Diversify and Combine: Improving Word Alignment for Machine Translation on Low-Resource Languages

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Abstract

We present a novel method to improve word alignment quality and eventually the translation performance by producing and combining complementary word alignments for low-resource languages. Instead of focusing on the improvement of a single set of word alignments, we generate multiple sets of diversified alignments based on different motivations, such as linguistic knowledge, morphology and heuristics. We demonstrate this approach on an English-to-Pashto translation task by combining the alignments obtained from syntactic reordering, stemming, and partial words. The combined alignment outperforms the baseline alignment, with significantly higher F-scores and better translation performance.

1 Introduction

Word alignment usually serves as the starting point and foundation for a statistical machine translation (SMT) system. It has received a significant amount of research over the years, notably in (Brown et al., 1993; Ittycheriah and Roukos, 2005; Fraser and Marcu, 2007; Hermjakob, 2009). They all focused on the improvement of word alignment models. In this work, we leverage existing aligners and generate multiple sets of word alignments based on complementary information, then combine them to get the final alignment for phrase training. The resource required for this approach is little, compared to what is needed to build a reasonable discriminative alignment model, for example. This makes the approach especially appealing for SMT on low-resource languages.

Most of the research on alignment combination in the past has focused on how to combine the alignments from two different directions, source-to-target and target-to-source. Usually people start from the intersection of two sets of alignments, and gradually add links in the union based on certain heuristics, as in (Koehn et al., 2003), to achieve a better balance compared to using either intersection (high precision) or union (high recall). In (Ayan and Dorr, 2006) a maximum entropy approach was proposed to combine multiple alignments based on a set of linguistic and alignment features. A different approach was presented in (Deng and Zhou, 2009), which again concentrated on the combination of two sets of alignments, but with a different criterion. It tries to maximize the number of phrases that can be extracted in the combined alignments. A greedy search method was utilized and it achieved higher translation performance than the baseline.

More recently, an alignment selection approach was proposed in (Huang, 2009), which computes confidence scores for each link and prunes the links from multiple sets of alignments using a hand-picked threshold. The alignments used in that work were generated from different aligners (HMM, block model, and maximum entropy model). In this work, we use soft voting with weighted confidence scores, where the weights can be tuned with a specific objective function. There is no need for a pre-determined threshold as used in (Huang, 2009). Also, we utilize various knowledge sources to enrich the alignments instead of using different aligners. Our strategy is to diversify and then combine in order to catch any complementary information captured in the word alignments for low-resource languages.

The rest of the paper is organized as follows.
We present three different sets of alignments in Section 2 for an English-to-Pashto MT task. In Section 3, we propose the alignment combination algorithm. The experimental results are reported in Section 4. We conclude the paper in Section 5.

2 Diversified Word Alignments

We take an English-to-Pashto MT task as an example and create three sets of additional alignments on top of the baseline alignment.

2.1 Syntactic Reordering

Pashto is a subject-object-verb (SOV) language, which puts verbs after objects. People have proposed different syntactic rules to pre-reorder SOV languages, either based on a constituent parse tree (Drábek and Yarowsky, 2004; Wang et al., 2007) or dependency parse tree (Xu et al., 2009). In this work, we apply syntactic reordering for verb phrases (VP) based on the English constituent parse. The VP-based reordering rule we apply in the work is:

\[ VP(VB*, *) \rightarrow VP(*, VB*) \]

where \( VB* \) represents \( VB, VBD, VBG, VBN, VBP \) and \( VBJ \).

In Figure 1, we show the reference alignment between an English sentence and the corresponding Pashto translation, where \( E \) is the original English sentence, \( P \) is the Pashto sentence (in romanized text), and \( E' \) is the English sentence after reordering. As we can see, after the VP-based reordering, the alignment between the two sentences becomes monotone, which makes it easier for the aligner to get the alignment correct. During the reordering of English sentences, we store the index changes for the English words. After getting the alignment trained on the reordered English and original Pashto sentence pairs, we map the English words back to the original order, along with the learned alignment links. In this way, the alignment is ready to be combined with the baseline alignment and any other alternatives.

2.2 Stemming

Pashto is one of the morphologically rich languages. In addition to the linguistic knowledge applied in the syntactic reordering described above, we also utilize morphological analysis by applying stemming on both the English and Pashto sides. For English, we use Porter stemming (Porter, 1980), a widely applied algorithm to remove the common morphological and inflexional endings from words in English. For Pashto, we utilize a morphological decomposition algorithm that has been shown to be effective for Arabic speech recognition (Xiang et al., 2006). We start from a fixed set of affixes with 8 prefixes and 21 suffixes. The prefixes and suffixes are stripped off from the Pashto words under the two constraints: (1) Longest matched affixes first; (2) Remaining stem must be at least two characters long.

2.3 Partial Word

For low-resource languages, we usually suffer from the data sparsity issue. Recently, a simple method was presented in (Chiang et al., 2009), which keeps partial English and Urdu words in the training data for alignment training. This is similar to the stemming method, but is more heuristic-based, and does not rely on a set of available affixes. With the same motivation, we keep the first 4 characters of each English and Pashto word to generate one more alternative for the word alignment.

3 Confidence-Based Alignment Combination

Now we describe the algorithm to combine multiple sets of word alignments based on weighted confidence scores. Suppose \( a_{ijk} \) is an alignment link in the \( i \)-th set of alignments between the \( j \)-th source word and \( k \)-th target word in sentence pair \( (S, T) \). Similar to (Huang, 2009), we define the confidence of \( a_{ijk} \) as

\[
    c(a_{ijk} | S, T) = \sqrt{q_{S|T}(a_{ijk} | S, T)q_{T|S}(a_{ijk} | T, S)},
\]

Figure 1: Alignment before/after VP-based reordering.
where the source-to-target link posterior probability
\[
q_{s\rightarrow t}(a_{ijk}|S,T) = \frac{p_i(t_k|s_j)}{\sum_{k'=1}^{K} p_i(t_{k'}|s_j)}, \hspace{1cm} (2)
\]
and the target-to-source link posterior probability
\[
q_{t\rightarrow s}(a_{ijk}|T,S) \text{ is defined similarly. } p_i(t_k|s_j) \text{ is the lexical translation probability between source word } s_j \text{ and target word } t_k \text{ in the } i\text{-th set of alignments.}
\]

Our alignment combination algorithm is as follows.

1. Each candidate link \( a_{jk} \) gets soft votes from \( N \) sets of alignments via weighted confidence scores:
\[
v(a_{jk}|S,T) = \sum_{i=1}^{N} w_i \cdot c(a_{ijk}|S,T), \hspace{1cm} (3)
\]
where the weight \( w_i \) for each set of alignment can be optimized under various criteria. In this work, we tune it on a hand-aligned development set to maximize the alignment F-score.

2. All candidates are sorted by soft votes in descending order and evaluated sequentially. A candidate link \( a_{jk} \) is included if one of the following is true:
   - Neither \( s_j \) nor \( t_k \) is aligned so far;
   - \( s_j \) is not aligned and its left or right neighboring word is aligned to \( t_k \) so far;
   - \( t_k \) is not aligned and its left or right neighboring word is aligned to \( s_j \) so far.

3. Repeat scanning all candidate links until no more links can be added.

In this way, those alignment links with higher confidence scores have higher priority to be included in the combined alignment.

4 Experiments

4.1 Baseline

Our training data contains around 70K English-Pashto sentence pairs released under the DARPA TRANSTAC project, with about 900K words on the English side. The baseline is a phrase-based MT system similar to (Koehn et al., 2003). We use GIZA++ (Och and Ney, 2000) to generate the baseline alignment for each direction and then apply grow-diagonal-final (gdf). The decoding weights are optimized with minimum error rate training (MERT) (Och, 2003) to maximize BLEU scores (Papineni et al., 2002). There are 2028 sentences in the tuning set and 1019 sentences in the test set, both with one reference. We use another 150 sentence pairs as a heldout hand-aligned set to measure the word alignment quality. The three sets of alignments described in Section 2 are generated on the same training data separately with GIZA++ and enhanced by gdf as for the baseline alignment. The English parse tree used for the syntactic reordering was produced by a maximum entropy based parser (Ratnaparkhi, 1997).

4.2 Improvement in Word Alignment

In Table 1 we show the precision, recall and F-score of each set of word alignments for the 150-sentence set. Using partial word provides the highest F-score among all individual alignments. The F-score is 5% higher than the baseline alignment. The VP-based reordering itself does not improve the F-score, which could be due to the parse errors on the conversational training data. We experiment with three options \((c_0, c_1, c_2)\) when combining the baseline and reordering-based alignments. In \( c_0 \), the weights \( w_i \) and confidence scores \( c(a_{ijk}|S,T) \) in Eq. (3) are all set to 1. In \( c_1 \), we set confidence scores to 1, while tuning the weights with hill climbing to maximize the F-score on a hand-aligned tuning set. In \( c_2 \), we compute the confidence scores as in Eq. (1) and tune the weights as in \( c_1 \). The numbers in Table 1 show the effectiveness of having both weights and confidence scores during the combination.

Similarly, we combine the baseline with each of the other sets of alignments using \( c_2 \). They all result in significantly higher F-scores. We also generate alignments on VP-reordered partial words \((X \text{ in Table 1})\) and compared \( B + X \) and \( B + V + P \). The better results with \( B + V + P \) show the benefit of keeping the alignments as diversified as possible before the combination. Finally, we compare the proposed alignment combination \( c_2 \) with the heuristics-based method \((gdf)\), where the latter starts from the intersection of all 4 sets of alignments and then applies grow-diagonal-final (Koehn et al., 2003) based on the links in the union. The proposed combination approach on \( B + V + S + P \) results in close to 7% higher F-scores than the baseline and also 2% higher than
We also notice that its higher F-score is mainly due to the higher precision, which should result from the consideration of confidence scores.

| Alignment | Comb | P   | R   | F   |
|-----------|------|-----|-----|-----|
| Baseline  |      | 0.6923 | 0.6414 | 0.6659 |
| V         |      | 0.6934 | 0.6388 | 0.6650 |
| S         |      | 0.7376 | 0.6495 | 0.6907 |
| P         |      | 0.7665 | 0.6643 | 0.7118 |
| X         |      | 0.7615 | 0.6641 | 0.7095 |
| B+V       | $c_0$ | 0.7639 | 0.6312 | 0.6913 |
| B+V       | $c_1$ | 0.7645 | 0.6373 | 0.6951 |
| B+V       | $c_2$ | 0.7895 | 0.6505 | 0.7133 |
| B+S       | $c_2$ | 0.7942 | 0.6553 | 0.7181 |
| B+P       | $c_2$ | 0.8006 | 0.6612 | 0.7242 |
| B+X       | $c_2$ | 0.7827 | 0.6670 | 0.7202 |
| B+V+P     | $c_2$ | 0.7912 | 0.6755 | 0.7288 |
| B+V+S+P   | $c_2$ | 0.7238 | 0.7042 | 0.7138 |
| B+V+S+P   | $c_2$ | 0.7906 | 0.6852 | 0.7342 |

Table 1: Alignment precision, recall and F-score (B: baseline; V: VP-based reordering; S: stemming; P: partial word; X: VP-reordered partial word).

### 4.3 Improvement in MT Performance

In Table 2, we show the corresponding BLEU scores on the test set for the systems built on each set of word alignment in Table 1. Similar to the observation from Table 1, $c_2$ outperforms $c_0$ and $c_1$, and $B + V + S + P$ with $c_2$ outperforms $B + V + S + P$ with $gdf$. We also ran one experiment in which we concatenated all 4 sets of alignments into one big set (shown as $cat$). Overall, the BLEU score with confidence-based combination was increased by 1 point compared to the baseline, 0.6 compared to $gdf$, and 0.7 compared to $cat$. All results are statistically significant with $p < 0.05$ using the sign-test described in (Collins et al., 2005).

| Alignment | Comb | Links | Phrase | BLEU |
|-----------|------|-------|--------|------|
| Baseline  |      | 963K  | 565K   | 12.67 |
| V         |      | 965K  | 624K   | 12.82 |
| S         |      | 915K  | 692K   | 13.04 |
| P         |      | 906K  | 716K   | 13.30 |
| X         |      | 911K  | 689K   | 13.00 |
| B+V       | $c_0$ | 870K  | 890K   | 13.20 |
| B+V       | $c_1$ | 865K  | 899K   | 13.32 |
| B+V       | $c_2$ | 874K  | 879K   | 13.60 |
| B+S       | $c_2$ | 864K  | 948K   | 13.41 |
| B+P       | $c_2$ | 863K  | 942K   | 13.40 |
| B+X       | $c_2$ | 871K  | 905K   | 13.37 |
| B+V+P     | $c_2$ | 880K  | 914K   | 13.60 |
| B+V+S+P   | $cat$| 3749K | 1258K  | 13.01 |
| B+V+S+P   | $gdf$| 1021K | 653K   | 13.14 |
| B+V+S+P   | $c_2$| 907K  | 771K   | 13.73 |

Table 2: Improvement in BLEU scores (B: baseline; V: VP-based reordering; S: stemming; P: partial word; X: VP-reordered partial word).

both higher F-score and higher BLEU score. The combination approach itself is not limited to any specific alignment. It provides a general framework that can take advantage of as many alignments as possible, which could differ in preprocessing, alignment modeling, or any other aspect.

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