarrow \{}$  
5: for $i = 0$ to min($|F|, |E|$) do  
6: for all $s \in S_i$ do  
7: for all $s' \in \text{NextStates}(s, M)$ do  
8: $S_{i+1} \leftarrow S_{i+1} \cup s'$  
9: if $\text{isTerminal}(s')$ then  
10: $S_{final} \leftarrow S_{final} \cup s'$  
11: $S_{i+1} \leftarrow \text{top}(k, S_{i+1})$  
12: $D = \arg \max_{D} \text{Score}(D|M)$  
13: return $D$

$Ncut$ can be expressed as the arithmetic mean of two F-measures between $U$ and $V$. For example, in the straight case, when $\{U : XY, V : XY\}$:

$$F_{avg}(U, V) = \frac{F_1(X,Y) + F_1(X,Y)}{2} = 1 - \frac{Ncut(U, V)}{2}$$

(5)

With this expression, minimizing $Ncut$ is equivalent to maximizing $F_{avg}$. Intuitively, it suffices to replace $Ncut$ with $F_{avg}$ to derive the following formula, which gives the probability of a parsing tree, i.e., the probability of a sequence of derivation $D$. The best derivation $D$ and the best word alignment $\hat{\alpha}$ can be defined as,

$$D = \arg \max_{D} \text{Score}(D_{\text{avg}}|M)$$

(6)

$$= \arg \max_{d_k \in D} \prod_{k=1}^{K} F_{avg}(d_k)$$

(7)

$$\hat{a} = Proj(D)$$

(8)

Here, $d_k$ denote the operation of derivation at step $k$ during parsing, defined as a triple $(i, j, \gamma)$, where $i, j$ are the splitting indices and $\gamma$ is either straight or inverted. Our incremental top-down BTG parsing algorithm with beam search is presented in Algorithm 1. We consider that the incremental parser has a parser state at each step. The state is defined as a four-tuple $(P, D, v, \tau)$. $P$ is the stack of unparsed blocks. $D$ is the list of previous derivations $\{d_0, \ldots, d_{i-1}\}$. A block denoted by $([i_0, i_1], [j_0, j_1])$ covers the source words from $f_{j_0}$ to $f_{j_1-1}$ and the target words from $e_{i_0}$ to $e_{i_1-1}$. $v$ records the current score. $\tau$ is set to true on termination (stack $P$ is empty) and is false elsewhere. At the beginning, the initial state contains only a block which covers all the words in $F$ and $E$. The block is split recursively and the node type $\gamma$ (straight or inverted) is decided when the splitting point is determined according to the defined score function. $\text{top}(k, S)$ returns the first $k$-th states from $S$ in terms of their scores $v$.

The computational complexity of the top-down parsing algorithm is $O(k \times n \times m \times \log \min(m, n))$ for sentence lengths $n$ and $m$, with a beam size of $k$. The log of $\min(m, n)$ stands for the parsing depth. For each iteration, each state in the history will be used to generate new states as shown in Algorithm 2. Algorithm 1 terminates when no new hypothesis is generated or when it has reached the maximum number of iterations $\min(m, n)$.

For the initialization of the matrix, there is a number of ways to define the weights of $w(f, e)$. The simplest one is to use the posterior probabilities of IBM model 1. (Moore, 2005) pointed at several disadvantages of IBM model 1: it is either too sensitive to rare words or over-weights frequent words (like function words). For this reason, we incorporate variational Bayes (VB) into our model as proposed in (Riley and Gildea, 2012). We assume the distribution of the target vocabulary to be a Dirichlet distribution, with a symmetric Dirichlet prior as $\theta(f|e) \sim \text{Dirichlet}(\alpha)$. After computation of the posterior probabilities with the EM algorithm, the symmetrical score of $\theta(f|e)$ is defined as the geometric mean of the lexical translation probabilities in both directions $p(f|e)$ and $p(e|f)$.

$$w(f_j, e_i) = e^\frac{\theta(f_j, e_i)}{\sigma_{\theta}} \times \left\{ \begin{array}{ll} p_0 & \text{otherwise} \\ e^\frac{\theta(f_j, e_i)}{\sigma_{\theta}} & \text{if } h < r \end{array} \right.$$  

(9)

$$\theta(f_j, e_i) = \log(\sqrt{\theta(f|e) \times \theta(e|f)})$$

(10)

$$\delta(j, i, n, m) = \log(1 - h(j, i, n, m))$$

(11)

where $\theta(f_j, e_i)$ is a word-to-word translation model and $\delta(j, i, n, m)$ is a distortion model. $r$ is a distortion model. $r \approx 0.01$.
is a distortion threshold depends on language. $\sigma_\theta$ and $\sigma_\delta$ are hyper-parameters and $h(j, i, n, m) = [j/n - i/m]$. Although this is not mandatory, we adjust values to a specified range $w(f_j, e_i) \in [p_0^2, 1], p_0 = 10^{-4}$. Since $Neut$ is a normalized score, it does not require any normalization term. The hyper-parameters $\sigma_\theta$ and $\sigma_\delta$ are fixed at the beginning of experimentation by maximizing the $Recall$ in the preliminary experiments.

## 4 Experiments

For evaluation of word alignment, we use the KFTT Corpus\(^2\) for English–Japanese. In the case of GIZA++ and fast\_align, we train word alignments in both directions with the default settings, i.e., the standard bootstrap for IBM model 4 alignment in GIZA++ ($1^5H^3C^5$) and 5 iterations for fast\_align. We then symmetrize the word alignments using $grow-diag-final-and (+gdfa)$ and evaluate with the final obtained alignments. Perhaps some comparison with other BTG alignment methods is necessary to confirm the advantages of our proposed method. For this consideration, we use an open-sourced BTG-based word aligner, pialign\(^3\). We run it with 8 threads and train the model with batch size 40 and only taking 1 sample during parameter inference. We extract phrases directly from the word-to-word alignment (many-to-many) with traditional heuristic \((\text{Koehn et al.}, 2003)\) for translation. For our implementation, named Hieralign, we limit the run-time to that of fast\_align for fairness. We perform 5 iterations EM estimation using IBM 1 with variational Bayes, with a beam size of 10 during parsing. Since reestimation of the Viterbi probability with the $gdfa$ heuristic (+VBH) is very fast, we also employ it before the step of the parsing. For the phrase-based SMT task, we conduct experiments in English–German (en–de) using the WMT 2008 Shared Task\(^4\); English–Japanese (en–ja) using the KFTT corpus. For translation evaluation, training, development, test sets are independent.

Table 1 shows that our proposed method achieves competitive performance on the KFTT Corpus with state-of-the-art alignment methods. AER (Hieralign) is behind fast align, even more than GIZA++. However, (Lopez and Resnik, 2006; Fraser and Marcu, 2007) question the link between this word alignment quality metrics and translation results. There is no proof that improvements in alignment quality metrics lead to improvements in phrase-based SMT performance. Since our method forces each source and target word aligned (many-to-many), it is prone to generate fewer entries in the translation tables. We thus measured the sizes of the translation tables obtained. Phrase tables extracted from the alignments by Hieralign are smaller by a third in comparison to those of the baseline.

The accuracy of the translations produced by our method are compared to those produced by GIZA++ (+gdfa), fast\_align (+gdfa) and pialign in Table 2, in which standard automatic evaluation metrics are used: BLEU (Papineni et al., 2002) and RIBES (Isozaki et al., 2010). There is no significant difference on the final results in en–de and even better in en–ja. Given the results in Table 2 with the distortion feature ($\sigma_\theta = 3, \sigma_\delta = 5$) and without distortion feature ($\sigma_\theta = 1$), we can also draw the conclusion that adding the distortion feature slightly improves the alignment results.

## 5 Conclusion

To summarize, we proposed a novel BTG-forest-based top-down parsing method for word alignment, we improved (Lardilleux et al., 2012) with better parameter initialization method and return a open-sourced software Hieralign. We

\(^2\)http://www.phontron.com/kftt/

\(^3\)http://www.phontron.com/pialign/

\(^4\)http://www.statmt.org/wmt08/shared-task.html
achieved comparable translation scores with state-of-the-art methods, while the speed is fast. For future work, we believe that incorporating neural models to build the soft-matrix for our method should make a positive influence.

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