Lexical Resources to Enrich English Malayalam Machine Translation

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Abstract

In this paper we present our work on the usage of lexical resources for the Machine Translation English and Malayalam. We describe a comparative performance between different Statistical Machine Translation (SMT) systems on top of phrase based SMT system as baseline. We explore different ways of utilizing lexical resources to improve the quality of English Malayalam statistical machine translation. In order to enrich the training corpus we have augmented the lexical resources in two ways (a) additional vocabulary and (b) inflected verbal forms. Lexical resources include IndoWordnet semantic relation set, lexical words and verb phrases etc. We have described case studies, evaluations and have given detailed error analysis for both Malayalam to English and English to Malayalam machine translation systems. We observed significant improvement in evaluations of translation quality. Lexical resources do help uplift performance when parallel corpora are scanty.

Keywords: Lexical Resources, Statistical Machine Translation, English-Malayalam Machine Translation

1. Introduction

Each Machine processing of Natural (Human) Languages has a long tradition, benefiting from decades of manual and semi-automatic analysis by linguists, sociologists, psychologists and computer scientists among others. Development of a full-fledged bilingual Machine Translation (MT) system for any two natural languages with limited electronic resources and tools is a challenging and demanding task. Since India is rich in linguistic divergence there are many morphologically rich languages quite different from English as well as from each other, there is a large requirement for machine translation between them. Development of efficient machine translation systems using appropriate methodologies and with limited resources is a challenging task. There are many ongoing attempts to develop MT systems for Indian languages (Antony, 2013; Kunchukuttan et al., 2014; Sreeleekha et al., 2014; Sreeleleka et al., 2015) using both rule based and statistical approaches. There were many attempts to improve the quality of Statistical MT systems such as: using Monolingually-Derived Paraphrases(Marton et al., 2009), Using Related Resource-Rich languages (Nakov and Ng, 2012) Considering the large amount of human effort and linguistic knowledge required for developing rule based systems, statistical MT systems became a better choice in terms of efficiency. Still the statistical systems fail to handle rich morphology.

Consider the English sentence,

He has been sent to the mosque for opening the door

The English–Malayalam SMT system translated it as,

Malayalam- അയച്ചു വന്നു മോസ്ക് വിടവ്വിൽ വഴി തുറന്നു
({avan ayachu mosque vathil thurannu})
{He sent mosque door opened}
{He sent mosque opened door}

Here the system fails to translate the verb phrase “has been sent to” together and it translated a part of the phrase “sent” as “അയച്ചു”{ayachu}{sent}, which is wrong in the context. The same way another verb phrase “for opening the door” has been translated partly as “തുറന്നു”{thurannu}{opened}. Also, the system has deficiency in vocabulary and it couldn’t translate the English word “Mosque”. In these kinds of situations in order to learn various inflected forms and verb phrases, lexical resources can play a major role. In this paper we discuss the usage of various lexical resources and how it can be used for improving the translation quality with a detailed analysis about various linguistic phenomena.

2. Challenges in English –Malayalam Machine Translation

Major design challenges in Machine Translation (MT) are the syntactic structural transfer, which is the conversion from a syntactic analysis structure of the source language to the structure of the target language and the ambiguities.

2.1 Challenge of Ambiguity

There are three types of ambiguities: structural ambiguity lexical ambiguity and semantic ambiguity.

2.1.1. Lexical Ambiguity

The Words and phrases in one language often have multiple meaning in another language.

For example, the English sentence,

English- He picked the photo
Malayalam- എടുത്തു ഫോട്ടോ എടുക്കുക
(avan photo eduthu)

Here in the above sentence “picked”, has ambiguity in meaning. It is not clear that whether the word “picked”, is used as the “clicked the photo” (ടോൺ കൊട്ട) in
Malayalam) sense or the “took” sense. However this is a good example where both in source language and target language ambiguity is present for the same word. This kind of ambiguity has to be identified from the context.

2.1.2. Structural Ambiguity
The In this case, due to the structural order, there will be multiple meanings. For example,

Malayalam- നാളെ കലാവാസം പെറിയും
{pokkamulla penkuttikalum ankuttikalum undayarumnu}

English - There were tall girls and boys there

Here from the words “നാളെ കലാവാസം പെറിയും” [pokkamulla penkuttikalum ankuttikalum] (tall girls and boys) it is clear that, girls are tall but it is not clear that boys are tall, since in Malayalam to represent tall girls and boys only one word “പൊക്കംലു” [pokkamulla] (tall) is being used. It can have two interpretations in English according to its structure.

{There were tall girls and boys there}
or
{There were tall girls and fat boys there}

One of the big problems in Machine Translation is to generate appropriate Machine Translations by handling this kind of structural ambiguity.

2.1.3. Semantic Ambiguity
The In this case, due to the understanding of the semantics, there will be multiple translations. For example, consider the English sentence,

I travel with bag and umbrella
I travel with my kids

Here this English sentence can be translated in Malayalam as,

മെയിൻ നാലെ കലാവാസം പേർ മെയിൻ നാലെ കലാവാസം കുടിക്കാടു
{njan bagum kadayum kontanu sancharikkarallathu} (I bags umbrella with travel)
or

മെയിൻ നാലെ കലാവാസം പേർ മെയിൻ നാലെ കലാവാസം കുടിക്കാടു
{njan ente kuttikaludoppamantu sancharikkarallathu} (I travel with my kids)

Here, in the two English sentences “with” gets translated to കുടിക്കാടു [kontanu] (with) and കുടിക്കാടു [oppamantu] (with) respectively. This disambiguation requires knowledge to distinguish between “bag- umbrella” and “kids”.

2.2 Structural Differences
There are word order differences between English and Malayalam such as, English language follows Subject -Verb- Object (SVO) and Malayalam language follows Subject- Object-Verb (SOV).

Consider an example for word ordering,

English- Gita went to market
{(S) (V) (O)}
Malayalam- ഗിത വരാൻ ക്രിയാ
{(Gita chanthayil poyi) (S) (O) (V)}

In addition, Malayalam is morphologically very rich as compared to English, wherein there are a lot of post-modifiers in the former as compared to the later.

For example, the word form “ആണ്” {kadalil} (in the sea) is derived by attaching “ൽ” [il] as a suffix to the noun “ആ” [kadal] (sea) by undergoing an inflectional process. Malayalam exhibits agglutination of suffixes which is not present in English and therefore these suffixes has equivalents in the form of pre positions. For the above example, the English equivalent of the suffix “ൽ” [il] is the pre position “in the” which is separated from the noun “sea”. This kind of structural differences have to be handled properly during MT.

2.3 Vocabulary Differences
Languages differ in the way they lexically divide the conceptual space and sometimes no direct equivalents can be found for a particular word or phrase of one language in another.

Consider the sentence,

ഉണ്ട് കലാശബിഭിഷേകം
{nale kalabhabhishekam undu}

Here the word, “കലാശബിഭിഷേകം” [kalabhabhishekam] as a verb has no equivalent in English, and this word have to be translated as “the pooja which will cover the idol with sandalwood”. Hence the sentence will be translated as,

Malayalam- ഉണ്ട് കലാശബിഭിഷേകം
{nale kalabhabhishekam undu}

English- Tomorrow, the pooja which will cover the idol with sandalwood is there.

Translating such language specific concepts pose additional challenges in machine translation.

3. Experimental Discussion
We now describe our experiments and results on phrase based baseline SMT system1 for English- Malayalam and Malayalam – English, specifically with the usage of lexical resources. We use Moses (Koehn et al., 2007) and Giza++2 for learning the statistical models (Och 2001). There are structural differences between Malayalam and English and in the generation of word forms due to the morphological complexity. In order to overcome this

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1 http://www.cfilt.iitb.ac.in/SMT-EM
2 http://www.statmt.org/
difficulty and make the machine to learn different morphological word forms, lexical resources can play a major role. Different word forms such as verb phrases, morphological forms prepositional phrases etc can be used. Moreover the SMT system lacks in vocabulary due to the small amount of parallel corpus. Comparative performance studies conducted by Och and Ney (2003) have shown the significance of adding lexical words into corpus and the improvement in the translation quality. We have used lexical words, IndoWordnet (Bhattacharyya, 2010), verb phrases etc. to increase the coverage of vocabulary. We have done many experiments to improve the quality of machine translation by augmenting various lexical resources into the training corpus. The statistics of lexical resources used are shown in Table 1 and the results are shown in Tables 2, 3, 4 and 5. Our experiments are listed as below:

| Sl. No | Corpus Source | Training Corpus [Manually cleaned and aligned] | Corpus Size [Sentences] |
|-------|---------------|-----------------------------------------------|-------------------------|
| 1     | ILCI          | Tourism                                       | 23750                   |
| 2     | ILCI          | Health                                        | 23750                   |
| 3     | Joshua        | Tourism                                       | 29518                   |
| Total |               |                                               | 77018                   |

| Sl. No | Lexical Resource Source | Lexical Resources in Corpus | Lexical Resource Size [Words] |
|--------|------------------------|----------------------------|------------------------------|
| 1      | CFILT, IIT Bombay      | Indo Wordnet Synset words  | 25341                        |
| 2      | CFILT IITB, Joshua, Olam | Lexical words              | 144505                       |
| 3      | CFILT IITB             | Verb Phrases               | 200544                       |
| Total  |                        |                             | 370390                       |

| Sl. No | Corpus Source | Tuning corpus (MERT) [Manually cleaned and aligned] | Corpus Size [Sentences] |
|--------|---------------|------------------------------------------------------|-------------------------|
| 1      | ILCI          | Tourism                                              | 250                     |
| 2      | ILCI          | Health                                               | 250                     |
| Total  |               |                                                      | 500                     |

| Sl. No | Corpus Source | Testing corpus [Manually cleaned and aligned] | Corpus Size [Sentences] |
|--------|---------------|-----------------------------------------------|-------------------------|
| 1      | ILCI          | Tourism                                       | 1000                    |
| 2      | ILCI          | Health                                        | 1000                    |
| Total  |               |                                               | 2000                    |

Table 1: Statistics of Corpus and Lexical resources used

3.1 SMT system with an unclean corpus
The learning of proper grammatical structures was prevented by the stylistic constructions, misalignments, wrong and missing translations etc. present in the unclean corpus (Refer Table-1). This reduced the translation quality. For example, consider a sentence from the corpus where the translation is wrong,

**English:** Tus is located on the banks of the Berach river near Udaipur and the Sun temple here has an important place in the study of sculpting tradition.

**Equivalent Malayalam Translation (wrong)**

{bedach nadiyude thadathilu sthithi cheyyunna tuse udaipurinte soorykshethrathile silpakalayude mahathwamundu}

{berach river’s bank located Tus Udaipur’s Sun temple sculpting importance}

{Tus located on berach river’s bank udaipur’s sun temple important sculptin tradition}

The comparative performance results of cleaned corpus over uncleaned corpus were shown in the Tables 2, 3, 4 and 5.

3.2 SMT system with cleansed corpus
In order to improve the quality of translation, we have removed the stylistic constructions, unwanted characters, wrong translations from the parallel corpus. We have corrected the grammatical structures, missing translations, wrong phrases, misalignments between parallel sentences which improves the learning of word to word alignments. Consider the sentence discussed in section 3.1, which has both source side and target side translation errors. We have corrected the translations as,

**English:** Tus located on the banks of the Berach river near Udaipur and the Sun temple have an important place in the study of sculpting tradition.

**Malayalam:** ഉടയപ്പരുടെ കരയിൽ സൂരയ് ഫേത്തത്തിൽ ഉദയ് ഫറിന്റെ സന്താനാവിൽ ശിൽകലയുക്തമിക്ക അതിന്റെ സൂത്രിപ്പ് ശൈലാംഗു മഹാത്മവത്തിന്

{udaipurinte aduthu bedachu nadiyude tadathil sthiti cheyyunna toosinum sooryakshethrathile silpakalyude padanathinu pratyekeya sthanamundu}

{Udaipur’s near Berach river’s bank located Tus and Sun temple sculpting tradition’s for study important place }

{Tus located on the banks of the Berach river near Udaipur and the Sun temple have an important place in the study of sculpting tradition.}

After cleaning, the translation quality improved to more than 14 times compared to system with unclean corpus. We observed during error analysis that, the machine lacks
in sufficient amount of vocabulary and hence we investigated on the usage of lexical words to improve the quality of machine translation.

3.3 Corpus with lexical words

We have extracted a total of 437832 parallel English-Malayalam lexical words from parallel corpus. We have also used dictionary words available from Joshua\(^3\) corpus and Olam\(^4\) dataset after manual validation. For example, while translating the English sentence,

\[ \text{He reached early on for the movie} \]

SMT system translated it in Malayalam as,

\[ \text{അവൻ മുൻ ുതപന്ന} \]

\[ \text{He cinema reached} \]

\[ \text{He reached cinema} \]

Here the system failed to translate the meaning of the multiword \textit{early on}. In lexicalWord list it has the following equivalent,

\[ \text{early on} : \text{മുൻ ുതപന്ന \{muputhanne\}} \]

We have augmented the extracted parallel lexical words into the training corpus. After training, the above sentence is translated correctly as,

\[ \text{അവൻ മുൻ ുതപന്ന} \]

\[ \text{He for the cinema early on reached} \]

\[ \text{He reached early on for the movie} \]

Since the lexical words are extracted from the same corpus, it helped in improving the translation quality to a great extent. During the error analysis we observed that even though the machine translation system is able to give considerably good quality translation, it faces difficulties in translating different words and its concepts. Hence we investigated the usage of word-synsets to make the system learn the words with its concepts.

3.4 Corpus with IndoWordnet synsets

We have used an algorithm to extract the bilingual words from IndoWordnet according to its semantic and lexical relations (Bhattacharyya 2010). Bilingual mappings are generated using the concept-based approach across words and synsets (Kumar et.al, 2008). We have considered all the synset word mappings for a single word and generated that many entries of parallel words. For example, the word \textit{beautify} has the following equivalent synset words in the IndoWordnet.

\textit{beautify}: ശോഹിക്കിക്കാ വിശേഷമായ പരിശന്ദിശ മതിപ്പിക്കുക

\[ \text{beautify: shining decorating arranging beautify} \]

\[ \text{beautify: ശോഹിക്കിക്കാ വിശേഷമായ പരിശന്ദിശ മതിപ്പിക്കുക} \]

Consider an English sentence,

\[ \text{Decorations should beautify the occasion} \]

The SMT system translated it in Malayalam as,

\[ \text{ബാലക്കരമോയും ഉദ്ഘാനാധിക്യം മധുരിക്കു} \]

\[ \text{decorations do occasion} \]

Here the system fails to translate the meaning of “beautify” correctly. After augmenting the synsets of beautify to the corpus, SMT system was able to translate the equivalent English meaning in Malayalam as,

\[ \text{ബാലക്കരമോയും ഉദ്ഘാനാധിക്യം മധുരിക്കു} \]

\[ \text{decorations should beautify occasions} \]

Since the synsets covers all common forms of a word, the augmentation of extracted parallel synset words in to the training corpus not only helped in improving the translation quality to a great extent but also, helped in handling the word sense disambiguation well. But we observed during error analysis that the system fails in handling case markers and inflected forms and further we investigated on handling it.

3.5 Corpus with verb phrases

In order to overcome the verbal translation difficulty we have programatically extracted English - Malayalam parallel verbal forms and their translations which contain various phenomena with a frequency count. In addition we have used pos-tagged corpus to extract verbal phrases. We have augmented the manually validated 200544 entries of verbal translations into the training corpus.

Consider an English sentence,

\[ \text{English: He took the decision for being alive} \]

SMT system translated it in Malayalam as,

\[ \text{അവൻ തീരുമാനും ജീവൻ} \]

\[ \text{avvan theerumanam eduthu jeever} \]

\[ \text{He decision took live} \]

Here the system fails to translate and convey the importance of verb phrase “for being alive” in this sentence. After augmenting the corpus with the equivalent meaning of English - Malayalam verb phrase pair,

\[ \text{for being alive: ജീവൻ കൈവരി വാങ്ങു} \]

\[ \text{nilanilkkan vendi} \]

\[ \text{being alive for} \]

the system translated the sentence correctly as,

\[ \text{അവൻ തീരുമാനും ജീവൻ} \]

\[ \text{avvan theerumanam eduthu} \]

\[ \text{He being alive for decision took} \]

\[ \text{He took the decision for being alive} \]
| English-Malayalam Statistical MT System | BLEU score | MET- EOR | TER |
|----------------------------------------|------------|----------|-----|
| With Unclean Corpus                    |            |          |     |
| Without Tuning                         | 1.26       | 0.110    | 96.06|
| With Tuning                            | 2.52       | 0.117    | 93.55|
| With Cleaned Corpus                    |            |          |     |
| Without Tuning                         | 25.06      | 0.193    | 84.05|
| With Tuning                            | 29.07      | 0.206    | 80.92|
| With Lexical words                     |            |          |     |
| Without Tuning                         | 31.78      | 0.262    | 78.91|
| With Tuning                            | 32.94      | 0.269    | 74.30|
| With Wordnet synsets                   |            |          |     |
| Without Tuning                         | 35.21      | 0.351    | 73.79|
| With Tuning                            | 36.05      | 0.353    | 70.06|
| With verb Phrases                      |            |          |     |
| Without Tuning                         | 38.15      | 0.355    | 67.94|
| With Tuning                            | 39.90      | 0.358    | 64.48|

Table 2: Results of English-Malayalam SMT BLEU score, METEOR, TER Evaluations

| Malayalam-English Statistical MT System | ADEQUACY | FLOUENCY |
|-----------------------------------------|----------|----------|
| With Unclean Corpus                     |          |          |
| Without Tuning                          | 12.87%   | 16.3%    |
| With Tuning                             | 15.56%   | 19.65%   |
| With Cleaned Corpus                     |          |          |
| Without Tuning                          | 51.01%   | 61.21%   |
| With Tuning                             | 54%      | 65.32%   |
| With Lexical words                      |          |          |
| Without Tuning                          | 59.08%   | 71.21%   |
| With Tuning                             | 62.01%   | 75.04%   |
| With Wordnet synsets                    |          |          |
| Without Tuning                          | 67.36%   | 79.21%   |
| With Tuning                             | 69.1%    | 81.68%   |
| Corpus with verb Phrases                |          |          |
| Without Tuning                          | 72.01%   | 84.32%   |
| With Tuning                             | 74.89%   | 85.34%   |

Table 3: Results of Malayalam-English SMT BLEU score, METEOR, TER Evaluations

| Malayalam-English Statistical MT System | ADEQUACY | FLOUENCY |
|-----------------------------------------|----------|----------|
| With Unclean Corpus                     |          |          |
| Without Tuning                          | 10.6%    | 14.8%    |
| With Tuning                             | 17.8%    | 24%      |
| With Cleaned Corpus                     |          |          |
| Without Tuning                          | 51.6%    | 62.3%    |
| With Tuning                             | 55%      | 66%      |
| With Lexical words                      |          |          |
| Without Tuning                          | 61.4%    | 72%      |
| With Tuning                             | 63.6%    | 76.2%    |
| With Wordnet synsets                    |          |          |
| Without Tuning                          | 67%      | 80.34%   |
| With Tuning                             | 69.99%   | 82%      |
| With verb Phrases                       |          |          |
| Without Tuning                          | 73.01%   | 86.01%   |
| With Tuning                             | 77.23%   | 87%      |

Table 4: Results of Malayalam-English SMT Subjective Evaluation

| English-Malayalam Statistical MT System | ADEQUACY | FLOUENCY |
|----------------------------------------|----------|----------|
| With Unclean Corpus                     |          |          |
| Without Tuning                          | 10.6%    | 14.8%    |
| With Tuning                             | 17.8%    | 24%      |
| With Cleaned Corpus                     |          |          |
| Without Tuning                          | 51.6%    | 62.3%    |
| With Tuning                             | 55%      | 66%      |
| With Lexical words                      |          |          |
| Without Tuning                          | 61.4%    | 72%      |
| With Tuning                             | 63.6%    | 76.2%    |
| With Wordnet synsets                    |          |          |
| Without Tuning                          | 67%      | 80.34%   |
| With Tuning                             | 69.99%   | 82%      |
| With verb Phrases                       |          |          |
| Without Tuning                          | 73.01%   | 86.01%   |
| With Tuning                             | 77.23%   | 87%      |

Table 5: Results of English-Malayalam SMT Subjective Evaluation
Figure 1. Malayalam - English SMT Analysis

Figure 2. English - Malayalam SMT Analysis
The error analysis has shown that the verb phrase augmentation helped in translating verbal inflections correctly and hence the quality of the translation has been improved drastically.

4. Evaluation & Error Analysis

We have tested the translation system with a corpus of 2000 sentences taken from the ‘ILCI tourism, health’ corpus as shown in Table 4. In addition we have used a tuning (MERT) corpus of 500 sentences as shown in Table 3. We have evaluated the translated outputs of both Malayalam to English and English to Malayalam SMT systems in all 5 categories using various methods such as subjective evaluation, BLEU score (Papineni et al., 2002), METEOR and TER (Agarwal and Lavie 2008). The results of BLEU score, METEOR and TER evaluations are displayed in Tables 2 and 3. We gave importance to subjective evaluation to determine the fluency (F) and adequacy (A) of the translation, since for morphologically rich languages subjective evaluations can give more accurate results compared to other measures. We have followed the subjective evaluation procedure with the help of linguistic experts as described in Sreekelka et.al.(2013) and the results are given in Table 4 and Table 5. Fluency is an indicator of correct grammatical constructions present in the translated sentence whereas adequacy is an indicator of the amount of meaning being carried over from the source to the target. For each translation we assigned scores between 1 and 5 depending on how much sense the translation made and its grammatical correctness.

We have observed that the quality of the translation is improving as the corpus is getting cleaned and more lexical resources are being used. Hence, there is an incremental growth in adequacy, fluency, BLEU score, METEOR score and reduction in TER score. In addition, we were able to handle the one-to-many mapping of phrases to a great extend by increasing the frequency of occurrence with the usage of linguistic resources. The performance comparison graph is shown in figure 1 and figure 2. The fluency of the translation is increased up to 85.34% in the case of Malayalam to English and up to 87% in the case of English to Malayalam, which is 4 times more than the baseline system results.

5. Conclusion

In this paper we have mainly focused on the usage of various lexical resources for improving the quality of Machine Translation for low resource languages. We have discussed the comparative performance of phrase based Statistical Machine Translation with various lexical resources for both Malayalam – English and English - Malayalam. As discussed in the experimental Section, Statistical Machine Translation quality has improved significantly with the usage of various lexical resources. Moreover, the system was able to handle the rich morphology to a great extend. We can see that there is an incremental growth in both the systems in terms of BLEU-Score, METEOR and a decrement of TER evaluations, which shows the translation quality improvement. Also, our subjective evaluation results show promising scores in terms of fluency and adequacy. This leads to the importance of utilizing various lexical resources for developing an efficient Machine Translation system for morphologically rich languages.

Our future work will be focused on investigating more effective ways to handle the rich morphology and hence to improving the quality of Statistical Machine Translation.

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