Triangulation of Reordering Tables: An Advancement Over Phrase Table Triangulation in Pivot-Based SMT

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Abstract

Triangulation in Pivot-Based Statistical Machine Translation(SMT) is a very effective method for building Machine Translation(MT) systems in case of scarcity of the parallel corpus. Phrase Table Triangulation helps in such a resource constrained setting by inducing new phrase pairs with the help of a pivot. However, it does not explore the possibility of extracting reordering information through the use of pivot. This paper presents a novel method for triangulation of reordering tables in Pivot Based SMT. We show that the use of a pivot can help in extracting better reordering information and can assist in improving the quality of the translation. With a detailed example, we show that triangulation of reordering tables also improves the lexical choices a system makes during translation. We observe a BLEU score improvement of 1.06 for Marathi to English MT system with Hindi as a pivot, and also significant improvements in 8 other translation systems by using this method.

1 Introduction

Pivot-Based Statistical Machine Translation(SMT) is a crucial and a well known methodology for building Machine Translation(MT) Systems for language pairs that are not so rich in terms of available resources. Low or no availability of parallel corpus for a language pair is one of the main reasons behind following a Pivot-Based approach. Pivot-Based approach makes use of a parallel corpus from source language to some language other than the target language, which is known as a "Pivot language" or simply a "Pivot", and a parallel corpus from the pivot language to the target language. Key idea behind using a pivot is, using one or more pivot languages to improve the quality of translation by making use of additional information that the pivot induces. This additional information is mainly in the form of a new set of phrase pairs that are extracted with the help of the pivot language. This method of extracting new phrase pairs in Pivot-Based SMT is known as the Triangulation method.

Current approaches and methods that discuss triangulation generally focus on the triangulation of the phrase tables from source language(source) to pivot language(pivot) and pivot language to target language(target). This improves the translation quality because of the newly added phrase pairs, but the reordering information for these newly added phrase pairs is not present in the reordering table. The focus of our work is to explore the possibility of extracting the reordering information for newly added phrase pairs by making use of the pivot language. To the best of our knowledge this is the first work that discusses the approaches for triangulation of reordering tables and shows significant improvements.

To begin with, Section 2 discusses the work related to Pivot-Based SMT and the Triangulation method. We then provide a background for our approaches for reordering table triangulation in Section 3. Section 4 discusses the mathematics involved in these approaches. We describe our approaches viz. Table Based approach and Count Based approach in detail, in Section 5. Section 6 explains the experimental setup. Results of our experiments are shown in Section 7 along with the discussion of those results. We conclude our work in Section 8 and also point out a few directions for future work.

2 Related Work

Use of a pivot in machine translation has been extensively studied by many researchers. Wang et al.

(2006) demonstrated the use of pivot languages for extracting better word alignments when a source-target parallel corpus is either unavailable or is very small in size. Wu and Wang (2007) proposed the entire formulation for a pivot based approach and triangulation of phrase tables and showed that a pivot can be used for inducing new phrase pairs that were not extracted while building a phrase table from the training corpus. This forms a basis for a valid speculation that, pivot may also prove to be useful in extracting reordering information.

Several strategies have been proposed for the use of a pivot. Utiyama and Isahara (2007) proposed two strategies, a phrase translation strategy that is similar to the triangulation method and a sentence translation strategy that makes use of two different MT systems - one from source-pivot and other from pivot-target. They showed through their experiments that the phrase translation strategy performs significantly better than the sentence translation strategy. Wu and Wang (2009) additionally introduced a Synthetic Method for Pivot based SMT, that synthesizes the source-target corpus from source-pivot and pivot-target corpora. It was found through their experiments that the Triangulation Method outperforms the Sythetic method as well. This encouraged us to focus our work on the triangulation approach.

Nakov and Ng (2012) showed that merging the phrase tables by giving priority to the original table that is extracted from a direct parallel corpus(direct table) and using additional features is a good strategy. In case of an interpolation, it refers to giving higher weight values to the translation probabilities from a direct source-pivot phrase table. Dabre et al. (2015) studied the use of more than one pivots simultaneously. They also mentioned that the use of pivot for reordering would be an interesting problem.

The reordering model on which we focus in our work is a lexicalized reordering model discussed by Koehn et al. (2005). Lexicalized reordering was first proposed by Tillmann (2004). Similar approach was suggested by Ohashi et al. (2005). Mirkin (2014) proposed several ways for incrementally updating the lexicalized reordering model when new training data is introduced and described a way to combine new and existing reordering models. To the best of our knowledge, no work has been done on triangulation of reordering tables in specific.

3 Background for Our Approaches

Our aim is to generate a source language to target language reordering table given a source language to pivot language reordering table and a pivot language to target language reordering table. This is called as Triangulation of Reordering tables or Reordering Table Triangulation. In this paper, we propose two approaches for triangulation of reordering tables. Both of them make use of reordering tables, which have a peculiar format in Moses, a statistical machine translation system (Koehn et al., 2007). Before going forward with the description of our approaches, we explain the concepts of reordering orientations and give a short overview of the structure of a reordering table in Moses.

3.1 Reordering Orientations: Monotone, Swap and Discontinuous

Moses implements reordering using three kinds of orientations - Monotone, Swap and Discontinuous (Koehn et al., 2005; Koehn, 2009). For each phrase and its corresponding translation, there are three possible orientations.

Let S_1, S_2 be phrases in source sentence, T_1, T_2 be their corresponding translations in the target sentence and T_1 be a phrase that immediately precedes T_2 in the target sentence. Then for the phrase pair (S_2, T_2) the orientation is :

- **Monotone**, if S_1 is a phrase that immediately precedes S_2 in the source sentence.

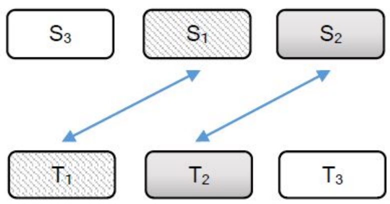


Figure 1: Monotone Orientation

- **Swap**, if S_1 is a phrase that immediately succeeds S_2 in the source sentence.

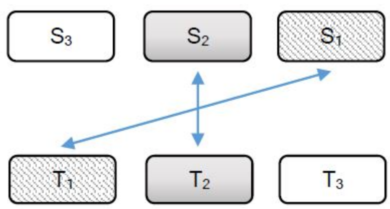


Figure 2: Swap Orientation

- **Discontinuous**, if S_1 and S_2 are not adjacent to each other in the source sentence.

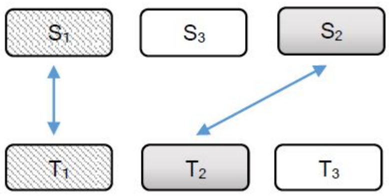


Figure 3: Discontinuous Orientation

Let us consider sentences from English-Marathi language pair shown in Figure 4.

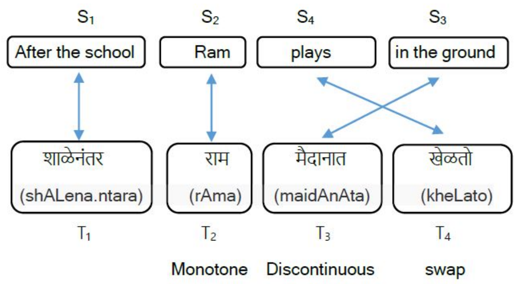


Figure 4: Example depicting all orientations

As per the definitions discussed above, the orientation exhibited by the phrase pair (Ram, राम) is a monotone since, the translation of the previous phrase of राम i.e. 'After the school' is also the previous phrase of 'Ram'. Similarly by definition, (plays, खेळतो) has a swap orientation and (in the ground, मैदानात) has a discontinuous orientation.

3.2 Structure of a Reordering Table in MOSES

As discussed in subsection 3.1, for each phrase pair, there are three reordering orientations possible. A typical reordering table in Moses consists of all such phrase pairs and their respective probability values for monotone, swap and discontinuous orientations.

Following is a sample entry from English-Marathi reordering table.
By looking |||पाहिल्यावर|||0.2 0.2 0.6 0.2 0.2 0.6

The first three values are the probability values of a phrase pair (By looking, पाहिल्यावर) being a monotone, swap and discontinuous respectively, with respect to the previous phrase of पाहिल्यावर (pAhilyAvara) in the target sentence. The next three values are the probability values of a phrase pair (By looking, पाहिल्यावर) being a monotone, swap and discontinuous respectively, with respect to the next phrase of पाहिल्यावर in the target sentence.

Reordering table is used during decoding to score the candidate translations. Scoring a particular candidate translation for reordering, involves scoring each phrase with respect to its previous and next phrase. This along with the Language Model, boosts up the scores assigned to better ordered candidate translations.

3.3 Objective of the Approach

Our objective is to determine the probability values discussed in Subsection 3.2, for phrase pairs that are newly extracted by phrase table triangulation, given the source-pivot and pivot-target reordering tables.

We propose two approaches for doing this. Our first approach only assumes the availability of two reordering tables mentioned above, whereas the second approach assumes the availability of a multilingual parallel corpus that is used for training, in addition to the two reordering tables.

4 Mathematical Formulation

For a language pair $L_1 - L_2$, (A, B) is a phrase pair if phrase A from L_1 translates to phrase B from L_2. We will use the notation $O(A \rightarrow B)$ to denote the orientation of a phrase pair (A, B). The possible values of O are {M,S,D}.
Where,
M(A $\rightarrow$ ***B)*** : (A, B) has a Monotone orientation
S(A $\rightarrow$ ***B)*** : (A, B) has a Swap orientation
D(A $\rightarrow$ ***B)*** : (A, B) has a Discontinuous orientation

For the discussion in this section, let X,Y and Z be the phrases from source, pivot and target languages respectively which are all translations of each other. In other words, (X, Y) is phrase pair from source to pivot, (Y, Z) is a phrase pair from pivot to target and (X, Z) is a phrase pair from source to target.

Let us assume that (X, Z) is a phrase pair that was not originally present in the phrase table and was induced during the phrase table triangulation process. Then our task is to determine the probability values $P[M(X \rightarrow Z)]$, $P[S(X \rightarrow Z)]$ and $P[D(X \rightarrow Z)]$ in order to include an entry for phrase pair (X, Z) in the reordering table.

There can be more than one pivot phrases Y for a particular phrase pair (X, Z). There are also multiple combinations of source-pivot and pivot-target orientations possible for (X, Y) and

(Y, Z) respectively.
Marginalizing over these variables we get,

$$P[M(X \rightarrow Z)] = \sum_{\substack{Y \\ O(X \rightarrow Y) \\ O(Y \rightarrow Z)}} P[M(X \rightarrow Z), O(X \rightarrow Y), O(Y \rightarrow Z)] \quad (1)$$

Applying the chain rule, we get,

$$P[M(X \rightarrow Z)] = \sum_{\substack{Y \\ O(X \rightarrow Y) \\ O(Y \rightarrow Z)}} P[M(X \rightarrow Z) | O(X \rightarrow Y), O(Y \rightarrow Z)]. \; P[O(X \rightarrow Y), O(Y \rightarrow Z)] \quad (2)$$

Since, $O(X \rightarrow Y)$ and $O(Y \rightarrow Z)$ are independent of each other, applying this independence assumption on second term, we get

$$P[M(X \rightarrow Z)] = \sum_{\substack{Y \\ O(X \rightarrow Y) \\ O(Y \rightarrow Z)}} P[M(X \rightarrow Z) | O(X \rightarrow Y), O(Y \rightarrow Z)]. \; P[O(X \rightarrow Y)].P[O(Y \rightarrow Z)] \quad (3)$$

$P[O(X \rightarrow Y)]$ and $P[O(Y \rightarrow Z)]$ are the reordering probability values from source-pivot and pivot-target and are directly available from the reordering tables that are used for triangulation. The first term i.e.

$$P[M(X \rightarrow Z) | O(X \rightarrow Y), O(Y \rightarrow Z)]$$

called a "**Multiplicative Factor**" henceforth, is a probability that for a particular orientation of $O(X \rightarrow Y)$ and $O(Y \rightarrow Z)$, source-target orientation for (X, Z) is a Monotone, in case of the calculation above. We worked out the mathematics for probability of (X, Z) being a Monotone. Similar calculations can be performed for determining the Swap and Discontinuous probability values. Therefore, similar kind of terms will exist for Swap and Discontinuous as well. The value for the Multiplicative Factor is not directly available to us. For calculating this value we propose two approaches in this paper.

5 Description of the Approaches

For calculating the Multiplicative Factor in Equation 3 we can follow one of the two paths, one is called a *Table Based Approach* and the other is called *Count Based Approach*.

5.1 Table Based Approach

This approach only assumes the availability of two reordering tables: a source language to pivot language reordering table and a pivot language to target language reordering table. Based on all possible source-pivot and pivot-target orientations, we designed an "**Orientation Table**" of all possible source-target orientations, which is shown in Table 1.

	M	**S**	**D**
Monotone (M)	M	S, D	S, D
Swap (S)	S	M, D	M, D
Discontinuous (D)	D	M ,S, D	M, S, D

Table 1: Orientation Table

The rows of the Orientation Table($O_i{}'s$) represent different orientations for a source-pivot phrase pair and the columns($O_j{}'s$) represent different orientation for a pivot-target phrase pair, where the pivot phrase is common. A cell which is in row O_i and column O_j lists all possible orientations from source-target when source-pivot orientation is O_i and pivot-target orientation is O_j. For example, assume that S, P, T are phrases from source, pivot and target languages respectively and are translations of each other. If the source-pivot orientation is a monotone for phrase pair (S, P) and the pivot-target orientation is swap for phrase pair (P, T), then for phrase pair (S, T) the orientation can either be a Swap or a Discontinuous. We studied numerous examples from the most general scenarios as well as from specific language pairs, in order to create this table.

We use this table for determining the Multiplicative Factor by looking up into the appropriate cell of the table while doing the computation. We also assume that if there are more than one orientations in a particular cell then all of them are equally likely. We have observed that there might be some wrong translations in the training data because of which the orientations which are not present in a particular cell may also be exhibited by some phrases in some situations, although, such occurrences are few in number. To factor in for such discrepancies, we assume that orientations present in the cells of the above table are the "most probable" ones and other orientations are also possible with a very small probability.

For example, for a phrase pair (S, P) the orientation is monotone and for (P, T) the orientation is

	En-Gu-Hi	En-Hi-Gu	En-Hi-Mr	Hi-Gu-En	Hi-Gu-Mr	Hi-Pa-En	Mr-Gu-Hi	Mr-Gu-En	Mr-Hi-En
DIR-DIR	25.97	16.03	10.12	29.87	33.69	29.78	41.66	16.72	16.77
INTER-DIR	25.83	17.37	13.11	30.01	36.09	29.86	42.58	17.97	19.04
INTER-TRI	25.08	16.94	12.57	28.54	36.13	28.38	42.47	17.70	19.09
INTER-INTER	26.30	17.71	13.19	30.52	36.28	30.39	42.67	18.55	20.10
IMPROVEMENT	**0.47**	**0.34**	**0.08**	**0.51**	**0.19**	**0.53**	**0.09**	**0.58**	**1.06**

Table 2: BLEU Scores for Count Based Approach
(IMPROVEMENT row shows improvement in INTER-INTER system over INTER-DIR system)

swap, then the multiplicative factor while calculating probability of (S, T) being a monotone i.e. $P[M(S \rightarrow T)|M(S \rightarrow P), S(P \rightarrow T)]$ can be assigned a small value, say 0.1, since monotone is not listed in the cell.
The other two orientations are assumed to be equally likely, so in this case
$P[S(S \rightarrow T)|M(S \rightarrow P), S(P \rightarrow T)] = 0.45$
and
$P[D(S \rightarrow T)|M(S \rightarrow P), S(P \rightarrow T)] = 0.45$

5.2 Count Based Approach

This approach assumes the availability of two reordering tables and the source-pivot-target multilingual parallel corpus that is used for training. By using the definition of probability, the Multiplicative Factor in equation (3) can be written as

$$P[M(S \rightarrow T)|O(S \rightarrow P), O(P \rightarrow T)] = \frac{count[M(S \rightarrow T), O(S \rightarrow P), O(P \rightarrow T)]}{count[O(S \rightarrow P), O(P \rightarrow T)]}$$

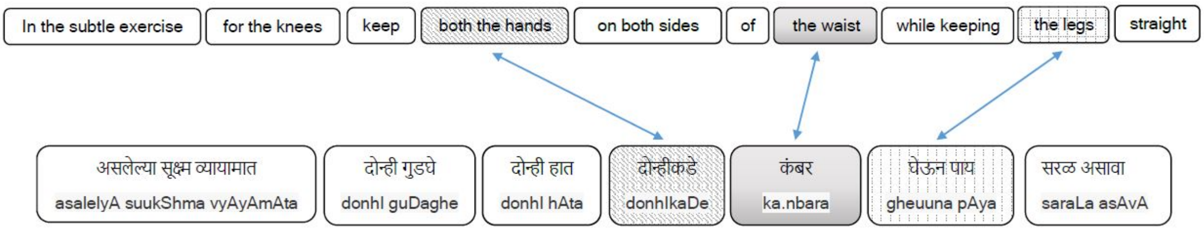
Here the numerator is the count of the number of occurrences where phrase pair (S, T) has a monotone orientation when phrase pair (S, P) has a particular orientation O_1 and (P, T) has an orientation O_2. The denominator is the count of the number of occurrences where phrase pair (S, P) has a particular orientation O_1 and (P, T) has an orientation O_2.

Basic idea in the Count Based Approach is to extract these kind of counts from the corpus for each source-target phrase pair. For extracting these counts, say for a phrase pair (S, T), we need to look at the phrases which immediately precede or succeed phrase T in a target sentence and the position of their translations with respect to the position of phrase S in the source sentence. The counts have to be extracted for each phrase pair and have to be stored separately in order to lookup while doing the computations for reordering table triangulation using this approach. This approach seems more intuitive since we use the parallel corpus for getting the count values and therefore we are likely to get more accurate values for the multiplicative factor.

6 Experimental Setup

We performed several experiments with both the approaches discussed in section 5. The parallel corpus used for the experiments was a Health and Tourism domain multilingual parallel corpus (Jha, 2010) which was divided into a training corpus of 46000 sentences, a tuning corpus of 500 sentences and a test corpus of 2000 sentences. The reason behind using a small sized corpus for our experiments is that, often in a realistic scenario, obtaining a large sized multilingual parallel corpus is difficult.

The tool used for translation was Moses 3.0 (Koehn et al., 2007). It was used for training, tuning(MERT based) and testing the translation systems. We experimented with four kinds of MT systems for 9 different source-pivot-target combinations from the language set {English(En), Hindi(Hi), Marathi(Mr), Gujarati(Gu), Punjabi(Pa)}, mentioned in Table 2. The differences in these systems were in the phrase table and reordering table which each system uses. A 'Direct Phrase table' and a 'Direct Reordering Table' are the tables that are obtained directly from source-target parallel corpus after training. A 'Triangulated Phrase Table' and a 'Triangulated Reordering Table' are the tables that are obtained through the process of triangulation. An 'Interpolated Phrase Table' is a phrase table ob-



(a)

the waist ||| कंबर ||| 0.38 0.07 0.53 0.53 0.07 0.38

(b)

Figure 5: Sample Translation from English-Hindi-Marathi INTER-DIR MT System

tained by linear interpolation of values from Direct Phrase Table and Triangulated Phrase Table. Interpolation of reordering tables can be performed either by linear interpolation or by Fill-up interpolation (Dabre et al., 2015) of Direct and Triangulated Reordering Tables. With this terminology in place, below is a small description of each system.

- **DIR-DIR** : This system uses a Direct Phrase Table and a Direct Reordering Table.
- **INTER-DIR** : This system uses an Interpolated Phrase Table and a Direct Reordering table.
- **INTER-TRI** : This system uses an Interpolated Phrase Table and a Triangulated Reordering table.
- **INTER-INTER** : This system uses an Interpolated Phrase Table and an Interpolated Reordering table.

7 Results and Discussion

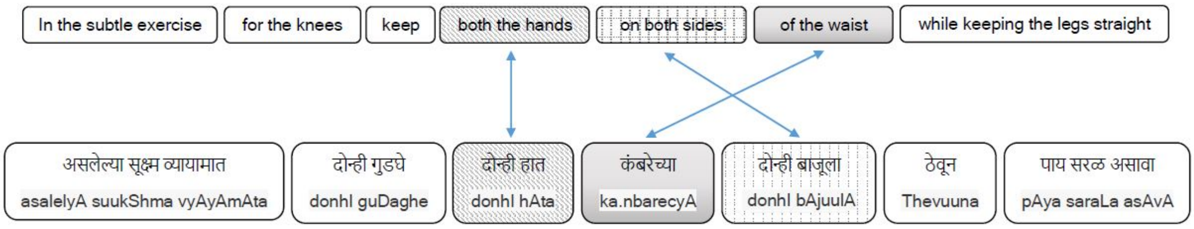
We performed experiments for both Table Based and Count Based approaches. The improvements were observed from the quantitative point of view - in the BLEU scores (Papineni et al., 2002) - as well as from the qualitative point of view - in the reordering of the translation that a system produces and better lexical choice in the translation.

7.1 Improvements in BLEU Scores

For the table based approach, we found an improvement of 0.48 in the BLEU score from 17.98 for INTER-DIR system to 18.46 for INTER-INTER system, for Marathi to English translation when Gujarati is used as a pivot. Small improvements were also observed for other systems, like Hindi-Gujarati-English (0.4), Hindi-Punjabi-English (0.33) and Hindi-Gujarati-Marathi (0.16). The improvements in other five systems were not as significant as these. This was an expected pattern in the results since, the Table Based approach does not actually look at the training data while calculating the Multiplicative Factor. In this approach, Multiplicative Factor is calculated based on the Orientation Table which is training data independent. Therefore, the approach was expected to perform better in some situations than others.

On the other hand, the Count Based approach extracts the counts for orientations from the training corpus. Thus the calculated Multiplicative Factor is more accurate as compared to the Table Based approach. So we expected the Count Based approach to outperform the Table Based and produce an improvement in the BLEU score for most of the source-pivot-target language combinations. This is indeed the case and the results for Count Based approach are shown in Table 2. The improvements vary with language combinations because of the difference in the quality of the counts that are extracted for each combination.

The improvement from DIR-DIR system to INTER-DIR system is because of the phrase table triangulation and addition of newly extracted phrase pairs in the phrase table. Therefore, in order to quantify the improvement in BLEU score that is solely achieved by our approach, we consider INTER-DIR system as our baseline for all experiments. We can see from Table 2, that significant improvements are achieved by INTER-INTER systems over INTER-DIR systems in case of most language combinations. INTER-TRI system does not outperform INTER-DIR system since, it uses only the Triangulated Reordering ta-



(a)

of the waist ||| कंबरेच्या ||| 0.27 0.27 0.45 0.27 0.45 0.27

(b)

Figure 6: Sample Translation from English-Hindi-Marathi INTER-INTER MT System

ble which mostly contains entries for only newly extracted phrase pairs. INTER-INTER systems perform better as expected, since knowledge from both, Direct and Triangulated Reordering tables is combined and used in these systems.

7.2 Qualitative Improvement in Reordering

Let us closely look at an actual translation example from the test corpus to clearly understand, how calculating reordering probability values for newly added phrase pairs helps in improving the quality of translation. It must be noted that, although the reordering information is not available for newly added phrase pairs in INTER-DIR system, they may still end up being a part of the best possible translation because of other factors involved such as Phrase Translation Probability and Language Model. For example, a newly induced phrase pair may have higher phrase translation probability than other phrase pairs, which results in that phrase being a part of the best candidate translation. This phenomenon is responsible for the improvement that is achieved by INTER-DIR system over DIR-DIR system.

Figure 5(a) shows the translation example from English-Hindi-Marathi INTER-DIR system and Figure 6(a) shows the translation example from English-Hindi-Marathi INTER-INTER system. From the phrase tables, we observed that the phrase pair (of the waist, कंबरेच्या) was added through triangulation of phrase tables. So, in INTER-DIR system, there are no reordering probability values available for this phrase pair, but in the INTER-INTER system, the reordering table has an entry for this phrase pair with reordering probability values. Figure 6(b) shows that reordering table entry for this phrase pair.

The translation produced by INTER-DIR system shown in Figure 5(a), will also be produced as a candidate translation by INTER-INTER system, but the INTER-INTER system discards it to choose the translation shown in Figure 6(a) as the best translation, since the reordering probability values for the new phrase pair play a vital role. If we look at figure 5(b), the reordering probability values for (the waist, कंबर) favour discontinuous orientation with respect to the previous phrase and monotone orientation with respect to the next phrase. But the translation that is generated has a discontinuous orientation for the phrase कंबर with respect to both previous and next phrases. Since the generated candidate is not in accordance with the values from reordering table, the candidate gets a relatively lesser score.

On the other hand, if we look at Figure 6(b), the reordering probability values for (of the waist, कंबरेच्या) favour discontinuous orientation with respect to the previous phrase and swap orientation with respect to the next phrase. The translation that is generated as a candidate, shown in Figure 6(a), also has discontinuous orientation with respect to the previous phrase and swap orientation with respect to the next phrase, for the phrase कंबरेच्या. Since the candidate is in accordance with the values from reordering table, the candidate gets a higher score as compared to the earlier candidate. There are also other factors like translation model and language model that contribute to the computation, but in this example the contribution by reordering probabilities is distinctly evident. We can see that the inclusion of reordering information for newly added phrase pair has also induced **better lexical choices** in the translation.

This leads to the translation shown in Figure

6(a) being selected as the best translation. It can be easily observed that the translation is a better one in terms of reordering. This shows that our approach works well to improve the quality of translation.

Following is another example from Marathi-Hindi-English system that shows qualitative improvement in the reordering of phrases in the output translation.

Input:
खूप अशक्त असूनही रुग्णाला आपले वजन जास्त वाटते.
(khuupa ashakta asuunahI rugNAlA Apale vajana jAsta vATate .)

English Equivalent (Reference):
Patient thinks his / her weight to be too much even on being very weak .

Output of INTER-DIR System:
Despite weight of the patient has to be extremely weak .

Output of INTER-INTER System:
despite being very weak patient feels more your weight .

It is evident from the example that the output of INTER-INTER system is better ordered than the output of INTER-DIR system. Except for the word “your”, the meaning of the source sentence is better conveyed by the output of INTER-INTER system.

8 Conclusion and Future Work

The issue of data scarcity has been addressed effectively by Phrase Table triangulation. In this paper we went a step further and proposed two new approaches for the triangulation of reordering tables viz. Table Based approach and Count Based approach. We conducted experiments with both these approaches on 9 different translation systems, each using a different combination of source-pivot-target languages and found significant improvements in the BLEU scores for most of the systems. We also discussed actual translation examples that showed a qualitative improvement in the reordering of the output, thereby vindicating the fact that better reordering information can be extracted through a pivot. Examples also showed that the lexical choices made by the system improved when our approach was used. We also observed that Count Based approach performed better than Table Based approach for most of the language combinations.

The focus of our work was on finding the reordering probability values for phrase pairs that are newly added to the phrase table through the use of a pivot. The question that remains is, whether a pivot can help beyond extracting these reordering values. Another interesting question is whether this approach scales well to a scenario where more than one pivots are used simultaneously. We will try to focus on these points in the future.

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