Alignment by Bilingual Generation and Monolingual Derivation

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ABSTRACT
One of the main issues in a word alignment task is the difficulty of handling function words that do not have direct translations which we call unique function words. They are often aligned to some words in the other language incorrectly. This is prominent in language pairs with very different sentence structures. In this paper, we propose a novel approach for handling unique function words. The proposed model monolingually derives unique function words from bilingually generated treelet pairs. The monolingual derivation prevents incorrect alignments for unique function words. The derivation probabilities are estimated from a large monolingual corpus, which is much easier to acquire than a parallel corpus. Also, the proposed alignment model uses semantic-head dependency trees where dependency relations between words become similar in each language. Experimental results on an English-Japanese corpus show that the proposed model achieves better alignment and translation quality compared with the baseline models.

KEYWORDS: monolingual derivation, semantic-head dependency tree, treelet alignment.

Title and Abstract in Japanese

二言語の生成と単言語の派生によるアライメント

単語アライメントタスクにおける主な問題の一つは、機能語の中でも相手言語に対して気をつける必要のある単語の難しさである。我々はこのような機能語を孤立機能語と呼び、孤立機能語は、相手言語の何らかの単語に不適切に対応付けられることが多く、これは特に文構造が大きく異なる言語対において顕著である。本論文では、孤立機能語を扱うための新しい手法を提案する。提案モデルは、二言語で生成された部分コーパスから、孤立機能語をそれぞれ単言語で派生することにより、孤立機能語が誤って対応付けられることを防ぐ。派生確率は、対訳コーパスに比べて入手が容易である大規模単言語コーパスから推定する。また提案モデルは、単語同士の依存関係が各言語で異なるように、意味主辞依存構造木を用いる。英日コーパスでの実験結果から、提案モデルはベースラインモデルと比べてより良いアライメントおよび翻訳精度を実現した。

Keywords: monolingual derivation, semantic-head dependency tree, treelet alignment.

Keywords in Japanese: 単言語の派生、意味主辞依存構造木、派生アライメント.
1 Introduction

Alignment accuracy is crucial for providing high quality corpus-based machine translation systems because translation knowledge is acquired from an aligned training corpus. For similar language pairs, alignment accuracy is high. Less than 10% alignment error rate (AER) for French-English has been achieved by the conventional word alignment tool GIZA++, an implementation of the alignment models called the IBM models (Brown et al., 1993), with some heuristic symmetrization rules. However, for distant language pairs such as English-Japanese, the conventional alignment method is quite inadequate (achieving an AER of about 20%).

There are two main issues in a word alignment task for distant language pairs: one is the word order difference, while the other relates to function words. The word order issue has to some extent been solved by using word dependency trees in the alignment model (Nakazawa and Kurohashi, 2011). Most of the remaining alignment errors are related to function words such as English articles and Japanese case markers (Wu et al., 2011) because they do not have counterparts in the other language. As an example, most of the errors in Figure 1 are related to function words: “has” and “_topic-marker” in example (A), and “although”, “_topic-marker”, “ACC” and “but” in example (B).

Several previous works focused on alignment errors of function words. Isozaki et al. (2010) inserted pseudo nodes in English sentences for Japanese function words. Wu et al. (2011) removed the alignment of some function words to effectively acquire translation rules using the underlying word alignment by GIZA++. Nevertheless, these methods for dealing with function words are ad-hoc and based on hand-crafted rules.

In this paper, we propose a novel approach for handling function words. If there is a direct translation for a function word, these words should be aligned with each other. For function words that do not have any counterparts, the conventional model is supposed to align them to NULL, but it does not always work well. They are often aligned to some words incorrectly. In contrast with the conventional model, our model derives such function words from content words in their own language. The derivation probabilities used in our proposed model are estimated from a large monolingual corpus for each language. Thus, we do not require a large parallel corpus. With this derivation model, we can reduce alignment errors for function words, which leads to a better translation resources such as a phrase table, which is acquired from a word-aligned parallel corpus. In the remainder of this paper, we use English-Japanese language pairs for explanation. However, it should be noted that the proposed model is completely language independent.

2 Semantic-head dependency tree

The proposed model utilizes word dependency trees on both the source and target sides. Dependency trees are effective for language pairs with very different word orders, such as English-Japanese, to achieve high quality alignment by absorbing the difference (Nakazawa and Kurohashi, 2011). There are two types of word dependency trees: syntactic-head and semantic-head. Our model adopts the latter. This section discusses the difference between syntactic-head and semantic-head, and the reason why we choose the semantic-head dependency tree.

The syntactic-head dependency tree has two main drawbacks. One is that distances between content words are excessively large for agglutinative languages such as Japanese. The other is that dependency relations differ because of the difference in head word definitions in each
language. On the other hand, in semantic-head dependency trees, function words giving additional information to content words are placed as children of the content words, thus it preserves the dependency relations between words over languages. In the semantic-head dependency tree (on the right of Figure 2), “medical treatment ↔ 治療”, “may ↔ かもしれない”, “not ↔ ない” and “weight ↔ 体重” are all children of “change ↔ 変化”, while the relations are not preserved in the syntactic-head dependency tree (on the left of Figure 2). Because of these advantages, our model uses semantic-head dependency trees.

In this paper, English sentences are first parsed by nlparser (Charniak and Johnson, 2005) which outputs phrase structures that are then converted into word dependency trees by defining the head word for phrases. The conversion rules follow Collins’ head percolation table (Collins, 1999) with some modifications for acquiring semantic-head dependency trees. The following head-specifying rules are examples in which the syntactic head (underlined) and the semantic head (double underlined) is different.

- VP → MD VB (ex. "may change" in Figure 2)
- VP → VBZ JJ (ex. "is large")

Japanese sentences are usually parsed based on a unit called a basic phrase, which consists of one content word followed by zero or more function words. In syntactic-head word dependency trees, on the left of Figure 2, the head word is the last function word (or the content word if there is no function word in a basic phrase), and other words depend on their following words (Hajić et al., 2009). In semantic-head dependency trees, while function words showing a relationship between content words such as case markers are placed as parents of content words, other function words are placed as children. We obtain semantic-head dependency trees by modifying the rule file of the Japanese dependency analyzer KNP (Kawahara and Kurohashi, 2006b).
Figure 2: Examples of syntactic-head (left) and semantic-head (right) dependency trees. The root of the tree is at the extreme left and words are placed from top to bottom. Japanese content words are indicated by “*”.

Several related studies use the semantic-head dependency trees in machine translation (Hong et al., 2009; Xu et al., 2009). They use English-side semantic-head dependency trees for pre-reordering of English sentences in order to make the word order closer to that of Subject-Object-Verb language sentences. The closer the word order is, the easier it is to train the model. However, certain hand-crafted rules are needed for reordering, and pseudo words are used to take care of function words. Compared with these studies, our proposed model uses semantic-head dependency trees on both sides and does not reorder sentences, and therefore it does not require any hand-crafted rules or pseudo words.

3 Handling function words

Although each language has a closed set of function words, the variety of function words differs between languages. For example, in Figure 2, some function words have direct translations in the other language (“may ↔ かもしれない”, “not ↔ ない” and “but ↔ か”), while others do not (“the”, “は (topic marker)” and “に より (by)”). The first case is less problematic, and any alignment model can correctly detect the link. The second case represents the issue addressed in this paper. We call function words that do not have direct translations unique function words.

One solution, adopted by almost all the existing alignment models, is to align unique function words to NULL. However, it is difficult to judge whether a unique function word has to be NULL-aligned or not, and often causes alignment errors as shown in Figure 1. Also, the NULL-aligned words behave as gaps between aligned words, making it harder to capture relations between aligned words. In Figure 2, “に より (by)” is a gap between “治療 (medical treatment)” and “変化 し (change)” whereas counterparts have a direct parent-child relation.

Another solution is to enhance the alignment model so as to handle a larger unit than a word, and include the unique function words in neighboring alignments. For example, “weight ↔ 体重” can include the Japanese “は (topic marker)” and become “weight ↔ 体重 は”. However, this solution can lead to a less appropriate parameter estimation for an alignment model because “weight ↔ 体重” and “weight ↔ 体重 は” are treated as different alignment patterns.
while the two patterns have essentially no difference.

The novel solution to this problem proposed in this paper is to derive unique function words from neighboring words monolingually. In the monolingual derivation model, “_topic marker” can be derived from “topic (weight)” without changing the original treelet pair “weight ← topic”, and therefore the model achieves good estimation of parameters. Note that it is also possible to derive “_topic marker” from “change” because they are contiguous in the tree structure. Another advantage of the monolingual derivation model is that it can reduce the gaps between alignments, and preserve the dependency relations between treelets over languages. For example, the model can derive “by” from “change” or “medical treatment” and let the dependency relation between “change” and “medical treatment” be direct parent-child like their English counterparts. This is effective for estimating the dependency relation probability described in Section 4.3.

4 Model overview

The proposed model is an extension of that proposed by Nakazawa and Kurohashi (2011). This earlier model was overcoming the long-distance reordering issue by incorporating dependency trees. However, it was suffering from alignment errors for function words, which our new model solves by incorporating a monolingual derivation model. First we describe the generative story for the joint alignment model in the same manner as in previous work (Marcu and Wong, 2002; DeNero et al., 2008; Nakazawa and Kurohashi, 2011).

1. Generate ℓ concepts from which bilingual treelet pairs are generated independently.
2. For each treelet pair, derive zero or more treelets monolingually from each treelet in the treelet pair.
3. Combine the treelets in each language so as to create parallel sentences.

The number of concepts ℓ (> 0) is parameterized using a geometric distribution

$$P(\ell) = p_\ell \cdot (1 - p_\ell)^{\ell-1}$$  \hspace{1cm} (1)

where $$p_\ell$$ is a constant. Each concept generates a bilingual treelet pair from an unknown distribution $$\theta_F$$. We call the treelet pair the core alignment denoting it as $$(e_C, f_C)$$. Either one of the treelets in a treelet pair can be NULL, which represents an unaligned treelet. Unaligned treelets must be composed of exactly one word (NULL-alignment restriction).

Each treelet $$e_C$$ and $$f_C$$ derives sets of treelets $$\{d_{eC}\}$$ and $$\{d_{fC}\}$$ monolingually which basically consist of unique function words. The numbers of monolingual derivations $$|\{d_{eC}\}|$$ and $$|\{d_{fC}\}|$$ (≥ 0) are parameterized using a geometric distribution

$$P(|\{d_{eC}\}|) = p_d \cdot (1 - p_d)^{|d_{eC}|}, \hspace{1cm} P(|\{d_{fC}\}|) = p_d \cdot (1 - p_d)^{|d_{fC}|}$$  \hspace{1cm} (2)

where $$p_d$$ is a constant. Each derivation is drawn from a known multinomial distribution $$\phi_{e_C}$$ and $$\phi_{f_C}$$, as explained in Section 4.2. We use the notation $$e$$ to represent the combination of $$e_C$$ and $$\{d_{eC}\}$$, and $$f$$ for $$f_C$$ and $$\{d_{fC}\}$$. Thus $$\langle e, f \rangle$$ contains $$\langle e_C, f_C \rangle, \{d_{eC}\}$$ and $$\{d_{fC}\}$$.

Finally, the treelet pairs are combined in each language. We denote the relation of treelets on the e-side as $$D_E = \{(j \rightarrow k)\}$$, where $$(j \rightarrow k)$$ denotes that treelet $$e_j$$ depends on treelet $$e_k$$, and on the f-side as $$D_F$$. $$D$$ refers to $$D_E$$ and $$D_F$$ as a whole. With these notations, the joint
Figure 3: Example showing the calculation of the bilingual generation probability and monolingual derivation probability.

The bilingual generation probability for an aligned sentence pair is defined as:

\[
P(\ell, \{\langle e, f \rangle \}, D) = P(\ell) \cdot P(D|\{\langle e, f \rangle \}) \cdot \prod_{\langle e, f \rangle} \theta_T(\langle e_C, f_C \rangle) \cdot \phi_{e_C}(d_{e_C}) \cdot P(\{d_{e_C}\}) \cdot \phi_{f_C}(d_{f_C}) \cdot P(\{d_{f_C}\}) \cdot \prod_{d_{e_C}} \phi_T(d_{e_C}) \cdot \prod_{d_{f_C}} \phi_T(d_{f_C}).
\]  

(3)

In Figure 3, we show an example of the calculation of bilingual generation probability and monolingual derivation probability for each treelet pair (ignoring \(P(\{d_{e_C}\})\) and \(P(\{d_{f_C}\})\) for ease of understanding). For the core alignment \(<\text{not, なかった}>\), there is no derivation, and only bilingual generation probability \(\theta_T(\langle \text{not, なかった} \rangle)\) is used. For \(<\text{change, 変化}>\), there are two derivations from “変化 (change)”; “に より (by)” and “し (light verb)”. Therefore, we need to calculate two monolingual derivation probabilities in addition to the bilingual generation probability.

The remainder of this section gives the details of the bilingual generation probability \(\theta_T\), monolingual derivation probability \(\phi\) and dependency relation probability \(P(D)\).

### 4.1 Bilingual generation probability

When generating bilingual treelets, we first need to decide whether to generate an unaligned treelet (with probability \(p_N\)) or an aligned treelet pair (with probability \(1 - p_N\)). Aligned treelet pairs are generated from an unknown probability distribution \(\theta_A\), which obeys the Dirichlet process (DP):

\[
\theta_A(\langle e_C, f_C \rangle) \sim DP(M_A, \alpha_A),
\]  

(4)
where $M_A$ is the base distribution and $\alpha_A$ is a concentration parameter. The base distribution is defined as:

$$M_A(\langle e_C, f_C \rangle) = [p(e_C)P_{WA}(f_C|e_C) \cdot P_f(f_C)P_{WA}(e_C|f_C)]^{\frac{1}{2}}$$

$$p(e_C) = p_t \cdot (1 - p_t)^{|e_C| - 1} \cdot \left(\frac{1}{n_e}\right)^{|e_C|},$$

$$P_f(f_C) = p_t \cdot (1 - p_t)^{|f_C| - 1} \cdot \left(\frac{1}{n_f}\right)^{|f_C|},$$

(5)

where $P_{WA}$ is the translation probability computed by IBM model1 (Brown et al., 1993), and $n_e$ and $n_f$ are the numbers of word types in each language. $\theta_A$ does not give a weight to an unaligned treelet.

Unaligned treelets are generated from another unknown probability distribution $\theta_N$:

$$\theta_N(\langle e_C, f_C \rangle) \sim DP(M_N, \alpha_N)$$

$$M_N(\langle e_C, f_C \rangle) = \begin{cases} P_{WA}(e_C|\text{NULL}) & \text{if } f_C = \text{NULL} \\ P_{WA}(f_C|\text{NULL}) & \text{if } e_C = \text{NULL}. \end{cases}$$

(6)

$\theta_N$ does not give a weight to an aligned treelet pair. Note that an unaligned treelet is always composed of only one word in our model. Finally, $\theta_T$ can be decomposed as:

$$\theta_T(\langle e_C, f_C \rangle) = p_N \theta_N(\langle e_C, f_C \rangle) + (1 - p_N)\theta_A(\langle e_C, f_C \rangle).$$

(7)

The earlier study (Nakazawa and Kurohashi, 2011) only considered treelets as alignment units. However, this is inadequate for semantic-head dependency trees, since a set of siblings in the word sequence. We suppose the term “treelet” includes siblings in this paper.

4.2 Monolingual derivation probability

We only explain the $e$-side derivations in this section, since the $f$-side is the same. We calculate the monolingual derivation probability using a large monolingual corpus. Derivations $d_{e_C}$ are conditioned on the treelet $e_C$ from which they were derived:

$$\phi_e(d_{e_C}) = p(d_{e_C}|e_C).$$

(8)

For example, $\phi_{\text{medical treatment}}(\text{the}) = p(\text{the}|\text{medical treatment})$. However, using a treelet as a condition is vulnerable to the data sparseness problem. We use an anchor word in $e_C$ as the condition instead of $e_C$. The derivation is connected to the anchor word in the word dependency tree:

$$p(d_{e_C}|e_C) \approx p(d_{e_C}|A(e_C, d_{e_C})).$$

(9)

The function $A(e_C, d_{e_C})$ returns the anchor word in $e_C$ for $d_{e_C}$. For example, $A(\text{medical treatment}, \text{the})$ is “treatment”.

$p(d_{e_C}|A(e_C, d_{e_C}))$ are calculated as follows:

$$p(d_{e_C}|A(e_C, d_{e_C})) = \frac{\text{Count}(d_{e_C}, A(e_C, d_{e_C}))}{\sum_d \text{Count}(d, A(e_C, d_{e_C}))}.$$
Table 1: The English derivations (left) and Japanese derivations (right) acquired from the sentences in Figure 3. ‘P’, ‘L’ and ‘R’ denote, respectively, Parent, pre-child (dependent from the Left), and post-child (dependent from the Right).

| Anchor | Derivations                                      | Anchor | Derivations                                      |
|--------|--------------------------------------------------|--------|--------------------------------------------------|
| the    | the P:treatment, P:treatment change               | 体重   | 体重 P:は, P:は 変化                              |
| medical| medical P:treatment, P:treatment change           |は      |は L:体重, P:変化                                  |
| treatment| treatment L:the, L:medical, P:change              |治療   |治療 L:に, P:に より, P:に より 変化                |
| may    | P:change                                         |に      |に L:治療, L:より, P:より 変化                      |
| not    | P:change                                         |より    |より L:治療に, P:変化                                |
| change | change L:treatment, L:the treatment, L:medical    |変化   |変化 L:は, L:体重は, L:より, L:に より, L:治療によ り, R:し, R:しない, R:もし, R:しない |
| the    | P:weight, P: change weight                       |し      |し P:変化                                        |
| weight | P:change, L: the                                 |ない    |ない P:変化                                      |

\[
\text{Count}(d_{ec}, A(e_C, d_{ec})) \text{ denotes the frequency with which } d_{ec} \text{ is connected to } A(e_C, d_{ec}) \text{ in the monolingual corpus. Taking each sentence in Figure 3 as an example sentence in the monolingual corpus, we can enumerate the derivations shown in Table 1 from the sentences. A derivation must be contiguous as a tree, and we do not consider sibling derivations. We distinguish three types of derivations: parent, pre-child (dependent from the left) and post-child (dependent from the right).}
\]

This lexicalized derivation is excessively specific. For example, the highest probability derivations from “Ph.D.” acquired from the English Web corpus (Kawahara and Kurohashi, 2006a) are “a”, “student”, “thesis” in order. Consequently, using only lexicalized derivation can cause many derivation errors. We consider not only the lexicalized derivation probability, but also another probability using part-of-speech (POS) is used as the condition. Using the notation \(A_{pos}(e_C, d_{ec})\) for the POS of the anchor word, the monolingual derivation probability is defined as:

\[
p(d_{ec} | e_C) = [p(d_{ec} | A(e_C, d_{ec})) \cdot p(d_{ec} | A_{pos}(e_C, d_{ec}))]^{1/2}. \tag{11}
\]

\(p(d_{ec} | A_{pos}(e_C, d_{ec}))\) is also acquired from the large monolingual corpus in the same manner as \(p(d_{ec} | A(e_C, d_{ec}))\). We take the geometric mean of the two probabilities because this eliminates noisy derivations of lexicalized probabilities while keeping the derivation preferences for each word.

Note that we do not need to discriminate between content words and function words in the enumeration of derivations and the calculation of derivation probabilities. Generally, the neighboring words of function words are content words. The vocabulary size of content words is much larger than that of function words. Therefore, the number of derivation patterns from function words is quite large, causing their probabilities to be very small. The probabilities naturally prefer deriving function words from content words than deriving content words from function words.

### 4.3 Dependency Relation Probability

Our model considers dependency relations between treelets and assigns a weight to each relation following the previous work (Nakazawa and Kurohashi, 2011). Here, each treelet includes both core and derivation treelets, and treelets in a treelet pair have the same index, for example, the counterpart of \(e_j\) is \(f_j\).
The dependency relations are considered on each $e$ and $f$ side in the same manner, thus we only explain the $e$-side. First, we find the nearest aligned parent treelet, which we call relational parent, for each treelet in $e$-side. The relational parent is searched by ascending the dependency tree to the root node until an aligned treelet is found. The number of unaligned treelets on the path to relational parent from $e_j$ is denoted as $N(e_j)$. $N(e_j) = 0$ if the relational parent is the direct parent of $e_j$. We consider an imaginary root as the relational parent for the root treelet of a sentence.

Suppose the relational parent treelet of $e_j$ is $e_k$. Then, we consider where their counterparts, $f_j$ and $f_k$, respectively, are on the dependency tree of the other side. We can assume that $f_j$ tends to depend on $f_k$ because the dependencies between concepts hold across languages. The dependency relation probability reflects this tendency. We define the function $rel(e_j, e_k)$ which returns a dependency relation between the counterparts of the two arguments, in other words, dependency relation between $f_j$ and $f_k$. For simplicity, we indicate the path with a pair of non-negative integers, where the first is the number of steps going up ($Up$) the dependency tree and the other is the number going down ($Down$). For example, in Figure 3, traveling from “medical treatment” to “weight” requires 1 step going up (to reach “change”) and 1 step going down, so the dependency relation is $(Up, Down) = (1, 1)$.

Finally, we assign the dependency relation probability to a triplet of non-negative integers $R_f = (N, Up, Down)$. The dependency relation probabilities for the $e$-side are drawn from an unknown probability distribution $\theta_{ef}$ and for the $f$-side from $\theta_{fe}$, with both obeying the DP:

\[
\theta_{ef}(R_e) \sim DP(M_{ef}, \alpha_{ef}) \quad M_{ef}(R_e) = p_{ef} \cdot (1 - p_{ef})^{N + Up + Down - 1},
\]

\[
\theta_{fe}(R_f) \sim DP(M_{fe}, \alpha_{fe}) \quad M_{fe}(R_f) = p_{fe} \cdot (1 - p_{fe})^{N + Up + Down - 1}.
\]

Using the notations and definitions above, the dependency tree-based reordering model $P(D|\{(e, f)\})$ is decomposed as:

\[
P(D|\{(e, f)\}) = \prod_{\left\langle e, f \right\rangle} \theta_{ef}(R_e) \cdot \theta_{fe}(R_f).
\]
Figure 4: Illustration of the sampling operators. A solid circle represents a single word, while a treelet is depicted surrounded by a broken line. A gray treelet represents a derivation. A link directly connected to a word denotes that the treelet must consist of exactly one word, whereas other treelets can consist of one or more words including derivations.

1. Take the intersection of the two results.
2. In the union of the two results, accept alignment points connected to at least one accepted point in terms of the dependency tree (corresponds to grow-diag).
3. In the union of the two results, accept alignment points between two unaligned words (corresponds to final-and).

Initial boundaries of treelets and their alignments, and also the counts of treelet pairs and dependency relations are thus acquired. Note that there is no derivations after the initialization step.

5.2 Sampling operators
Our sampler repeatedly uses the six operators illustrated in Figure 4, to generate samples. Each application of an operator generates one new sample. We could, of course, use all the generated samples. However, since successive samples are almost the same, except for one local part, it is futile keeping all the samples. Thus, for each iteration, we keep only one sample, which is the final outcome after applying all the operators to all the possible points in all the sentence pairs in the training corpus.

SWAP
The SWAP operator exchanges the counterparts of two treelets, which may have derivations. There are two cases: [SWAP-1] both treelets are aligned, and [SWAP-2] one of the two treelets is unaligned and the other consists of exactly one word.

TOGGLE
The TOGGLE operator adds or removes an alignment. If \( f_j \) and \( e_k \) are both unaligned treelets, TOGGLE links the two treelets. Alternatively, if \( f_j \) and \( e_j \) are aligned, TOGGLE cuts the link
and makes each of the treelets unaligned. Because of the NULL-alignment restriction, $f_j$ and $e_j$ must consist of exactly one word.

**MERGE**
The MERGE operator combines a one-to-one alignment with the neighboring alignment as derivations from each treelet, or separates derivations from each treelet as an independent alignment.

**BOUNDARY**
The BOUNDARY operator moves the boundary between two treelets by one word. This operator does not change the type (core or derivation) of the boundary word.

**TRANSFORM**
The TRANSFORM operator changes the type of a word from core to derivation or vice versa.

**EXPAND**
The EXPAND operator expands or contracts an aligned treelet. If an unaligned treelet is next to an aligned one, EXPAND merges the unaligned and aligned treelets, either as a part of core treelet or derivation treelet. As the opposite direction, it excludes a marginal node from a treelet, and to make the excluded node unaligned.

### 6 Alignment experiments

We conducted alignment experiments on the English-Japanese corpus to show the effectiveness of the proposed model.

#### 6.1 Settings

For the experiments, we used the JST\(^1\) paper abstract corpus. This corpus was created by NICT\(^2\) from JST's 2M English-Japanese paper abstract corpus using the method of Utiyama and Isahara (2007). This corpus consists of 996K parallel sentences: 24.7M words in English and 27.5M words in Japanese. Unfortunately, this corpus is not publicly available now, but they will become available in the near future.

As gold-standard data, 500 sentence pairs were annotated by hand using two types of annotations: sure (S) alignments and possible (P) alignments (Och and Ney, 2003). The unit of evaluation was the word. We used precision, recall, and alignment error rate (AER) as evaluation criteria. All the experiments were run on the original forms of words. The hyper parameters for our model used in the experiments are as follows: $p_s = 0.1$, $p_d = 0.9$, $p_N = 0.1$, $p_f = 0.8$, $\alpha_A = 100$, $\alpha_N = 100$, $\alpha_{fe} = 100$, $\alpha_{ef} = 100$, $p_{fe} = 0.5$, $p_{ef} = 0.5$. They are borrowed from the previous work (DeNero et al., 2008; Nakazawa and Kurohashi, 2011) and changed a little. The training time was about 1 day using 200 CPU cores. It is much slower than the word-sequence-based models because considering tree structures is computationally more complex.

The derivation probabilities were calculated from English and Japanese Web corpora each consisting of 550M sentences (Kawahara and Kurohashi, 2006a). We limited the maximum size of a derivation treelet to three words. We only consider top-20 frequent derivations for each word and POS.

\(^1\)http://www.jst.go.jp/
\(^2\)http://www.nict.go.jp/
English sentences were converted into phrase structures using Charniak's nlpars
(Charniak and Johnson, 2005), and then they were transformed into dependency structures
by rules defining head words for phrases (Collins, 1999). Japanese sentences were converted
into dependency structures using the morphological analyzer JUMAN (Kurohashi et al., 1994)
and the dependency analyzer KNP (Kawahara and Kurohashi, 2006b).

For comparison, we used GIZA++ (Och and Ney, 2003), which implements the well-known
word-based statistical alignment model of the IBM Models. We conducted word alignment
bidirectionally with the default parameters and merged them using the grow-diag-final-and
heuristics (Koehn et al., 2003). We also tested the BerkeleyAligner\(^3\) (DeNero and Klein, 2007)
in the unsupervised training mode with default settings.

### 6.2 Experimental result and discussion

The experimental results are given in Table 2. “Syntactic-head” is the alignment accuracy of the
baseline system by Nakazawa and Kurohashi (2011), while “Semantic-head w/o derivation”
is the result of using the baseline model on semantic-head dependency trees. The results of
incorporating the monolingual derivation are given in the bottom two rows, where “all” means
that we evaluated all the alignments including derivations, while “core” means that we only
evaluated the core alignments.

As mentioned in Section 1, the baseline model has already shown much better alignment
accuracy than the conventional models, GIZA++ and BerkeleyAligner. There was a slight
improvement using semantic-head dependency trees (0.36% absolute AER reduction).

The proposed model further improved the alignment accuracy. Compared with the baseline
model, we achieved 0.6% and 1.34% improvement in absolute AER by evaluating all the align-
ments and only the core alignments respectively. The relative error reduction in AER is about
10% for the core alignment, which can be considered as a significant improvement. The reason
of the further AER decrease when using only the core alignments is as follows: although the
monolingual derivation can prevent from incorrect alignments for unique function words, it
sometimes causes over derivations. This is discussed in detail later.

Figure 5 shows the alignment results by the proposed model for sentences in Figure 1. The
proposed model reduced the alignment errors for unique function words by deriving them
monolingually, and found correct alignments which the baseline system failed to find.

There are two main causes of alignment errors in the proposed model. One is the granularity
of the derivation probability. We used the product of the two probabilities, lexicalized and
POS-based, to take advantage of them, but this is insufficient. For example, in the sentence
fragment “the possibility that ...”, the proposed model failed to derive the unique word “that”
from “possibility”. In another fragment “the patient who ...”, the proposed model failed to
derive “who” from “patient”. The reason for these failures is the low probability in the POS-
based derivation. The possible solution for the granularity problem is to use word classes
where each word class contains the words which have similar derivation distribution. For
example, some abstract nouns such as “possibility” and “fact” tend to derive appositive “that”,
and person-category nouns tend to derive a relative “who”.

The other cause of alignment errors is the over derivation typically created by the noise in
a parallel sentence and parsing error. On the left of Figure 6, the fragment of the Japanese

\(^3\)http://code.google.com/p/berkeleyaligner/
Table 2: Results of English-Japanese alignment experiments.

| Alignment model                                         | Pre. | Rec. | AER  |
|---------------------------------------------------------|------|------|------|
| GIZA++ & grow-diag-final-and                            | 83.00| 83.01| 16.99|
| BerkeleyAligner                                         | 85.69| 74.13| 20.32|
| Syntactic-head (baseline)                               | 88.59| 83.78| 13.66|
| Semantic-head w/o derivation                            | 88.82| 84.28| 13.30|
| Semantic-head w/ derivation (all)                       | 87.83| 85.81| 13.06|
| Semantic-head w/ derivation (core)                      | 90.51| 84.49| 12.32|

Figure 5: Alignment results by the proposed model. The solid and open squares depict core alignments and derivations, respectively.

sentence “音列の (of tone sequence)” has no corresponding part in the English sentence. “音列 (tone sequence)” is correctly aligned to NULL, but the function word “の (of)” is incorrectly derived from “法 (method)”. On the right of Figure 6, the Japanese “HDMI は” should not depend on “異なる (different)”, but on “使用 (use)”. Because of this parsing error, the topic marker “は” is incorrectly derived from “異なる (different)”. One possible short-term solution for the parsing problem is to use the n-best parsing results in the model. An alternative solution was proposed by Burkett et al. (2010), who described a joint parsing and alignment model that exchanges useful information between the parser and aligner.

7 Translation experiments

We conducted English-to-Japanese and Japanese-to-English translation experiments on the same corpus used in the alignment experiments. We translated 500 paper abstract sentences from the JST corpus. Note that these sentences were not included in the training corpus. We use Joshua⁴, a Java-based opensource implementation of the hierarchical decoder, version 4.0 (Ganitkevitch et al., 2012) with default settings. It was tuned using another 500 development sentence pairs.

Table 3 shows the BLEU (Papineni et al., 2002) scores for the translations. The proposed

⁴http://joshua-decoder.org
Figure 6: Alignment errors of the proposed model caused by a NULL part (left) and a parsing error (right).

| Alignment model                              | En $\rightarrow$ Ja | Ja $\rightarrow$ En |
|----------------------------------------------|---------------------|----------------------|
| GIZA++ & grow-diag-final-and                 | 23.84               | 17.75                |
| Syntactic-head (baseline)                    | 24.16               | 17.83                |
| Semantic-head w/o derivation                | 24.11               | 18.06                |
| Semantic-head w/ derivation (all)           | 24.55†              | 18.46†‡              |
| Semantic-head w/ derivation (core)          | 24.45               | 17.76                |

Table 3: BLEU scores for English-to-Japanese and Japanese-to-English translation experiments. † and ‡ marks indicate significant difference by bootstrap resampling (Koehn, 2004) from the decoder using GIZA++ & grow-diag-final-and alignment and baseline alignment respectively ($p < 0.05$).

The model using all the alignments including derivations achieved the best translation quality. We believe this improvement is due to the reduction in function word alignment errors. The BLEU score decreased when only core alignments were used. This is because the exclusion of the derivations increased the ambiguity of the translation rules.

**Conclusion and future work**

In this paper, we proposed a novel approach for handling unique function words based on semantic-head dependency trees. The proposed model monolingually derives unique function words from bilingually generated treelet pairs. The derivation probabilities are acquired from a large monolingual corpus for each language. We showed that semantic-head dependency trees are more effective than syntactic-head dependency trees for high quality alignment, and that the treelet derivation model can reduce alignment errors for function words resulting in better translation quality.

To further validate the effectiveness of the proposed model, we need to apply our model to other language pairs, including the Korean language, which is also an agglutinative language. In addition, we need to resolve the issues discussed in Section 6.2.

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