Abstract

We present in this paper our work on comparison between Statistical Machine Translation (SMT) and Rule-based machine translation for translation from Marathi to Hindi. Rule Based systems although robust take lots of time to build. On the other hand statistical machine translation systems are easier to create, maintain and improve upon. We describe the development of a basic Marathi-Hindi SMT system and evaluate its performance. Through a detailed error analysis, we, point out the relative strengths and weaknesses of both systems. Effectively, we shall see that even with a small amount of training corpus a statistical machine translation system has many advantages for high quality domain specific machine translation over that of a rule-based counterpart.

1 Introduction

Machine Translation is the process of translating text or speech from one natural language to another with the help of machines. There are many ongoing attempts to develop MT systems for various regional languages using rule-based as well as statistical-based approaches. MT systems can be called as a bilingual system if it is designed specifically for two particular languages and can be called as a multilingual system if it is designed for more than a single pair of languages. Development of efficient machine translation (MT) systems using appropriate methodologies and with limited resources is a challenging 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 great need for machine translation between them (Nair et.al, 2010). It has 18 constitutional languages, which are written in 10 different scripts. Even though MT in India started more than two decades ago, it is still an ongoing process (Antony, 2013). This paper discusses various approaches used in Indian language to Indian language MT systems especially in Marathi – Hindi MT systems.

Handling the structural difference between the two languages and handling the ambiguity are the two major difficulties in Machine Translation.

1.1 Challenge of Ambiguity

There are two types of ambiguity: structural ambiguity and lexical ambiguity.

1.1.1 Lexical Ambiguity

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

For example, in the sentence,

Marathi- मी फोटो काढला {me photo kadhla}
Hindi- मैने फोटो ननकाला {maenne photo nikala}
English- I took the photo

Here in the above sentence “काढला”{kadhla}, “ननकाला”{nikala}, and “took” have ambiguity in meaning. It is not clear that whether the word “काढला”{kadhla} is used as the “clicked the photo” (“ननकाला” ‘nikala’) in Hindi sense or the “took” (nikala) sense.

However this is a good example where both in source language and target language ambiguity is present for the same word.

This will usually be clear from the context, but this kind of disambiguation is generally non-trivial.
1.1.1 Structural Ambiguity

Due to the structural order there will be multiple meanings. For example,

Marathi - तिथे उंच मुली आणि मुलें होती . {tithe oonch muli aani mulen hoti}
{There were tall girls and boys there}

Here from the words “उंच मुली आणि मुलें ” {oonch muli aani mulen} it is clear that tall girls but it is not clear that boys are tall, since in Marathi to represent tall girls and boys only one word “उंच” {oonch} {tall} is being used. It can have two interpretations in Hindi and English according to its structure.

Hindi - वहाँ लंबी लड़कियाँ और लड़कें थे | {vahan lambi ladkiyam our ladken the}
{There were tall girls and boys there}

Handling this kind of structural ambiguity is one of the big problems in Machine Translation.

1.2 Structural Differences

In the case of Marathi – Hindi machine translation both languages follow the same structural ordering in sentences, such as Subject- Object-Verb (SOV). Even though there is ordering similarity, there are morphological and stylistic differences which have to be considered during translation.

Marathi is morphologically more complex than Hindi, wherein there are a lot of post-modifiers in the former as compared to the later (Dabre et al, 2012, Bhosale, 2011).

For example, the word form “सातपुरियों” {saptapuriyom} {of / about the seven pilgrimage spots} is derived by attaching “चया” {chya} as a suffix to the plural form “सातपुरी” {saptapurim} which is derived from the noun “सातपुरी” {sapturi} {seven pilgrimage spots in India} by undergoing an inflectional process. Marathi exhibits agglutination of suffixes which is not present in Hindi and therefore these suffixes have equivalents in the form of post positions. For the above example, the Hindi equivalent of the suffix “चया” {chya} is the post position “के” {ke} which is separated from the plural noun “सातपुरियों” {saptapuriyom}. Hence the translation of “सातपुरियों” {saptapuriyom} will be “सातपुरियों के” {saptapuriyom ke}.

Similarly the Marathi verb form “जाणार्या” {janaaryaa} {the one who is going} which is derived by affixing “णा” {naa} and “र्” {ryaa} to the stem “जा” {jaa} {go} has a Hindi translation “जाने वाला” {jaane wala}.

In the case of sentence ordering both Marathi and Hindi follows SOV. For example,

Hindi- हरिद्वार को गंगा द्वार भी कहते हैं | {haridwar ko ganga dwar bhi kehte hai}
(S) (O) (V)
Marathi- हरिद्वाराला गंगाद्वार असेही म्हटले जाते .
(S) (O) (V)
English-{Haridwarala gangadwar asehi mehtale jaate}
{Haridwar is also known as Ganga}
(S) (V) (O)

This is an advantage for statistical machine translation system as we shall see a later section.

1.3 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, “काल आनंदीये केठवण होते . ”

Here “ केठवण ” as a verb has no equivalent in Hindi, and this sentence has to be translated as, “काल आनंदी का संगाई होने के बाद एवं शादि के पहले लड़का या लड़की को संबंधियों द्वारा दिया जाने वाला उलझा था ।”

{“Kal aanandii ka sagaayi hone ke baad evam shaadi ke pahle ladka ya ladki ko sambandhiyon dwara diya jaane wala bhoj tha . ”}
The lunch which the relatives are giving before marriage to bride or groom has been given to Ananthi yesterday.

The obvious difficulty is in determining the translation of such language specific concepts which pose additional challenges in machine translation.

1.4 Different types of Machine Translation

The Vacquois triangle in the figure 1 depicts three different types of Machine Translation namely, Transfer based, Interlingua based and Statistical. They differ in the amount of linguistic processing performed before transferring concepts and structure from the source side to the target side. As can be seen Interlingua requires complete processing, Transfer based requires some and Statistical (a type of direct translation) requires none. The base of the triangle indicates the distance between the two languages and linguistic processing helps bridge the gap.

The rest of the paper is divided into three sections, wherein Section 2 deals with Rule Based Machine Translation (RBMT), Section 3 deals with Statistical Machine Translation (SMT), Section 4 deals with Experiments conducted, Evaluations and Error analysis which concludes the main components of the paper.

2 Rule Based Machine Translation (RBMT)

Rule based MT systems work based upon specification of rules for morphology, syntax, lexical selection and transfer and generation. Collection of rules and a bilingual or multilingual lexicon are the resources used in RBMT. In the case of English to Indian languages and Indian language to Indian language MT systems, there have been many attempts with all these approaches (Dave et al., 2002). The transfer model involves three stages: analysis, transfer and generation. Each of them is described below. Refer to figure 2 for the complete flow of translation in the form of a pipeline.
2.3.1 Analysis

During this phase, from the input text information about the morphology, parts of speech, shallow phrases, entity and word sense disambiguation information is extracted.

2.3.2 Lexical transfer

The lexical transfer phase involves two parts namely word translation and grammar translation which is performed using high quality bilingual dictionary and transfer grammar rules.

2.3.3 Generation phase

Generation involves correction of the genders of the translated words since certain words are masculine in the source language but feminine in the target and vice versa. This is followed by short distance and long-distance agreements performed by intra-chunk and the inter-chunk modules concluded by word generation.

3 Statistical Machine Translation (SMT)

The statistical approach comes under Corpus Based Machine Translation systems, which tries to generate translations based on the knowledge and statistical models extracted from parallel aligned bilingual text corpora. Statistical models take the assumption that every word in the target language is a translation of the source language words with some probability (Brown et al., 1993). The words which have the highest probability will give the best translation. Consistent patterns of divergence between the languages (Dorr et al., 1994, Dave et al., 2002, Ramanathan et al., 2011) when translating from one language to another, handling reordering divergence are one of the fundamental problems in MT. Figure 3 shows the functional flow diagram of an SMT system. The three major steps in SMT are:

3.1 Corpus preparation

To prepare a properly cleaned and well aligned parallel corpus is the major requirement of an SMT system. The quality of the resultant translation will be based upon the quality of the parallel sentence translation in the source corpus. Corpus preparation, alignment and its cleaning is done in the Pre-Processing step.

3.2 Training

Training is a process in which a supervised or unsupervised statistical machine learning algorithms are used to build statistical tables from the parallel corpora (Zhang et al., 2006). In Statistical Machine Translation, word by word and phrase based alignment plays the major role during parallel corpus training. During training Translational model, Language Model, Distortion Table, Phrase table etcetera are modeled.

3.3 Decoding

Decoding (Och and Ney, 2001, Och and Ney, 2003, Koehn, 2007) is the most complex task in Machine Translation (Knight, 1999) where the trained models will be decoded. This is the main step in which the target language translations are being decoded using the generated phrase table and language model. Decoding complexity and target language reordering (Kunchukuttan and Bhattacharyya 2012) are the two major concerns with SMT.
4 Experimental Discussion

4.1 Statistical Machine Translation System Experiments

We now describe the development of our Marathi- Hindi SMT system, the experiments performed and the comparisons with the results, in the form of an error analysis, of the Rule Based system described above. For the purpose of constructing with statistical models we use Moses and Giza++.

4.1.1 Pre-processing

Usually parallel corpus available for Indian languages is not of sufficiently high quality which is quite important in order to improve the quality of the translation. The factors that indicate a poor quality corpus are six fold namely:

1. Misalignment between parallel sentences which prevents learning of word to word alignments.
2. Too many stylistic constructions in the parallel corpus which prevent the learning of grammatical structures in terms of phrases for small corpus.
3. Missing translations in corpus on source or target side.
4. Missing words and phrases in the corpus leading to incorrect alignments.
5. Unwanted characters present in corpus which leads to garbage in the output due to incorrect alignments.
6. Wrong translations in the corpus leading to wrong outputs.

We manually cleaned a 90000 sentence parallel corpus for Marathi- Hindi, corrected the grammatical structure of the sentences and tokenized it thereby making available a high quality corpus for training. We also injected 0.4 million Marathi- Hindi bilingual dictionary words extracted from the IndoWordnet to the phrase table through the training corpus to increase the number of words that the SMT system can translate. Since Moses tokenization tools are not customized for Devanagari scripts, we tokenized the corpus using our own tokenization tools.

4.1.2 Training

Table 1 and 2 describe the complete resources we have used for training. The dictionary words were used to improve the quality of the translation system. It increased both the language model and phrase table size to a great extent. We followed the training steps of Moses baseline system.

| Sl.No | Corpus Source | Training Corpus | Corpus Size |
|-------|---------------|-----------------|-------------|
|       |               | [Manually cleaned and aligned] | [Sentences] |
| 1     | ILCI          | Tourism         | 25000       |
| 2     | ILCI          | Health          | 25000       |
| 3     | DIT           | Tourism         | 20000       |
| 4     | DIT           | Health          | 20000       |
|       |               | Total           | 90000       |

Table 1: Statistics of Training Corpus

| Sl.No | Dictionary Source | Dictionary Words in Corpus | Dictionary Size |
|-------|-------------------|---------------------------|-----------------|
| 1     | CFILT, IIT Bombay | Indo Wordnet Synset words | 400000          |
|       |                   | Total                     | 400000          |

Table 2: Statistics of the Dictionary words

| Sl. No | Corpus Source | Testing corpus | Corpus Size |
|--------|---------------|----------------|-------------|
|        |               | [Manually cleaned and aligned] | [Sentences] |
| 1      | EILMT         | Tourism        | 100          |
|        |               | Total          | 100          |

Table 3: Statistics of Testing Corpus

1 http://www.statmt.org/
2 http://www.cfilt.iitb.ac.in/indowordnet/
4.1.3 Testing

We have tested the translation system with a corpus of 100 sentences taken from the ‘EILMT tourism health’ corpus as shown in Table 3. The added advantage was the SOV ordering similarity between Marathi and Hindi. However there were difficulties in handling inflected words. Since Hindi has comparatively less amount of inflections such as suffix words etcetera as compared to Marathi.

For example,

तो घरी जाणायांबरोबर जाई.
{to ghari jaanaryaambarobar jaie}
{He used to go with the ones who used to go home}.

The SMT system is translated into Hindi as वह घर में कटने वाले के साथ जाता था.
{vah ghar maen katnevale ke saath jat tha}

100 sentences from EILMT corpus for verifying the translation quality.

Consider the same sentence as before:

तो घरी जाणायांबरोबर जाई.
{to ghari jaanaryaambarobar jaie}
{He used to go with the ones who used to go home}.

The Rule Based output for this sentence is वह घर में कटने वाले के साथ जाता था.
{vah ghar maen katnevale ke saath jat tha}

For example,

िो घरी जाणार् यां बरोबर जाई.
{to ghari jaanaryaa m barobar jaie}
{He used to go with the ones who used to go home}.

The SMT system is translated into Hindi as वह घर में कटने वाले के साथ जाता था.
{vah ghar maen katnevale ke saath jat tha}

4.2 Rule-Based Machine Translation System Experiments

Using the Marathi-Hindi Rule Based Machine Translation system described before we tested 100 sentences from EILMT corpus for verifying the translation quality.

Consider the same sentence as before:

तो घरी जाणायांबरोबर जाई.
{to ghari jaanaryaambarobar jaie}
{He used to go with the ones who used to go home}.

The Rule Based system flow for the word “जाई”{jaaie} {used to go} is given in the figure 4.

1. Analysis: The morphological analyzer identifies the word “जाई”{jaaie} as either a noun or a verb in past tense. After POS tagging, it is identified that the word is a Verb and the Chunker determines that it is a part of a Verb Group. After WSD the appropriate sense is determined.

2. Transfer: The lexical transfer module translates it to “जाना” {jaana} {to go}.

3. Generation: Since the sentence is short the agreement phenomenon is not so significant. The word generator takes the information about "past tense" to give the final word form: “जाता था” {jaaa} {used to go}.

However the translation is far from good, considering that the translation of जाणायांबरोबर {jaanaryaambarobar} is कटने वाले के साथ
which is not accurate. Here the system is not able to accurately determine the correct translation sense of “जा”{ja} leading to a poor lexical choice. Also the plural information is lost as the suffix “वाले”{vale} is generated instead of “वालों”{valon}. In the output sentence the post position में {maen} {in} is not a fluent translation; its absence is preferred.

We observed that although, rule based MT was able to handle rich morphology, leading to meaning transfer, it was unable to effectively handle the appropriate translation and generation of function words and common word senses which are handled well by SMT, which improve fluency (Ahsan, et al., 2010).

As can be seen from the above described example, the translation of a single word requires a number of steps, each involving considerable linguistic inputs. Hence we can come to a conclusion that the rule-based machine translation process is extremely time consuming, difficult, and fails to analyze accurately and quickly a large corpus of unrestricted text due to inherent errors in the modules which are part of the system.

4.3 Evaluation

In order to evaluate the quality of the translations we have used subjective evaluation to determine fluency (F) and adequacy (A). We did consider BLEU scores (Papineni et al.) for evaluation made and its grammatical correctness. The basis of scoring is given below:

- 5: If the translations are perfect.
- 4: If there are one or two incorrect translations and mistakes.
- 3: If the translations are of average quality, barely making sense.
- 2: If the sentence is barely translated.
- 1: If the sentence is not translated or the translation is gibberish.

S1, S2, S3, S4 and S5 are the counts of the number of sentences with scores from 1 to 5 and N is the total number of sentences evaluated. The formula (Bhosale et al., 2011) used for computing the scores is:

\[
A/F = 100 \times \frac{(S5 + 0.8 \times S4 + 0.6 \times S3)}{N}
\]

We consider only the sentences with scores above 3. Moreover we penalize the sentences with scores 4 and 3 by multiplying their count by 0.8 and 0.6 respectively so that the estimate of scores is much better. As these scores are subjective, they vary from person to person in which case an inter annotator agreement is required. Since we had only one evaluator we do not give these scores. The results of our evaluations are given in Table 4 and Table 5.

| MT System      | Adequacy | Fluency |
|----------------|----------|---------|
| Rule Based     | 69.6%    | 58%     |
| Statistical    | 62.8%    | 73.4%   |

Table 4: Results of Subjective Evaluation

| MT System      | BLEU Score |
|----------------|------------|
| Rule Based     | 5.9        |
| Statistical    | 9.31       |

Table 5: Results of BLEU score Evaluation

4.4 Error Analysis

We have evaluated the translated outputs of both Rule Based and Statistical Machine Translation system. The detailed error analysis is shown in Table 6 for five sentences exhibiting a variety of linguistic phenomena.
| Sr. No. | Source Sentence | Meaning | Rule based system | Statistical System | Explanation of phenomena |
|--------|-----------------|---------|-------------------|-------------------|--------------------------|
| 1      | केंद्रीय सरकारी संग्रहालय १८७६मध्ये प्रिन्स औफ वेल्सच्या भारतेंद्रीयचा बेडी उभारण्यात आले व १८८६ साली ते जनतेसाठी खुले करण्यात आले. | इन 1886 the national central museum was established during the visit of the Prince of Wales and in 1886 was opened for the public. | केंद्रीय सरकारी संग्रहालय 1876 में प्रिंस औफ वेल्स के भारतेंद्रीय बार में उठाया गया व 1886 में वह जनता के लिए खोल दिया गया। | In the rule based system since each word was morphologically analysed the overall meaning is conveyed however “1886 सालें” {1886 saale} {year (plural) 1886} is not a grammatically good construction. This is overcome in the SMT system by replacing it by a more fluent form “1886 में” {1886 mein}. Moreover the proper from of वह {waha} {it} is picked in the SMT system but not in the rule based system namely “वे” {wey} {they}. However, the content words are not translated in the SMT system due to lack of learned word forms. |
| 2      | दीग पॅलेस भक्कम व प्रचंड किल्ला आहे, जो भरतपूरच्या शासकांचे ग्रीष्मकाळीन निवासस्थान होता. | Deeg palace, which was the rural era residence of the rulers of Bharatpur, is tough and huge. | दीग पैलेस मजबूत व बहुत किल्ला है, जो भरिपूरच्या शासकांचे ग्रीष्मकाळीन आवास हो। | The RB system makes a mistake in sense disambiguation of the word “प्रचंड” {prachand} {huge} which also has the sense of many, which the SMT system does not. SMT is also able to overcome the number agreement between “का” and “ग्रीष्मकाळीन” leading to a more fluent translation. Due to the morphological richness of Marathi ”भरतपूरच्या” is translated correctly as “भरिपूर के” by RB system but not by SMT system (it gives “भरिपूरच्या के”). |
| 3      | मारवाड हा राजस्थानमधील मुख्य उत्सव, अक्टूबर महीन्यात मिळण्यासाठी संपन्न होतो. | Marwad, a major festival in Rajasthan, takes place in the month of October. | मारवाड हा राजस्थान में के मुख्य उत्सव अक्टूबर महीने में संपन्न हो। | Since “मारवाड” was not present in the training corpus and the input dictionary the SMT system made a wrong translation. However function word translation of “मधील” {madhil} {of} is better done by the SMT system. Overall the RB translation is clear but not as fluent as the SMT system. |
| 4      | शेकडी आणण हजारो पर्यटक सॅंड ड्युनमध्ये निवासस्थाने मोहक कालांतरक ३० पहाटकारता राजस्थानला येतात व ते ठिकाण सर्वसमिक्यात उन्नतीज्या सफरीने पाहासे जाऊ शकते. | Hundreds of thousands of travellers come to Som Sand Dunes in Rajasthan to view the artistic sights and that place can be viewed best by a camel safari. | शेकडी आणि हजारो पर्यटक सॅंड ड्युनमध्ये निवासस्थाने मोहक कालांतरक ३० पहाटकारता राजस्थानला येतात व ते ठिकाण सर्वसमिक्यात उन्नतीज्या सफरीने पाहासे जाऊ शकते. | The sentence is quite long with many grammar constructions which both, the RB system and the SMT system are not able to handle well. However the translations of content words fares better in the RB translation. In this case many source words are not translated in the SMT output which adversely affects its... |
We observed that translation quality of Statistical Machine Translation is relatively high as compared to the Rule Based system, considering that the efforts required to build RBMT systems is huge. The result of BLEU score evaluation is displayed in Table 5 and the result of Subjective evaluation is displayed in Table 4. The fluency of the SMT outputs was very good compared to RBMT indicated by a fluency of 73.4% for SMT system where as 58% for RBMT. The reason that the SMT system had a very high fluency was due to plentiful evidences of good quality phrase pairs recorded in the phrase table. Moreover the language model used, helped in generating more natural translations. But in terms of adequacy RBMT showed slight improvement as compared to SMT, since Marathi is a morphologically complex language. Also SMT which cannot split suffixes by itself was unable to handle the translation of suffix words in some cases. RBMT being able to use the morph analyzer, can easily separate the suffixes from the inflected words and generate translations inflected with correct gender number person, tense, aspect and mood (GNPTAM). However due to poor quality Word Sense Disambiguation incorrect translations are generated. This is mitigated by SMT since it records phrase translations with respect to frequency which acts as a more natural sense disambiguation mechanism.

5 Conclusion
In this paper we have mainly focused on the comparative performance of Statistical Machine Translation and Rule- Based Machine
Translation for Marathi - Hindi. As discussed in the experimental section, SMT, although lacks the ability to handle rich morphology, does not fall much behind RBMT. It has a staggering advantage over RBMT in terms of fluency and the ability to capture natural Hindi structure. This leads to the requirement of a hybridized approach for Machine Translation between Marathi and Hindi.

Our future work will be focused on the integration of Rule-Based system components namely the Morphological Analyses into the Statistical Machine Translation system and there by develop a Hybridized MT system for Marathi-Hindi Machine Translation.

References

Ananthakrishnan Ramanathan, Pushpak Bhattacharyya, Karthik Visweswariah, Kushal Ladha, and Ankur Gandhe. 2011. *Clause-Based Reordering Constraints to Improve Statistical Machine Translation*. IJCNLP, 2011.

Anoop Kunchukuttan and Pushpak Bhattacharyya. 2012. *Partially modelling word reordering as a sequence labeling problem*, COLING 2012.

Antony P. J. 2013. *Machine Translation Approaches and Survey for Indian Languages*, The Association for Computational Linguistics and Chinese Language Processing, Vol. 18, No. 1, March 2013, pp. 47-78

Arafat Ahsan, Prasanth Kolachina, Sudheer Kolachina, Dipti Misra Sharma and Rajeev Sangal. 2010. *Coupling Statistical Machine Translation with Rule-based Transfer and Generation*. amta2010.amtaweb.org

Bonnie J. Dorr. 1994. *Machine Translation Divergences: A Formal Description and Proposed Solution*. Computational Linguistics, 1994.

Franz Josef Och and Hermann Ney. 2003. *A Systematic Comparison of Various Statistical Alignment Models*. Computational Linguistics, 2003.

Franz Josef Och and Hermann Ney. 2001. *Statistical Multi Source Translation*. MT Summit 2001.

Ganesh Bhosale, Subodh Kembhavi, Archana Amberkar, Supriya Mhatre, Lata Popale and Pushpak Bhattacharyya. 2011. *Processing of Participle (Krudanta) in Marathi*. ICON 2011, Chennai, December, 2011.

Kevin Knight. 1999. *Decoding complexity in word-replacement translation models*, Computational Linguistics, 1999.

Kishore Papineni, Salim Roukos, Todd Ward and Wei-Jing Zhu. 2002. *BLEU: a Method for Automatic Evaluation of Machine Translation*, Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL), Philadelphia, July 2002, pp. 311-318.

Latha R. Nair and David Peter S. 2012. *Machine Translation Systems for Indian Languages*, International Journal of Computer Applications (0975 – 8887), Volume 39– No.1, February 2012.

Peter E Brown, Stephen A. Della Pietra, Vincent J. Della Pietra, and Robert L. Mercer*. 1993. *The Mathematics of Statistical Machine Translation: Parameter Estimation*. Association for Computational Linguistics.

Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison-Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, Chris Dyer, Ondrej Bojar, Alexandria Constantin, Evan Herbst. 2007. *Moses: Open Source Toolkit for Statistical Machine Translation*, Annual Meeting of the Association for Computational Linguistics (ACL), demonstration session, Prague, Czech Republic, June 2007.

Raj Dabre, Archana Amberkar and Pushpak Bhattacharyya. 2012. *Morphological Analyzer for Affix Stacking Languages: A Case Study of Marathi*, COLING 2012.

Shachi Dave, Jignashu Parikh and Pushpak Bhattacharyya. 2002. *Interlingua based English-Hindi Machine Translation and Language Divergence*.