Can SMT and RBMT Improve each other's Performance?- An Experiment with English-Hindi Translation

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Abstract

Rule-based machine translation (RBMT) and Statistical machine translation (SMT) are two well-known approaches for translation which have their own benefits. System architecture of SMT often complements RBMT, and the vice-versa. In this paper, we propose an effective method of serial coupling where we attempt to build a hybrid model that exploits the benefits of both the architectures. The first part of coupling is used to obtain good lexical selection and robustness, second part is used to improve syntax and the final one is designed to combine other modules along with the best phrase reordering. Our experiments on a English-Hindi product domain dataset show the effectiveness of the proposed approach with improvement in BLEU score.

1 Introduction

Machine translation is a well-established paradigm in Artificial Intelligence and Natural Language Processing (NLP) which is getting more and more attention to improve the quality (Callison-Burch and Koehn, 2005; Koehn and Monz, 2006). Statistical machine translation (SMT) and rule-based machine translation (RBMT) are two well-known methods for translating sentences from one to the other language. But, each of these paradigms has its own strengths and weaknesses. While SMT is good for translation disambiguation, RBMT is robust for morphology handling. There is no systematic study involving less-resourced languages, where the coupling of SMT and

RBMT has been shown to achieve better performance. In our current research we attempt to provide a systematic and principled way to combine both SMT and RBMT for translating product related catalogs from English to Hindi. We consider English-Hindi scenario as an ideal platform as Hindi is a morphologically very rich language compared to English. The key contributions of our research are summarized as follows:
(i). Proposal of an effective hybrid system that exploits the advantages of both SMT and RBMT.
(ii). Developing a system for translating product catalogues from English to Hindi, which is itself a difficult and challenging task due to the nature of the domain. The data is often mixed, comprising of very short sentences (even the phrases) and the long sentences. To the best of our knowledge, for such a domain, there is no work involving Indian languages.Below we describe SMT and RBMT very briefly.

1.1 Statistical Machine Translation (SMT)

Statistical machine translation (SMT) systems are considered to be good at capturing knowledge of the domain from a large amount of parallel data. This has robustness in resolving ambiguities and other related issues. SMT provides good translation output based on statistics and maximum likelihood expectation (Koehn et al., 2003a):

$$e_{best} = argmax_e P(e|f)$$
$$= argmax_e [P(f|e)P_{LM}(e)]$$

where f and e are the source and target languages, respectively. $P_{LM}(e)$ and $P(f|e)$ are the language and translation model, respectively. The best output translation is denoted

by e_{best}. Language model corresponds to the n-gram probability. The translation probability $P(f|e)$ is modeled as,

$$P(f_1^{-I}|e_1^{-I}) = \prod_{i=1}^{I} \phi(\bar{f}_i|\bar{e_i})d(start_i - end_{i-1} - 1)$$

ϕ is phrase translation probability and d(.) is distortion probability.

$start_i - end_{i-1} - 1$, which is the argument of d(.) is a function of i, whereas $start_i$ and end_{i-1} are the starting positions of the translation of ith phrase and end position of the $(i-1)^{th}$ phrase of e in f. In the above equation, it is well defined that most probable phrases present in training corpora will be chosen as the translated output. This could be useful in handling ambiguity at the translation level. The work reported in (Dakwale and Monz, 2016) focuses on improving the performance of a SMT system. Along with the translation model authors allow the re-estimation of reordering models to improve accuracy of translated sentences. The authors in their work reported in (Carpuat and Wu, 2007) show how word sense disambiguation helps to improve the performance of a SMT system. Literature shows that there are few systems available for English-Indian language machine translation (Ramanathan et al., 2008; Rama and Gali, 2009; Pal et al., 2010; Ramanathan et al., 2009).

1.2 Rule-based Machine Translation (RBMT)

Rule-based system generates target sentence with the help of linguistic knowledge. Hence, there is a high chance that translated sentence is grammatically well-formed.There are several steps required to build linguistic rules for translation. Robustness of a rule-based system greatly depends on the quality of rules devised. A set of sound rules ensures to build a good accurate system. Generally, the steps can be divided into three sub parts:

1. Analysis
2. Transfer
3. Generation

Analysis step consists of pre-processing, morphological analysis, chunking, and pruning. Transfer step consists of lexical transfer, transliteration, and WSD. Finally, generation

step consists of genderization, vibhakti computation, TAM computation, agreement computing, word generator and sentence generator. The agreement computing can be accomplished with three sub steps: intra-chunk, inter-chunk and default agreement computing. In (Dave et al., 2001) authors have proposed an inter-lingua based English–Hindi machine translation system. In (Poornima et al., 2011), authors have described how to simplify English to Hindi translation using a rule-based approach. AnglaHindi is one of the very popular English-Hindi rule-based translation tools proposed in (Sinha and Jain, 2003). Multilingual machine aided translation for English to Indian languages has been developed in (Sinha et al., 1995). Apertium is an open source rule-based machine translation tool proposed in (Forcada et al., 2011). Rule-based approach for machine translation has been proposed with respect to Indian language (Dwivedi and Sukhadeve, 2010).

1.3 Hybrid Machine Translation

A hybrid model of machine translation can be developed using the strengths of both SMT and RBMT. In this paper, we develop a hybrid model to exploit the benefits of disambiguation, linguistic rules, and structural issues. Knowledge of coupling is very useful to build hybrid model of machine translation. There are different types of coupling, *viz.* serial coupling and Parallel coupling. In serial coupling, SMT and RBMT are processed one after another in sequence. In parallel coupling, models are processed in parallel to build a hybrid model. In Indian languages, few hybrid models have been proposed as in(Dwivedi and Sukhadeve, 2010; Aswani and Gaizauskas, 2005).

The rest of the paper is structured as follows. We present a brief review of the existing works in Section 2. Motivations and various characteristic features have been discussed in Section 3. We describe our proposed method in Section 4. Experiential setup and results are discussed in Section 5. Finally, we conclude in Section 6.

2 Related work

In rule-based MT, various linguistic rules are defined and combined in (Arnold, 1994). Statistical machine translation models have resulted from the word-based models (Brown et al., 1990). This has become so popular because of its robustness in translation only with the parallel corpora. As both of this approaches have their own advantages and disadvantages, there is a trend nowadays to build a hybrid model by combining both SMT and RBMT (Costa-Jussa and Fonollosa, 2015). Various architectures of hybrid model have been compared in (Thurmair, 2009). Among the various existing architectures, serial coupling and parallel coupling are the most popular (Ahsan et al., 2010).Rule-based approach along with post-processed SMT outputs are described in (Simard et al., 2007). A review for hybrid MT is available in (Xuan et al., 2012). In (Eisele et al., 2008), authors proposed an architecture to build a hybrid machine translation engine by following a parallel coupling method. They merged phrase tables of general training data of SMT and the output of RBMT. However, they did not consider the source and target language ordering characteristics. In this paper, we combine both SMT and RBMT in order to exploit advantages of both the translation strategies.

3 Necessity for Combining SMT and RBMT

In this work we propose a hybrid architecture for translating English documents into Hindi. Both of these languages are very popular. English is an international language, whereas Hindi is one of the very popular languages. Hindi is the official language in India and in terms number of native speakers it ranks fourth in the world.Linguistic characteristics of English and Hindi are not similar and their differences are listed below:

- Hindi is a relatively morphologically richer language compared to English.

- Word orders are not same for English and Hindi. Subject-Object-Verb (SOV) is the standard way to represent Hindi whereas SVO ordering is followed for English.

- Hindi uses postposition whereas English uses preposition.

- Hindi uses pre-modifiers, whereas English uses post-modifiers.

SMT and RBMT can not solve the problems as mentioned above independently.So, main focus of our current work is to develop a hybrid system combining both SMT and RBMT which can efficiently solve the problems.In addition to combining these two methods we also introduce reordering to improve the translation quality. Our main motivation was to make use of the strength of SMT (better in handling translation ambiguities) and RBMT (better for dealing with rich morphology)

3.1 Morphology

As already mentioned Hindi is a morphologically richer language compared to English. Morphology plays an important role in the translation quality of English-Hindi. Let us consider the examples: case: ए (e – plural direct) or ओं (on – plural oblique) is used as plural-marker for "boy". But in the case of "girl" याँ (on) is used for plural direct, and ओं (on) is used for plural oblique.

Singular direct:
E: The boy is going.
H: लड़का जा रहा है।
HT: Ladka ja raha hai.
E: The girl is going.
H: लड़की जा रही है।
HT: Ladki ja rahi hai.

Plural direct:
E: The boys are going.
H: लड़के जा रहे हैं।
HT: Ladke ja rahe hain.
E: The girls are going.
H: लड़कियाँ जा रही हैं।
HT: Ladkiya ja rahi hae.

Singular oblique:
E: I have seen a boy.
H: मैं ने एक लड़के को देखा।
HT: Main ne ek ladke ko dekha.
E: I have seen a girl.
H: मैं ने एक लड़की को देखा।
HT: Main ne ek ladki ko dekha.

plural oblique:

E: I have seen five boys.

H: मैं ने पाँच लड़कों को देखा।

HT: Main ne paanch ladkon ko dekha.

E: I have seen five girls.

H: मैं ने पाँच लड़कियों को देखा।

HT: Main ne paanch ladkiyon ko dekha.

Tense: Tenses are directed by the verbs. For example, एगा (aega) and एगी (aegi) denote future connotation in singular form for masculine gender and feminine gender, respectively. आएगा (ayega), आएगी (ayegee). एंगे (aenge) and एंगी (aengi) denote future tense in plural form for masculine and feminine geneder, respectively. Here we show the few usages:

Singular form in future tense:-

E: The boy will come.

H: लड़का आएगा ।

HT: ladka ayenga

E: The girl will come.

H: लड़की आएगी ।

HT: ladki ayegi

Plural form in future tense:-

E: Boys will come.

H: लड़के आएंगे ।

HT: ladke ayenge.

E: Girls will come.

H: लड़कियाँ आएंगी ।

HT: ladkiyan ayengi.

The above examples describe how morphology influences the structure and meaning of the language. A root word can appear in different forms in different sentences depending upon tense, number or gender. Such kinds of diversities can not be handled properly by a SMT system because of lack of data or enough grammatical evidences. This can, however, be handled efficiently in a RBMT system due to the richness of linguistic rules that it embeds. It is very important to have all the morphological forms and case structures along with their equivalent representations in the target language. Under this scenario, hybridization of SMT and RBMT is a more preferred approach.

3.2 Data Sparsity

While translating from English to Hindi we encounter with the problems of data sparsity

due to the variations in morphology and case marking in source and target language pairs.

From the examples shown in the previous subsection, it is seen that same word may appear in different positions of a sentence, often followed or preceded by different words, due to varying morphological properties such as case, gender and number information. For example, the English word 'girl' can be translated to लड़की (ladki), लड़कियाँ (ladkiyan), लड़कियों (ladkiyon) etc. in Hindi based on case and number information. Even though both लड़कियाँ (ladkiyan) and लड़कियों (ladkiyon) are in plural forms, they convey differnt meanings based on the context. The word लड़कियों (ladkiyon) is placed with case markers, but लड़कियाँ (ladkiyan) is used without it. The word 'Child' can be बच्चा (bachcha) and बच्चे ने (bachche ne) in singular form in direct and oblique cases, respectively. Here, ने is followed by बच्चों (bachchon), but if बच्यो ने (bachchon) ne) does not occur in corpora then it can not be translated.

Such problems can be resolved using proper linguistic knowledge, which is the strength of a rule-based system.In statistical approach, system is modeled using a probabilistic method that retrieves the target phrase based on maximum likelihood estimates. Hence, this may not be possible to resolve the issues using a SMT system. In contrast, RBMT has the power to deal with such situation that incorporates proper grammatical knowledge.

3.3 Ambiguity

Ambiguity is a very common problem in machine translation. Ambiguities can appear in many different forms. For example, the following sentence has ambiguities at the various levels:

E: I went with my friend Washington to the bank to withdraw some money, but was disappointed to find it closed.

Bank may be verb or noun-Part of speech ambiguity.

Washington may be a person name or place-Named entity ambiguity.

Bank may be placed for the borders of a water body or financial transaction- Sense ambiguity.

The word `it` has to be disambiguated to

understand its proper reference-Discourse/co-reference ambiguity.

It is not understood who was disappointed for the closure of bank (Pro-drop ambiguity).

3.3.1 Semantic Role Ambiguity

Let us consider the following example sentence:

H: मुझे आपको मिठाई खिलानी पड़ेगी

HT: Mujhe aapko mithae khilani padegee.

In this sentence, it is not properly disclosed who will feed the sweets (to/by me or to/by you). Thus, English sentence for the above Hindi sentence may take any of the following forms:

E1: I have to feed you sweets.

E2: You have to feed me sweets.

3.3.2 Lexical Ambiguity

We discuss the problem of lexical ambiguity with respect to the following example sentence.
E: I will go to the bank for walking today.

Here, bank may be a financial institution or the shore of a river or sea. It is difficult to interpret exact meaning of bank. Context plays an important role in interpreting the current sense. Here, bank is used in the context of walk. Hence, there is a greater chance that it denotes the `bank of river`' instead of `financial institution`. Use of proverbs complicates translation further.

E: An empty vessel sounds much.

H: थोथा चना बाजे घना. / अधजल गगरी छलकत जाय.

HT: Thotha chana baaje ghana./ adhajal gagaree chhalkat jai.

Its actual meaning should be जिसको कम ज्ञान होता है वो दिखावा करने के लिए अधिक बोलता है. (jisko kam gyan hota hai wo dikhava karne ke liye adhik bolta hai.)

All of the above mentioned issues can not be efficiently handled by statistical or rule-based approach independently. Some of the issues are better handled by a RBMT approach whereas some are better handled by a SMT system. In this paper we develop a hybrid model by combining the benefits of both rules and statistics.

3.4 Ordering

We further study the effect of ordering in our proposed model. Ordering can be considered as a basic structure of any language. Different languages have different structure patterns at sentence which can be achieve after merging PoS. For example, English uses subject-verb-object (SVO) whereas Hindi uses subject-object-verb (SOV). These structural differences of language pair can be the vital cause of affecting the accuracy. So, we shall incorporate the concept of ordering along with SMT and RBMT to build the hybrid model.

4 Proposed MT Model: A Multi-Engine Translation System

We propose a novel architecture that improves translation quality by combining the benefits of both SMT and RBMT. We also devise a mechanism to further improve the performance by integrating the concept of reordering at the source side. This architecture is trying to combine the best parts from multiple hypothesis to achieve maximum advantages of different MT engines and remove the pitfall of the translated texts so that the quality of the translated text could be improved. Translation models are combined in such a way that the overall performance is improved over the individual models. In literature it was also shown that an effective combination of different complimentary models could be more useful (Rayner and Carter, 1997; Eisele et al., 2008).

Combining multiple models of machine translations is not an easy task because of the following facts: RBMT is linguistically richer than SMT; RBMT can produce different word orders in the target sentence compared to SMT; and there may have different word orders for the SMT and RBMT outputs. After using linguistic rules at the source side of the test set, we combine the outputs obtained to the training set, and generate new hypothesis to build a better phrase table. Finally, we use argmax computation of SMT decoder to find the best possible sequence. A combined model can not produce expected output if the individual component models are not strong enough. Word ordering plays an important role to improve the quality of translation, es-
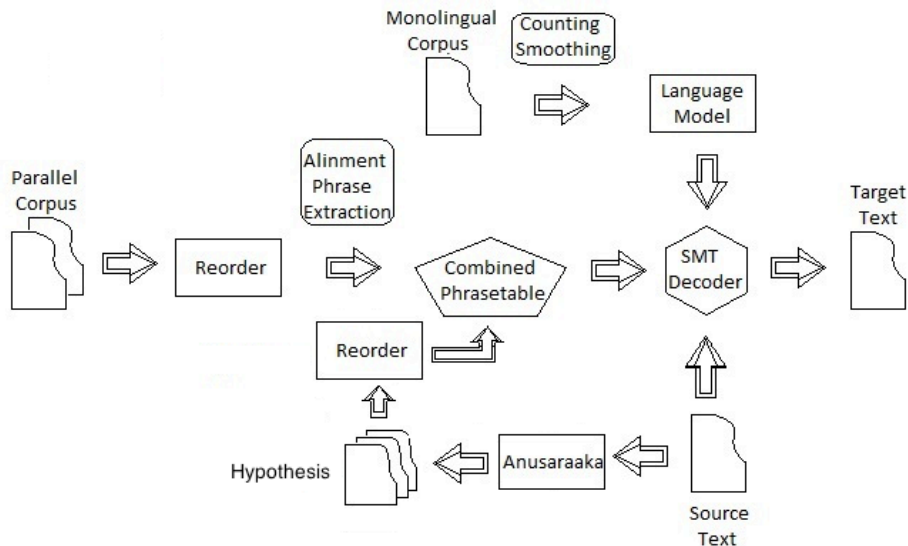
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Figure 1: Architecture for multi-engine MT driven by a SMT decoder

pecially for the pair of languages where source language is relatively less-rich compared to the target. Our source language, which is English, follows a Subject-Verb-Object (SVO) fashion whereas Hindi follows a Subject-Object-Verb (SOV) ordering scheme. At first we extract syntactic information of the source language. The syntactic order of source sentence is converted to the syntactic order of target language. The source language sentences are pre-processed following the set of transformation rules as detailed in (Rao et al., 2000).

$$SS_m V V_m OO_m C_m \quad \rightarrow \quad C'_m S'_m S' O'_m O' V'_m V'$$

where,
S: Subject
V : Verb
O: Object
X': Hindi corresponding constituent, where X is S, V, or O X_m: modifier of X
C_m: Clause modifier

Pre-ordering alters the English SVO order to Hindi SOV order, and post-modifiers generate the pre-modifiers. Our prepossessing module performs this by parsing English sentence and applying the reordering rules on the parse tree to generate the representations in the target side. After pre-ordering of source sentences, we combine the RBMT and SMT based models.After pre-ordering of training and tuning corpora we also do the same for the test set. Alignment was done using the hypothesis of

RBMT.Beam search algorithm of SMT decoder is used to obtain the best target sentence. Detailed architecture of the proposed technique is shown in Figure 1. In this figure, lower portion represents different modules and resources used in the RBMT model, whereas the upper portion represents the SMT model. Because of this effective combination we obtain a model that produces target sentences of better qualities compared to either RBMT or SMT with respect to morphology and disambiguation (at the level of lexical and structural).

Sets	Number of sentences
Training Set	111,586
Tune Set	602
Test Set	5,640

Table 1: Datasets statistics

5 Data Set, Experiential setup, Result and analysis

5.1 Data Set

In this paper we develop a hybridized translation model for translating product catalogs from English to Hindi.The training corpus consists of 111,586 English-Hindi parallel sentences. Tune and test sets comprise of 602 and 5,640 sentences, respectively. Brief statistics of training, tune and test sets are shown in Table 4. The domain is, itself, very challenging due to the mixing of various types of sentences. There

Approach	BLEU Score
Baseline (Phrase-based SMT)	45.66
RBMT	5.34
SMT & RBMT	46.66
Our Approach	50.71
Improvement from Baseline	11.06%
Improvement from SMT & RBMT	8.67%

Table 2: Results of different models

are sentences of varying lengths consisting of minimum of 3 tokens to the maximum of 80 tokens. Average length of the sentences is approximately 10. In one of our experiments we distributed the sentences into short and long sets, containing less than 5 and more than equal to 5 sentences, respectively. Training, tuning and evaluation were then carried out, which reveals that performance deteriorates due to the reduction in size. Hence, we mix all kinds of sentences for training, and then tune and test.

5.2 Experiential Setup

We use the pre-order tool developed at CFILT lab. (Dwivedi and Sukhadeve, 2010) We use Moses [1] setup for SMT related experiments. The model is tuned using a tuning set. We use ANUSAARAKA (Ramanathan et al., 2008) rule-based system for translation. Phrase tables are generated by training SMT model on the parallel corpora of English-Hindi. The RBMT system is evaluated on the test data. The outputs produced by this model are used as the silver standard data. The SMT model is trained on this silver standard data to produce a phrase table. The phrase table, thus obtained, is added to the phrase table generated using the original training data. Secondly, the silver standard parallel corpora is added to the original training corpora and a new parallel corpora is generated. The SMT model is again built on this new data-set. This generated model is used to evaluate the test set thereafter.

5.3 Results and Analysis

We report the experimental results in Table 4. Accuracy is calculated using the standard evaluation metric called BLEU (Papineni et al., 2002). A baseline model (Phrase-based SMT model) is developed by training Moses

with default parameter settings (Koehn et al., 2003b). We achieve a BLEU score of 45.66. Our proposed hybrid model attains a BLEU score of 46.66, which is 2.19% higher compared to the baseline model. When re-ordering is performed at the source side, we obtain the BLEU score of 50.71, which is nearly 8.68% higher compared to the hybrid model (without re-ordering) . This is 11.06% higher compared to the baseline phrase-based model. Generated outputs of the proposed model are better in various respects like structure, morphology etc. With the following examples, we describe how the proposed model can be used to improve the performance over SMT or RBMT model. Here ST, SMT, AMT, HMT, and PMT denote source sentence, SMT output, RBMT output, output of the hybrid model and output of the proposed system, respectively.

a. SMT output is incomplete while PMT output is complete and better than SMT output.

ST: All applicable shipping fees and custom duties up to customers address are included in the price

SMT: डिलीवरी तक लागू सभी कस्टम और शुल्क जोड़े जा चुके हैं इस दाम में

HT: Delivery tak lagu sabhi custom aur shulk joden ja chuke hain is daam mein

PMT: डिलीवरी तक लागू सभी कस्टम और शुल्क ग्राहक के घर तक शिपिंग के मूल्य में शामिल हैं

HT: Delivery tak lagu sabhi custom aur shulk grahak ke ghar tak shipping ke mullya mein samil hain

AMT: सब ग्राहकों जहाँ तक कि शुल्क और रिवाज कार्य जहाज से भेजता हुआ लागू होना पते मूल्य में सम्मिलित हुए गये हैं

HT: Sab grahakon jahan tak ki shulk aur rivaz karya jahaz se bhejta hua lagu hona pate mulya mein sammilithue gaye hain

[1] http://www.statmt.org/moses/

b. PMT output is a reordered version of SMT which is an exact translation. Hence, this is better compared to the others. Also PMT retrieves proper phrase to generate better quality. ST: Add loads of flirty colours to your wardrobe!

SMT: में शोख रंगों को शामिल करें अपनी अलमारी

HT: mein shokh rangon ko shamiln karen apni almaree

PMT: अपनी अलमारी में शोख रंगों को शामिल करें

HT:apni almaree mein shokh rangon ko shamil karen

AMT: आपकी अलमारी को इश्कबाज रङ्गों के बहुत जोडिए!

HT:aapki almaree ko ishqbaaz radgon ko bahut jodiye

c. PMT is capable to select better sentence of generated translated output by both of the systems. AMT is better than SMT. PMT produces quite simliar output as AMT. Hence, the overall quality will improve.

ST: A classy way to hang your clothes

SMT: एक उत्तम दर्जे के तरीका अपने कपड़े सिर्फ लटका कर

HT Ek utam darje ke tareeka apne kapde sirf latka kar

PMT: एक विशेष एवं उच्चतम मार्ग आपके वस्त्र लटकाने का

HT: Ek vishesh evam uchchtam marg apke vastra latkane ka.

AMT: एक विशेष एवं उच्चतम मार्ग आपके वस्त्र लटकाने का

HT: Ek vishesh evam uchchtam marg apke vastra latkane ka.

d. PMT output is better because it is in correct syntax order (ends in verb).

ST: 11 Diamonds provides lifetime manufacturing & exchange warranty

SMT: प्रदान करता है 11 हीरे और एक्सचेंज वारंटी जीवन भर निर्माण

HT: Pradan karta hai 11 hire or exchange warranty jeevan bhar nirman

PMT: 11 डायमंड आजीवन निर्माता और एक्सचेंज वारंटी देता है

HT: 11 diamond aajeevan nirmata aur exchange warranty deta hai

AMT: 11 डाइमन्ड्ज जीवन-काल उत्पादन और अदला बदला अधिकार देता है

HT: Diamond jeevan-kaal utpadan aur adla badla adhikar deta hai

It is out-of-scope to compare the existing English-Hindi MT systems (as mentioned in the related section) as none of the techniques was evaluated on the product catalogue domain. Since the domain as well as the training and test data are different, we can not directly compare our proposed system with the others. It is also to be noted that none of the existing systems makes use of an infrastructure like ours. The multi-engine MT model proposed in (Eisele et al., 2008) can not be compared as this was not evaluated for the language pair and domain that we attempted.

6 Conclusion

In this paper we have proposed a hybrid model to study whether RBMT and SMT can improve each other's efficiency. We use an effective method of serial coupling where we have combined both SMT and RBMT. The first part of coupling has been used to obtain good lexical selection and robustness, second part has been used to improve syntax and the final one has been designed to combine other modules along with source-side phrase reordering. Our experiments on a English-Hindi product domain dataset show the effectiveness of the proposed approach with improvement in BLEU score. In future we would like to evaluate the proposed model on other domains, and study hierarchical SMT model for the product catalogues domain.

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